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Martin Paegelow · María Teresa Camacho Olmedo (*Eds.*)

Modelling Environmental Dynamics

Advances in Geomatic Solutions

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Prof. Martin Paegelow
Université de Toulouse II
GEODE UMR 5602 CNRS
Maison de la Recherche
5 allées Antonio Machado
31058 Toulouse
France
paegelow@univ-tlse2.fr

Prof. María Teresa Camacho Olmedo
Universidad de Granada
Dpto. de Análisis Geográfico
Regional y Geografía Física
Campus de Cartuja, s/n
18071 Granada
Spain
camacho@ugr.es

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Foreword

Humans have always created and used environmental models, whether the models are expressed as traditional fables that are designed to convey ancient wisdom concerning how we should interact with nature or as computerized algorithms that are designed to give advice concerning the how we should draft environmental legislation. In both cases, the models express what we think we know about human-environment interactions and what the implications are for natural resource management. In both cases, scenarios are commonly used as communication device, since a scenario is a story about the way the future could unfold, based on the consequences of human decisions. A major difference between today's models and previous models is that digital technology is now available to help to organize the story teller's thoughts and to communicate the teller's messages. Today's digital modelling techniques can have substantial influence on both the people designing the stories, e.g. the scientists, and the people interpreting the stories, e.g. the decision makers and the public.

Some of today's models, such as those that produce weather forecasts, are so common that both the scientists and the public seem to interpret them with ease. For example, people who have access to the internet can easily see a map of a weather forecast and usually know intuitively how much trust they can have in the prediction for their particular region. We has been able to develop this intuition because we can engage in a frequently repeated validation exercise by seeing such forecasts and comparing them to the weather that we personally experience. We have had much less direct experience with other types of simulation models that produce maps. For example, some models produce maps that predict the environmental impacts of anticipated global climate change. It is not immediately clear how humans should interpret maps from models that attempt to predict phenomena that have never happened before. Even scientist themselves are challenged by creating and interpreting models concerning processes that either have not occurred before or occur gradually over long time scales, such as climate change and land change. Nevertheless, it is precisely these types of changes that are important to model, because many of their consequences are large and practically irreversible.

This book presents some of the most recent work in modelling the interaction between humans and the environment, especially where anthropogenic land change is a central focus. Land change is important to model due its particular characteristics. First of all, many of the effects of land change are physically irreversible, such as loss of biodiversity, deposition of hazardous wastes, or construction on high quality agricultural soil. For those land transitions that are theoretically reversible, many are unlikely to be reversed for social reasons, since many actors become rapidly invested financially and legally in an established land use pattern. Furthermore, land use has substantial implications for how individual lifestyle choices are constrained. For example, the landscape in the United States is designed for travel by car, not by bicycle or by foot. The consequences are that greenhouse gas emissions from American cars have become a threat to global health, and obesity in the United States has become a primary threat to Americans' personal health. Many other countries are presently developing similar landscapes, and are likely to face similar consequences if they choose to follow the American style of suburbanization and urban sprawl.

How should scientist and the public address such issues? Land change modelling offers a potentially useful set of tools, while such modelling has its challenges. Scientists, policy makers, and the public do not have as much experience in interpreting output from land change models over several decades as they do for other types of forecasts. Land transformation processes are relatively slow compared to weather changes, so it is difficult for scientists and non-scientist to develop an intuitive feel for how much trust we should have in such models. Calibration of these models can be complicated in some places where we would like to simulate a phenomenon that has never occurred before, such as building entirely new roads through virgin forests. Validation can be complicated by the fact that the processes during the calibration time interval may be different than the processes during the validation time interval, due to a sudden change in agricultural policy for example. Moreover, there are a seemingly infinite number of ways to calibrate a model and to measure its accuracy during a validation step. Some of the measurements of accuracy that are most intuitive initially, such as percent of pixels classified correctly, can be extremely misleading. The method by which the model is used to inform policy may be even more important than the particular computer algorithm used. It is helpful when models can offer insight to a wide variety of decision-makers, while we cannot expect non-experts to grasp immediately the differences among neural nets, cellular automata, agent based models, fuzzy logic, and logistic regression. However, if the model design allows for it to be used in a participatory fashion, then a larger number of people can be involved in an interactive process of modelling and decision-making.

Regardless of what you may think of environmental models, they are here to stay and will become even more important in the coming decades. Land change models in particular will become ever more influential as our global society wrestles with policies to reduce greenhouse warming. One proposed policy calls to implement carbon offset projects that would offer financial incentives to reduce deforestation. This plan is being carried out via a carbon credit trading system, where a credit is awarded for a conservation project that prevents deforestation that would have occurred, had it not been for the project. How do we compute how much deforestation the conservation project prevented from occurring? The answer is land change modelling. In the coming years, billions of dollars will be exchanged annually for greenhouse gas credits that are based on output from such environmental models. There is big money on the line based on the output from environmental models. More importantly, the viability of our most precious ecosystems is also on the line.

Some critics express concern that such models contain substantial uncertainties. Uncertainties will always exist in any type of model. But one thing is for certain: if we wait for the uncertainties of these models to be eliminated before we implement policy to preserve valuable ecosystems, then those ecosystems and their accompanying services will be lost, because the processes of land disturbance are already well underway in some of our planet's most important locations. Therefore, we need methods to design, to use, and to interpret models in intelligent ways that both appreciate the level of the model's uncertainty and acknowledge the urgency of our environmental challenges. This book marks a major step forward in advancing the agenda concerning the implementation and interpretation of environmental models. Whereas our traditional models in the form of fables expressed general guiding principles for behaviour, we need for our next generation of models in the form of computer code to give specific guidance concerning our options for environmental management. Hopefully, humans will learn how to use these models to integrate and to communicate important lessons of ancient and modern wisdom, before it is too late.

Robert Gilmore Pontius Jr.

Department of International Development, Community and Environment, Graduate School of Geography, Clark University, Worcester, United States of America
http://www.clarku.edu/~rpontius

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The editors are very thankful to all of the contributing authors. The strength of this book lies in the international cooperation, which creates a rich diversity of modelling approaches and themes.

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Preface

This book begins with the observation that modelling environmental dynamics becomes more urgent everyday. It becomes all the more pressing because modelling results can contribute to a better understanding of current, complex phenomena and time projections using predictions and scenarios which can resolve many of the challenges that occur in daily life: global climatic changes, biodiversity, deforestation, risk prevention and land planning at the local level, etc. A great deal of research has been completed. In spite of this, actual modelling tools remain exploratory rather than operational and most of them can't be applied in common policy instruments intended to avoid or even resolve the above-mentioned problems. Also today's accessibility of user-friendly modelling tools also brings with it some risks; it seems easy to model practically anything. Particularly newsworthy topics such as global change links to the increase of temperature, the melting of ice caps or the discussed cessation of the Gulf Stream have become subject to numerous publications using models and predicting more or less catastrophic simulations. In spite of numerous, serious research results and crucial planetary stakes we have to remain humble and critical and ask ourselves about the degree of our understanding of complex environmental systems, the amount and the quality of the data used and the validation of model results. These are major topics in this book, which presents various research results in modelling environmental dynamics in a transparent way focussing on result validation.

What is this book about?

The main objective of this book is to contribute to advances in modelling environmental dynamics involving both: the spatial and the temporal dimension. The goal is to perform simulations either as probabilistic predictions or scenarios showing 'what will be if'. The aims of modelling are various and cover a wide range stretching from better comprehension to decision support.

During the last few years, the modeller's toolbox has become significantly enriched by novel methods such as fuzzy logic, multi-agent systems or neural networks to resolve geographical problems. This book, starting with an introductory overview about the challenges and modelling approaches, provides a sample of actual research results using a variety of modelling methods and tools applied to an assortment of environmental dynamic situations. It also shows a wide range of model results and topical modelling conceptualisation like participatory modelling. All of these contributions follow the same structure and emphasize mainly the methodological aspects such as model calibration and model validation.

What is this book not about?

Modelling is, from a conceptual point of view, a current and important issue in many research areas. A lot of concepts and methods are emerging. This book doesn't offer new conceptual or methodological advances but it shows validated modelling results based on innovative methods like neural network, multi-agent system, cellular automaton, fuzzy modelling and more traditional, mostly stochastic, approaches.

For this reason, this is a first actual set of case studies, and some theoretical aspects can't be discussed in depth. However, in part A of this book, there is an attempt at creating a synoptic summery with numerous references to help the user find further reading.

However with the harmonized presentation of the contributions, this book is neither a manual nor a tutorial.

How to use this book

This book is written for academics, students and professionals belonging to a wide range of disciplines like geography, geomatics, environmental sciences, land planning and urbanism with at least an initial experience with spatio-temporal data, GIS and modelling. It also may be a welcome application example for specialists the in computer sciences dealing with spatio-temporal data. The gradual concept of the book and the presentation of performed research results, which are presented using the same structural set-up in each chapter, may make it useful for more thematic experts too.

Since the audience has various levels of knowledge and experience in geomatics and modelling and different academic and professional backgrounds, the book starts with a succinct overview about modelling (what, with what and for what?). Advanced readers may skip this introductory part and turn their attention directly to the following case studies. Each of them provides a large list of references for further reading.

Structure of the book

This book contains two main parts: a brief introduction to modelling and a set of case studies.

Part A launches basic ideas about modelling environmental dynamics starting with its challenge. In this chapter the reader will find the scientific context of this work and its objectives: *What*? Environmental dynamics. *With what*? Geomatics solutions. *For what*? Outcome, modelling for simulation. This first chapter is completed with a summary of the opportunities created by this book as well as references to some earlier works.

The second chapter of part A is about modelling approaches and shows a methodological overview followed by a description of commonly used modelling tools (software). As this book is particularly interested in the validation of model outputs; a topic presents model validation techniques.

Part A ends with the description of case studies to follow in Part B. At this point, the authors compare the thirteen contributions presented by developing and discussing a list of relevant topics: themes and objectives, related time scales, chosen modelling approaches and tools, involved databases, used study areas and scales, performed calibration, results and validation techniques and the outcome and originality of each work.

Part B of this book is a collection of thirteen case studies carried out by researchers from Brazil, France, Italy, Mexico and Spain. Each contribution deals with spatio-temporal data and presents validated model outputs in the form of time projections: predicting simulation or scenarios. Considering that the modelled objects, the conceptual and methodological approaches as well as the finality of modelling are very diverse, therefore each contribution follows the same structure. Abstracts offer a summery accessible to a large readership. Every contribution begins with an introduction clarifying the context and the main problems. The description of the test areas and data sets ensure transparency with regard to the performed results. The methodological part is split into two subchapters to improve the readability: methodology and practical application of the data sets. The presentation of the achieved results is followed by their validation and discussion. All articles have a conclusion and an outlook and are completed with acknowledgements and references.

Toulouse and Granada, April 2008

Martin Paegelow and María Teresa Camacho Olmedo

Contents

List of authors

Francisco Aguilera Benavente
Laboratorio de Urbanismo y Ordenación del Territorio, Universidad de Granada, Spain.
http://www.urbanismogranada.com/
E-mail: franab@ugr.es

José I. Barredo
Institute for Environment and Sustainability. European Comission–Joint Research Centre, Ispra, Italy.
http://ec.europa.eu/dgs/jrc/index.cfm?id=1550&lang=en
E-mail: jose.barredo@jrc.it

Blas Benito de Pando
Departamento de Botánica, Universidad de Granada, Spain.
http://www.ugr.es/~botanica/index.htm
E-mail: blasbp@ugr.es

Roberto Bruno
Dipartimento di Ingegneria Chimica, Mineraria e Delle Tecnologie Ambientali, DICMA, Università di Bologna, Italy.
http://www.dicma.unibo.it/DICMA/default.htm
E-mail: roberto.bruno@mail.ing.unibo.it

María Teresa Camacho Olmedo
Departamento de Análisis Geográfico Regional y Geografía Física. Universidad de Granada, Spain.
http://www.ugr.es/~geofireg/centro.htm
E-mail: camacho@ugr.es

Gabriela Cuevas
Centro de Investigaciones en Geografía Ambiental-Universidad Nacional Autónoma de México, Morelia, Mexico.
http://www.ciga.unam.mx/ciga/
E-mail: gcuevas@pmip.unam.mx

Michel Etienne
INRA, Unité d'Ecodéveloppement, Avignon, France.
http://www.avignon.inra.fr/les_recherches__1/liste_des_unites/ecodeveloppement__1
E-mail: etienne@avignon.inra.fr

Frédéric Ferraty
Institut de Mathématiques de Toulouse UMR 5219 CNRS, Université Toulouse III, France.
http://www.math.ups-tlse.fr/
E-mail: ferraty@univ-tlse2.fr

Louis Ferré
Institut de Mathématiques de Toulouse UMR 5219 CNRS, Université Toulouse III, France.
http://www.math.ups-tlse.fr/
E-mail : loferre@univ-tlse2.fr

Marco Follador
Institute for Environment and Sustainability. European Commission – DG Joint Research Centre, Ispra, Italy.
http://ec.europa.eu/dgs/jrc/index.cfm?id=1550&lang=en
E-mail: marco.follador@jrc.it

Jean-François Galtié
GEODE UMR 5602 CNRS, Université de Toulouse – Le Mirail, France.
http://w3.geode.univ-tlse2.fr/
E-mail : galtie@univ-tlse2.fr

Pilar García Martínez
Departamento de Antropología, Geografía e Historia. Universidad de Jaén, Spain.
http://www.ujaen.es/dep/terpat/
E-mail: pgarcia@ujaen.es

Annick Gibon
DYNAFOR UMR 1201, INRA, Toulouse, France.
http://www.inra.fr/toulouse_dynafor/
E-mail: annick.gibon@toulouse.inra.fr

Montserrat Gómez Delgado
Departamento de Geografía, Universidad de Alcalá, Spain.
http://www.geogra.uah.es/inicio/index.php
E-mail: montserrat.gomez@uah.es

Gabriela Guerrero
Centro de Investigaciones en Ecosistemas, Universidad Nacional Autónoma de México, Mexico.
http://www.oikos.unam.mx/cieco/
E-mail: 1gguerrer@oikos.unam.mx

Marcela Godoy
AngloGold Ashanti Brasil Mineração, Nova Lima, Minas Gerais, Brazil.
http://www.anglogold.com.br/default.htm
E-mail: marcelamgg@yahoo.com

Sylvie Ladet
DYNAFOR UMR 1201, INRA, Toulouse, France.
http://www.inra.fr/toulouse_dynafor/
E-mail : sylvie.ladet@toulouse.inra.fr

Jean-François Mas
Centro de Investigaciones en Geografía Ambiental-Universidad Nacional Autónoma de México, Morelia, Mexico.
http://www.ciga.unam.mx/ciga/
E-mail: 2jfmas@ciga.unam.mx

Omar Masera
Centro de Investigaciones en Ecosistemas, Universidad Nacional Autónoma de México, Mexico.
http://www.oikos.unam.mx/cieco/
E-mail: omasera@oikos.unam.mx

Alberto Matarán Ruiz
Laboratorio de Urbanismo y Ordenación del Territorio, Universidad de Granada, Spain.
http://www.urbanismogranada.com/
E-mail: mataran@ugr.es

Tania Mezzadri-Centeno
Departamento Acadêmico de Informaticá, Universidade Tecnológica Federal do Parana, Curitiba, Brazil.
http://www.dainf.cefetpr.br/
E-mail: mezzadri@dainf.cefetpr.br

Emilio Molero Melgarejo
Laboratorio de Urbanismo y Ordenación del Territorio, Universidad de Granada, Spain.
http://www.urbanismogranada.com/
E-mail: emiliomolero@ugr.es

Claude Monteil
DYNAFOR UMR 1201, INPT-ENSAT, Toulouse, France.
http://www.inra.fr/toulouse_dynafor/
E-mail: monteil@ensat.fr

Martin Paegelow
GEODE UMR 5602 CNRS, Université de Toulouse – Le Mirail, France.
http://w3.geode.univ-tlse2.fr/
E-mail: paegelow@univ-tlse2.fr

Rocío Pérez Campaña
Laboratorio de Urbanismo y Ordenación del Territorio, Universidad de Granada, Spain.
http://www.urbanismogranada.com/
E-mail: rociopc@ugr.es

Julio Peñas de Giles
Departamento de Botánica, Universidad de Granada, Spain.
http://www.ugr.es/~botanica/index.htm
E-mail: jgiles@ugr.es

Fernanda Renno
GEODE UMR 5602 CNRS, Université de Toulouse – Le Mirail, France & & The Capes Fondation, Ministry of Education of Brazil.
http://w3.geode.univ-tlse2.fr/
E-mail: renno@univ-tlse2.fr

Pascal Sarda
Institut de Mathématiques de Toulouse UMR 5219 CNRS, Université Toulouse III, France.
http://www.math.ups-tlse.fr/
E-mail: sarda@univ-tlse2.fr

Gilles Selleron
GEODE UMR 5602 CNRS, Université de Toulouse – Le Mirail, France.
http://w3.geode.univ-tlse2.fr/
E-mail: selleron@univ-tlse2.fr

David Sheeren
DYNAFOR UMR 1201, INPT-ENSAT, Toulouse, France.
http://www.inra.fr/toulouse_dynafor/
E-mail : david.sheeren@ensat.fr

Britaldo Silveira Soares-Filho
Centro de Sensoriamento Remoto / Centro de Desenvolvimento e Planejamento Regional. Universidade Federal de Minas Gerais, Belo Horizonte, Brazil.
http://www.csr.ufmg.br/
E-mail: britaldo@csr.ufmg.br

Christophe Simon
DYNAFOR UMR 1201, INRA, Toulouse, France.
http://www.inra.fr/toulouse_dynafor/
E-mail: christophe.simon@toulouse.inra.fr

José Alberto Soria Lara
Laboratorio de Urbanismo y Ordenación del Territorio, Universidad de Granada, Spain.
http://www.urbanismogranada.com/
E-mail: jsoria@ugr.es

Luis Miguel Valenzuela Montes
Laboratorio de Urbanismo y Ordenación del Territorio, Universidad de Granada, Spain.
http://www.urbanismogranada.com/
E-mail: lvmontes@ugr.es

Nathalie Villa
Institut de Mathématiques de Toulouse UMR 5219 CNRS, Université Toulouse III, France.
http://www.math.univ-toulouse.fr
E-mail: nathalie.villa@math.univ-toulouse.fr

PART A

CONCEPTS, TOOLS AND APPLICATIONS

1 Advances in geomatic simulations for environmental dynamics

Paegelow M and Camacho Olmedo MT

Abstract
Modelling environmental dynamics aids in the understanding and anticipation of future evolutions. Their prospective simulation supports decision-making for environmental management. This introductory chapter gives an overview about the context, objectives and opportunities (the challenges), followed by a summery of the methodological approaches commonly used in environmental modelling and simulation. Based on this general opening, the third part presents comprises chapters, which are case studies applying various models to a large array of themes: deforestation in tropical regions, fire risk, natural reforestation in European mountains, agriculture, biodiversity, urbanism, and land management. In this section, authors provide a comparison of these case studies based on several criteria such as objectives, scales, data, study areas, calibration and validation techniques, results and outcome.

Keywords: Modelling, spatio-temporal dynamics, environment, validation, geomatics.

1.1 Challenge

1.1.1 Context

The modelling of environmental dynamics means the simulation of the behaviour of an environmental system in space and through time. This research challenge has many aspects such as a better comprehension of complex environmental processes or decision support for environmental management and land planning. Anticipating 'what would happen if' has become a routine question in many research domains such as risk prevention, environmental impact studies, etc. Geomatics, and especially Geographical Information Systems (GIS), deal with spatio-temporal data. At first GIS was only able to process spatial queries such as the overlaying of different layers or attribute queries based on relational data bases. During the last few decades, these traditional GIS functions were enhanced with new components including a temporal dimension. Today various GIS software offers either generic or objective specific modelling tools of interest for geography and environmental sciences, which are able to assist in research challenges such as global climate change or land use/land cover dynamics. While classical GIS achieves only one step in order to resolve actual problems in land planning and environmental management, and must be connected to one or several specific software, the latest generation of geomatic tools, such as GIS, offers integrative and flexible toolboxes.

Geocomputation (Atkinson and Martin 2000, Openshaw and Abrahart 2000) is a new term referring to this new group of more complex techniques in GIS that includes computer techniques such as artificial neural networks, fuzzy logic or genetic programming. Brimicombe (2003) talks about a new paradigm (the geocomputational paradigm) combining GIS, simulation modelling and engineering.

Buzai (2006) points out that geocomputation, together with geographical information science and integrated social sciences form the three new fields in geography. Following Buzai, geocompution, also called 'advanced methods', creates spatial results, but the principal data processing functions, performing alternative solutions and scenarios have an undoubtedly decisional character.

As geocomputation stresses computer science, we prefer to talk about geomatics, a word that first appeared in French-speaking Canada, particularly at the University of Laval during the 1980's. The term geomatics, including all forms of spatial data processing, is rather midway between geography and computer sciences. Laurini and Thompson (1992) made one of the first definitions about geomatics. Presently it's an important line of research in geography and environmental sciences. If spatio-temporal models can be used with two objectives – description and explanation of dynamics and their simulation or possible scenarios – we focus on the latter: simulation models offering geomatic solutions, that is to say geomatic simulations.

Simulations can be created for current situations in order to compare them with real maps but also to anticipate future changes. Different scenarios correspond to divergent evolutions and can offer important keys for planners and policy measures. Applying and comparing models and validating and evaluating results, offer a rich source of knowledge both in thematic and in methodological research. A bibliographic overview of recent research in environmental modelling confers an optimistic image of the accomplished advances. However, as recently as the 1990's the situation wasn't as optimistic. Le Berre and Brocard (1997) noticed that GIS capabilities were widely under-employed and that the majority of modelling research in geography was rather static and done simply to resolve spatial distribution problems. They explain the lack of dynamic models and spatio-temporal simulations by the precedence of static models such as urban models (city types, centrality, and attractivity).

Langlois and Philipps (1997), according to the origins of modern modelling, emphasize the relation between technological innovation and paradigm change. They illustrate this with an example: the important role of factor analysis in the change from a mechanical to a multi-dimensional view of the world. Based on the research of Spearman (1904), only a few researchers employed this statistical method before the availability of computers at the end of the 1950's. The change in the paradigm to a dynamic and systemic approach in understanding and analyzing complex ecosystems and geosystems was driven by numerous advances (e.g., ecological deterministic models, quantitative geography, expansion of computer sciences, etc.).

During the last two decades the methodological approaches for modelling were profoundly enhanced or, at least, popular in human and social sciences. Classical stochasticity became complemented by artificial intelligence based approaches, like neural networks and multi agent systems, but also by techniques like cellular automaton and fuzzy logic. Today researchers have at their disposal a wide range of modelling concepts and methods. Nevertheless, a lot of work has to be done to improve, validate and generalize models for spatio-temporal simulation of complex environmental dynamics, in order to create standard tools, which can be used by non-specialists. Consequently, the actual context may be described as 'how to transform advances in research into operational tools.' Thus trying to satisfy an increasing social demand for decision support for environmental management, sustainable development, and risk prevention from the local level to a global scale.

1.1.2 Objectives

Bregt et al. (2002) describe a three step approach in order to classify models dealing with spatial and temporal data. These authors distinguish between an initial state (the *What is where* question), which requires only spatial data to be exploited by classical models in GIS, and a second state (the *What is changing where?* question). To answer this second question, the database must also include temporal data like time intervals, in order to understand the process of change and the interaction between factors by the use of models for space-time data. For the third question (*What will be where?*), these models call on not only on explanations of past dynamics, but also on time projections such as prospective prediction or scenarios. Accordingly the standard database and GIS functions must be complemented by some additional, modelling specific, software components.

With these three questions we intend to describe the principal terms that describe the content of this book.

- *What?* First, it's necessary to understand what our objective theme is. We define environmental dynamics in a broad sense, including natural risks, forest or agricultural dynamics and urban growth. Several chapters focus on land cover/land use change at a regional or local scale.
- *With what?* What are the tools we can use? A spatio-temporal database must be built and exploited and its elaboration is one of the most delicate and decisive operations for the correct use of the models. Among the different models used for environmental dynamics, we choose preferentially geomatic solutions calling on GIS, remote sensing and other specific tools.
- *For what?* What is the outcome of these procedures? Chronologically, perhaps it's possible to see an evolution from the more classical analysis and description of outcomes in the spatio-temporal database exploitation to the more recent models. Scientists have procured explanations from the phenomena, before trying to model them.

But, modelling for what? Earlier, we referred to the two principal objectives of spatio-temporal models: explanation/description of the dynamics, and simulation/projection of them. Also Skidmore (2002) states that an environmental model seeks to understand or explain environmental systems, but also can be used to predict future scenarios or to compare the predictions with reality. They remark that "However, a model should not be used for both prediction and explanation tasks simultaneously…"

In this book, we focus primarily on modelling for predictive simulation and time projection. Regardless, some simulations have tried to explain particular dynamics, and to analyse past and present environmental processes.

What? **OBJECT**	***With what?*** **TOOLS**	***For what?*** **OUTCOME**
Environmental dynamics	**Geomatics**	
		Spatio-temporal database
		Analysis – Description
		Modelling for explanation
		Modelling for simulation

Fig. 1.1 Basic questions in modelling

The following pages intend to study thoroughly these three, above-mentioned questions (Fig 1.1). In spite of focussing on the content of the present book, these paragraphs are also relevant to this research area in general.

1.1.2.1 What? (Object): Environmental dynamics

When discussing the object of modelling environmental dynamics, temporal and spatial scales must be considered. If we begin with *time,* there are several approaches: dynamics can be progressive or regressive, slow or fast; time account into the model can be short, middle or long. Time can be continuous or split into discrete time steps and the model can run in real time or not. Temporal resolution also depends on databases or modelling methods (some models need more dates to work correctly than others). Finally, environmental modelling occurs more frequently as a prospective simulation. Retrospective modelling or historic simulation is rarely undertaken with geomatic solutions (See Chap. 9).

Time scale is linked to the *spatial* scale. Scale in GIS is often "…handled poorly in such systems…" (Tate and Atkinson 2001). Like time, spatial scales are affected by diversity and overlapping: global, middle or local spatial scales are, all of them, the objects for modelling as any quick bibliographical query can attest to. One can find studies from the local scale (small areas with fine spatial resolution) through regional scales to the continental and even at the global level (large areas with small spatial resolution). Many of the more recent works in environmental modelling focus on thematics encompassing vast areas, from the continental to the global scale (as examples: 140 million cells at 1 km² performed to analyse land use changes in the whole Amazonian basin by Soares Filho et al. 2006, the continental-scale urban modelling approach of Reginster et al. 2006). In any case, local and regional scales continue to be the common preference for geomatic based model implementation.

A comparison between these application scales can lead to several conclusions, such as that all of them have advantages and disadvantages and that models built for small or larger areas often can not be adapted to a different scale. This fact can be explained by numerous considerations (see Sect. 14.4). On the one hand, the number of land use categories and the sense of the nomenclature depend on scale. On the other hand, a lot of thematics need spatial accuracy or deal with scale-dependent phenomena such as spatial patterns (e.g., road-influenced, radial or diffuse growth). Also some thematics are dependent on data that are only available at one-scale.

Consequently, time and spatial scales are linked, and they are also linked to the *thematic objective*. A complete overview about specific fields of interest for environmental modelling with GIS was undertaken by Goodchild et al. (1993, 1996), bringing together more than a hundred contributions and showing all the variety of thematics.

Recently, we have raised awareness and concern about global changes, including efforts for modelling them. Monitoring the deforestation, ozone layer depletion, food early warning systems, monitoring of large atmospheric-oceanic anomalies, climate and weather prediction, ocean mapping and monitoring, wetland degradation, vegetation mapping, soil mapping, natural disaster and hazard assessment and mapping, and land cover maps for input to global climate models are some of the most important objectives of this research branch in environmental modelling at the global scale (Skidmore 2002).

In Wainwright and Mulligan (2004), environmental modelling is prominent in many disciplines such as climate, soil, hydrology, fluvial processes, ecosystem, biogeochemical modelling, among others. Another example is the forest landscape change models, which also use longer temporal series, related to some topics familiar to global change research such as sustainability, ecosystem management, and biodiversity protection (Mladenoff and Baker 1999).

We just mentioned some references offering an exhaustive overview about the thematics belonging to or overlapping environmental dynamics. Repeating this is not the objective here. Thus we only want to stress some of the 'most popular' themes with the aim to emphasize the social utility and the urgency to contribute to resolving these problems: natural disaster and natural and technological risks, climate change, wildlife modelling, ecological and landscape modelling, deforestation, LUCC (land use/land cover change) often related to land planning, food watch and urban growth.

1.1.2.2 With what? (Tools): Geomatics solutions

We note a chronological evolution in geomatics from spatio-temporal analysis toward spatio-temporal modelling. Spatial data at time intervals (a spatio-temporal database) is our principal source and we have found a great number of contributions in which the terms "time – space – modelling – geomatics" are used in the last decades.

Geomatics integrate all the techniques of geographical information systems (GIS), remote sensing (RS) and other disciplines, methods and tools deal with spatial data. It's important to remember the known complementarities between GIS and remote sensing, particularly in modelling because spatial components are linked to temporal components in an integrated tool. Both GIS and RS often work together, remote sensing offering regular temporal databases for monitoring environmental dynamics.

But we must remember that modelling in geomatics has been traditionally developed in spatial analysis. *Spatial modelling* with GIS and other tools is a very important line of research. As a part of what often is called 'geostatistics' (Burrough and McDonnell 1998) or 'geospatial analysis' (Longley et al. 2007), research in spatial models sometimes emphasizes the integration of different spatial analysis functions with a focus on problem solving in practical cases (Longley and Batty 1996, 2003, for urban planning, transportation, and economic development; Stillwell and Clarke 2004, for geo-business, transport or spatial planning) or for policy evaluation (Fischer and Nijkamp 1993).

Other more methodological works show the new potential and innovative modelling approaches in spatial models and GIS (Fotheringham and Wegener 2000) and the complementarities between geostatistics and the machine-learning algorithms (Kanevski and Maignan 2004). In some cases, modelling of spatial data focuses only on one type of model, like the fuzzy process (Petry et al. 2005) or on a specific thematic objective, like geological sciences applied to mineral exploration (Bonham-Carter 2002).

However the irruption of the *temporal factor* in geomatics, which began about two decades ago (Langran 1992, 1993, Egenhofer and Golledge 1994), has turned the concept of *time* into one of the more important components in new technologies. Previously mentioned authors and other researchers (e.g., Cheylon et al. 1994, Lardon et al. 1997) deserve the merit for the implementation of time into GIS, since then it has been called temporal GIS (TGIS) (Christakos et al. 2001). Theoretical thought and methodological aspects about the integration of time into GIS can be consulted in Ott and Swiaczny (2001), a work including additional case studies for several thematics.

Discussion around the concept of 'time' in geomatics is complex and unending. Decisions about temporal scales and temporal steps are a common problem in modelling environmental dynamics. The notion of 'granularity' (Claramunt 1994, Paque 2004) or the concept of a 'spatiotemporal continuum' (Christakos et al. 2001) are still some of the points of contention in the question of how to integrate time into GIS. In 1998, Molenaar discussed the need of linking the spatial and temporal character of the geographic phenomena in order to better develop GIS theory and tools. One of the great challenges of spatial information science at the end of the 20th century was the development of methods on a more abstract level able to represent spatio-temporal phenomena adequately so as to describe correctly changes in space over time.

The description and characterization of changes (*spatio-temporal analysis*) have a long tradition in the more integrated functions of GIS, but also in remote sensing techniques. Precisely, one of the best contributions from remote sensing for environmental analysis is its capacity for monitoring dynamics processes. Multi-temporal functions, applied to satellite imagery to detect changes (Chuvieco 2006, 2008), have proved their adaptability and power to understand temporal phenomena.

The possibilities of GIS and remote sensing to process spatio-temporal databases exceed the capabilities of the analytical step. It is at this point that we can talk about *modelling,* and the more important objective in environmental modelling must be "finding simplicity in complexity" (Wainwright and Mulligan 2004). We will think about what a model is in Sect. 1.2.1. At this point we want to retain two different concepts of models. First, a model is a representation of a real phenomenon (any data or map can be a model and it can offer knowledge about the system to be modelled). The explanation for environmental change models may be only visual or they may be automated analyses of multi-temporal images, which monitor the process (Skidmore 2002) and, in such cases, explanatory models are confused with the classical spatio-temporal analysis process. DeMers (2002), argues that spatio-temporal modelling is more than just map algebra functions and traditional cartographic modelling. Another viewpoint, particularly in geocomputation, is that a model is a mathematical abstraction for understanding the system and also for simulating how they run over time (Coquillard and Hill 1997). Atkinson and Martin (2000) linked spatio-temporal modelling to cyberspace, as a more developed step in the conception of time simulation and projection.

Nowadays, the most common GIS and RS software have incorporated modelling functions. Different types of modelling approaches are implemented in many accessible tools. Some of them are relativity easy to use, while others first require a more theoretical approach. This will be discussed further in Sect. 1.2.2. GIS and simulation models are often proposed as an integrated tool (a 'vertical' module) to resolve conflicts in sustainable development (Giacomeli 2005). Other authors, contemplating about modelling for simulation and prospective scenarios, often call this a 'spatial decision support system' (SDSS), in which a standard GIS is complemented with some additional software components to facilitate decision support (Bregt et al. 2002).

This succinct overview may explain the rapid evolution of modelling research in the last decade.

1.1.2.3 For what? (Outcome): Modelling for simulation

Environmental phenomena are inherently dynamic and a static representation or a descriptive model alone can't cover the system's dynamics and complex processes (Batty 2003). We call modelling for the purpose of simulation/prospective scenarios the spatio-temporal models group, which not only focus on an explanation and/or analysis of temporal changes, but also provide solutions to simulated time changes.

In order to grasp the notion of modelling Bregt et al. (2002), in particular with their second *(What is changing where?)* and their third question (*What will be where?)* discuss the configuration of spatial data at time intervals and the applications of models for space-time data. “Combinations of data, representing the initial status, and some rules or models describing the change of the environment over time, are needed. These rules range from relatively simple expert tables describing change in discrete intervals over time to complex dynamic simulation models describing change at continuous time intervals…” (Bregt et al. op.cit.). Thus these authors think that, in practice, it is impossible to answer this question with any great precision.

That is one of the most evident conclusions in spatio-temporal modelling. The results, quantitatively complex and often abstract, are perhaps close to reality, but the objective is rather the design of possible lines of development, by the form of scenarios, than a real prediction of future evolution.

But what are we looking for when applying a simulation model? We will find different kinds of answers or, more precisely, several news questions:

- *What can I obtain?* In other words: what kind of results can be attained by a spatio-temporal model? There are several terms like *prediction* or *scenario* related to the notion of *simulation* and, sometimes, they aren’t clearly differentiated in their use.
  - *Simulation*: It is the more general word to designate the result of a time projection model but also the process to do so. Some authors give the same significance to the terms ‘model’ and ‘simulation’ while other note the difference between them. We lean towards the definition of Hill (1993 quoted in Coquillard and Hill 1997) that states that simulation is different from modelling in that simulation is always time-embedded. “Simulation consists to make evolving a system abstraction over time so as to understand the functioning and the behaviour of the system and to grasp some of its dynamic characteristics with the aim to evaluate different decisions.” (Coquillard and Hill op. cit.). Simulation can be obtained for a present situation (in order to compare with reality and to validate the model), past situation (to understand a historic evolution) or future evolution. However modelling is a popular term and many authors use it in the sense of simulation.
  - *Prediction:* A simulation may be done for an interval of time, for which starting and ending points are known (interpolation). On the contrary, prediction is time extrapolation and the –predicted– result shows what will happen at an unknown moment, generally in the future (prospective simulation).

  - *Scenario*: In simple terms a scenario shows, an opposition to the term prediction, what *can* happen. Commonly modellers apply different underlying conditions (such as macroeconomic parameters) or dynamic variables (that are changing during the simulation) so that the simulations diverge in results, which describe a framework of possibilities providing predictive answers.
- *For what?* Outcomes of the simulation/time projection model can be split into different groups; they are all partially overlapping.
  - *Knowledge objective*: Understanding temporal processes is one of the objectives of a simulation model. Here simulation is used to better understand a phenomenon and its evolution. The model is like an 'intellectual crutch,' which aids in greater comprehension of complex processes. Retrospective simulation projection used to add the territorial dimension to historical studies (See Chap. 9) is an example for this outcome.
  - *Methodological objective*: Some works focus on testing tools, comparative methods or result validation. The aim is to use the model *sensu stricto*. These studies are helpful to define the degree of possible generalization of a model or method, its thematic application domains and required data. In other words, this type of work has it in mind to perform metadata for models.
  - *Operational objective*: simulation of the future or prospective modelling, which seek practical applications such as prediction. Getting a probable image of a future situation and being able to estimate its likelihood is a powerful form of decision support. Forecasting negative impacts in order to avoid or to mitigate them becomes everyday work in many domains (natural and technological risks, weather forecast, environmental impact studies) from the local scale to global scale.

1.1.3 Opportunities

This book is the result of collaboration between several research groups and built on the contact between scientists, who work in the same field. Modelling environmental dynamics using geomatic tools leading to simulations – either prediction or scenarios – is our central focus. In Part B, the chapters (case studies) include all model types, and are written in a consistent and simple presentation. The topics include environmental objects and application area, modelling approaches, (geomatic) tools, results (simulation, scenarios), validation and a critical discussion of results.

This work is the continuation of a line of research, in which the spatio-temporal model's application is more and more developed in the context of environmental sciences. It is also necessary to refer to some earlier studies and books, which have enriched our contribution and whom we gratefully wish to acknowledge. Among numerous works we especially wish to note the following sources.

- First, the earliest books on environmental modelling using GIS are some of the most important in this thematic: Goodchild et al. (1993, *Environmental modeling with GIS)* and Goodchild et al. (1996, *GIS and Environmental modeling: progress and research issues)*. In 1993, the authors said, "This book is for researchers, academics, and professionals with geographic information systems (GIS) experience who need to know more about environmental modeling. It is also intended for environmental modelers who want to know more about GIS, its advantages, and its problems…" In almost fifty contributions, the authors provide a complete overview of the technical aspects of environmental modelling, spatial statistics and thematics illustrated by case studies. In the work of 1996, ninety contributions concentrate on environmental databases and environmental modelling linked or built with GIS. Both works are a constant reference in bibliographies, even if time (modelling in the simulation acceptance of the term) is not always at the centre of interest.
- Coquillard and Hill (1997, *Modélisation et simulation d'écosystèmes. Des modèles déterministes aux simulations à événements discrets*) offer in this book an in-depth reflection on methodological questions in ecological models. Their model's classification is a reference for a better compression of these tools. The completed sorting of modelling methods remains relevant today, even as artificial intelligence-based approaches became very popular during the last ten years and branched into different areas showing substantial progress.
- Briassoulis (2000, *Analysis of Land Use Change: Theoretical and Modelling Approaches*) offers a theoretical and methodological reflexion about the models applied to land use change. Her model classification gives a complete overview of the variety of approaches, from statistical and econometric models to spatial, optimization and integrated models. Several GIS linked models are similar to our objectives.
- In 2002, Skidmore published *Environmental modelling with GIS and remote sensing*, which is focused on the information and how the information is used in environmental modelling and management. Different chapters show data and application to global and thematic environmental models (vegetation, biodiversity, hydrology, weather, natural hazards, environmental impact and land use planning, etc.). This work

also includes a more methodological chapter where the authors propose a taxonomy of GIS environmental models and the conclusions of the principal problems in the use of GIS and remote sensing for environmental modelling. Perhaps the principal difference between this book and our work is that case studies in Skidmore focus more frequently on explanation rather than on time projection.

- DeMers (2002, *GIS modeling in raster*), supplies a synopsis about raster representation specific tools to process cell data. He shows that spatio-temporal modelling is more than map algebra functions.
- Brimicombe (2003, *GIS, Environmental Modelling and Engineering*), provides a technological vision about complementarities between GIS, simulation modelling for environmental problems and engineering. The author demonstrates how GIS and simulation modelling are joined and consequently offer "…tremendous possibilities for building versatile support systems for managing the environment…" Case studies complete this work, in which the spatio-temporal component is always present and methodological questions such as model validity are discussed.
- The work of Kanevski and Maignan (2004, *Analysis and modelling of spatial environmental data*) mainly focus on geostatistics and spatial prediction modelling. Authors show methodological aspects like monitoring network analysis, artificial neural networks, support vector machines, stochastic simulations and GIS tools. They apply these concepts to environmental data but the time aspect and validation of results are not major considerations.
- Wainwright and Mulligan (2004, *Environmental Modelling: Finding simplicity in complexity*) published a book about simulation models: "Central to the concept of this book is the idea that environmental systems are complex, open systems. The approach that the authors take is to present the diversity of approaches to dealing with environmental complexity and to encourage readers to make comparisons between these approaches and between different disciplines...." Keeping this in mind, their chapters focus on an overview of methods and tools, calibration, validation and errors in modelling, the future of environmental modelling and offer several contributions related to various thematics (climatology, ecology, hydrology, geomorphology and engineering spatial modelling and GIS), some of which are more methodological, while others are for management. Perhaps, such as in other works, it lacks in the consideration of time in modelling.
- Recently Petry et al. (2005, *Fuzzy Modeling with Spatial Information for Geographic Problems*) presented an interesting work about how fuzzy logic and fuzzy modelling are useful in modelling spatial data. They

provide solutions for geographical applications especially if limits of geographical entities are continuous rather than discrete.

This book, based on the advances summarised in the above-mentioned publications, intends to give an actual overview about geomatic models applied to simulate environmental dynamics and particularly focuses on methodological aspects, such as model calibration and validation.

1.2 Modelling approaches

Among the variety of modelling approaches, the authors deliberately restrict the panel of methods and software implementation to those which deal with both space and time. For instance, a lot of models developed in economics, medical diagnostics or engineering, are outstanding but don't take up time. The explicit inclusion of the spatial dimension is essential to tackle environmental dynamics and to select criterion for here presented – and further implemented – modelling approaches.

An important issue is the concept of time and space – continuous or discrete – reflecting a fundamental discussion in geography and digital representation of data in GIS (raster versus vector). The temporal aspect, particularly the notion of temporality, temporal scales in environmental dynamics and the idea of granular time is discussed, among others, by Coquillard and Hill (1997) and Worboys and Duckham (2004).

What's a model? A variety of definitions exists. The most basic of them states that a model is a representation of a real phenomenon. This means that any data or map is a model. In geomatics, the common definition includes the behaviour of the phenomena to be simulated. Following this train of thought, a model is a functional representation of reality able to help us in understanding its action or predicting its behaviour. Minsky (1965) already insisted on the functional aspect by defining a model: "To an observer B, an object A* is a model of an object A to the extent that B can use A* to answer questions that interest him about A." By insisting on processes rather then the form, the term model is closer to the notion of a system, which is defined by functional concepts like relationship, feedback, system effect (the difference between cumulative proprieties and constitutive proprieties), hierarchic organisation and complexity, which means that we don't have an exhaustive knowledge about the modelled object. The outcome use of a model may be a gain in knowledge or decision support. The first one aims at scientific progression in the understanding of complex phenomena, while the second one specifies a practical objective in management processes like risk prevention or land planning tasks. Some authors distinguish between modelling and simulation. Simulation explicitly refers to the temporal dimension and means model behaviour during a time period which may be prospective. A simulation means creating an evolving system abstraction over time to help us understand system behaviour, how a system works and some of its dynamic characteristics with the aim of evaluating different possible decisions (Hill 1993).

An important issue is the performance of a model. We will return to this aspect in the fourth section about model calibration and validation. Here we only want to point out that the relationship between the complexity of a model and its performance is not linear. A model is a simplification of reality. The temptation to make a model more complex in order to enhance its performance is great. Coquillard and Hill (1997) even noticed that adding of new variables and additional weights doesn't necessarily signify a proportional gain of knowledge and facilities in the model validation. They even demonstrated that trying to increase model complexity may decrease the model efficiency (difficulties to control the model, to validate its results). Also the complexity of the computing implementation increases in the best case scenario linearly with the model complexity; however this augmentation may be exponential.

The following pages give a concise presentation of common methodological approaches used to model environmental dynamics. The material of the second section is an overview about the practical implementation of models: available software. Finally, a critical point will be discussed: the calibration and validation of models.

1.2.1 Methodological overview

Model typologies may be based on various criteria such as the modelling objective (descriptive, explanatory, predictive, decision support), the underlying methodology, the spatial and temporal explicitness (the spatial and temporal levels and resolutions taken into account), the types of environmental dynamics considered, etc.

Briassoulis (2000) presents a chronological literature overview of model typology schemes: "Wilson (1974) proposes a classification scheme based on the dominant technique used in model building (pp 173-176). Batty (1976) distinguishes between substantive and design criteria for model classification (pp 12-15). Issaev et al. (1982) mention four possible approaches to model classification: (a) construction of a list of attributes characterizing aspects of the models, (b) specification of a set of criteria serving as a general evaluation framework, (c) construction of an 'ideal' model as a frame of reference for judging all other models, and

(d) cross-comparison of models on the basis of general structure characteristics of these models (Issaev et al. 1982, 4). Stahl (1986) suggests a number of substantive criteria for classifying business location models including issues of theory and model purpose (Stahl 1986, 769-771)."

Choosing the methodological criterion, the literature suggests a variety of typologies (among others Coquillard and Hill 1997, Kanevski and Maignan 2004). Generally authors distinguish between deterministic, stochastic and artificial intelligence based models, a group becoming ramified during the 1990ies into several branches like cellular automaton, multi agent systems and neural networks. In practice, we often notice combinations of two or more approaches. Also models are frequently enhanced by, not presented in this chapter, methods like macroeconomic approaches (Verburg et al. 2006b) or expert systems (Giarratano and Rilay 2005). All of them are very useful and interesting and their practical interest may be estimated by reading the following case studies. Nonetheless any of them includes explicitly space. Other methods, for example decision support techniques like multi-criteria evaluation and multi-objective evaluation (Eastman et al. 1993) deal with space but are designed to perform suitability maps that may be used in simulations, and some authors did so (see Part B).

1.2.1.1 Deterministic models

Using a mathematical formula, the modelled object is entirely described excluding any probabilism. Most of them, handling with continuous space and time and resolved differential equations, are also called analytic or mechanic models. Their mathematical rigour facilitates implementation but also limits their area of application, generally restricted to a high level of system abstraction. A famous example for analytic models is Odum's Silver Springs model (Odum 1957) applied to energetic ecosystem flows at a global level. Only a few deterministic models include a spatial variation like competition models (Tilman 1977, Huston and De Angelis 1994). The principal limits of deterministic methods in modelling of environmental dynamics are the poor degree of spatialization and data uncertainty. Generally deterministic models consider the space homogeneous; a hypothesis which rarely matches with reality. Also complex dynamics often contain uncertainty including data with a low level of confidence but also ignored or unknown variables.

1.2.1.2 Stochastic models

They are also called probabilistic models. If the model is evolving in time, which is considered discrete, we also call them stochastic simulation or Monte Carlo models.

The basic idea is that observation reflects the realisation of a system state among possible states. The list of possible states is known and finite. A famous illustration is throwing a dice. Each throw realizes one of the six possible states which are, for an instant t, exclusive and time independent. Consequently, it is a random or stochastic variable. The successive realisations form a discrete process. This means that the variable can not change continuously in time but only into an ascending series of real positive numbers called instants. The system state only changes from one instant to the next. Because we deal with a random variable, deterministic approaches can not model this process. Considering time as discrete offers a lot of advantages. So the model may be performed for specific time scales, events or activities. Discrete modelling (some authors prefer the term simulation) became powerful with the development of object based languages such as C++ (Bouzeghoub et al. 2000, Frihida et al. 2002).

The applications of stochastic models are numerous. The Monte Carlo simulation is known since the 1950's (Metropolis and Ulam 1949) and based on a random number generator with the aim to model systems, which elements are insufficiently known and may be approached by probabilistic.

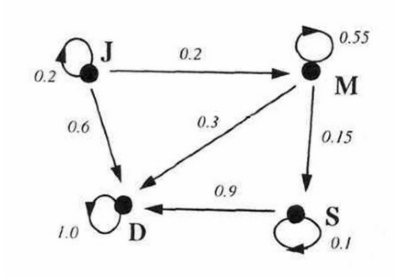
- Markov chain analysis (MCA)

Today, Markov chain analysis is one of the most used stochastic approaches in ecological and environmental modelling. The mechanism of Markov chain analysis may be introduced by an example developed by Coquillard and Hill (1997): the observation of the development of a population in time. The individuals of the population may belong to four different states: juvenile (J), maturity (M), senescence (S) and death (D). Fig. 1.2 gives an illustration of these states and transition probabilities.

This Markov chain is qualified first order as a stochastic and discrete process with a finite number of states and the probability that the system realizes a given state at instant t+1 depends only on its state at instant t. This means that it is possible to predict a variable knowing only its actual state. Consequently the specialists qualify a first order Markov chain as a stochastic model *without* memory – a severe restriction in modelling environmental dynamics that generally need a detailed historical knowledge.

Markov chain became a popular tool for a large spectrum of environmental applications but also in image processing (Flamm and Turner 1994). The number of publications about land use/land cover changes (LUCC) calling on Markov chain analysis is vast. We can only give some examples. Lippe et al. (1985) uses Markov chains to model heathland succession. Logofot and Lesnaya (2000) discuss their application in forest dynamics and Balzter (2000) is resuming the prediction power of more than 20 Markovian models applied to grassland ecosystems. Tucker and Arnaud

(2004) use this methodology, always without a spatial component, to study vegetation recolonisation and restoration. Markov chains were also proposed as a possible modelling approach in the LUCC program (Nunes and Augé 1999). Finally, some research (Roman 2004) emphasizes the advantages obtained by coupling deterministic and stochastic models.



		Final states			
		J	**M**	**S**	**D**
Initial states	**J**	0.2	0.2	0	0.6
	M	0	0.55	0.15	0.3
	S	0	0	0.1	0.9
	D	0	0	0	1.0

Fig. 1.2 Time transition for a given population with four possible states (nodes) and probability transitions (arcs) represented also (on the right) as a transition matrix. Coquillard and Hill 1997 (modified)

The main restrictions of Markov chains are, once more, intrinsic. Coquillard and Hill (1997) outline their independence from time (model without or with little memory, dependent upon Markov chain's order) and, particularly, their independence from space (such as for deterministic models). Space is neither homogenous nor isotropic. So the probability that a pixel becomes reforested depends, among other parameters, on its distance to existent forest limits but also to isolated trees, topographic conditions and wind directions.

1.2.1.3 Artificial intelligence based models

The literature gives different definitions of artificial intelligence (AI), some more restrictive than others. Particularly, the question of whether cellular automata belong to AI continues to be controversial (for instance: Langlois and Philipps 1997, Lee 2004). In this context, we will simply consider that AI based systems are computer programs simulating the human brain processing or other complex mechanisms. Some authors also qualify the modelling approaches using AI as artificial life. All modelling approaches based on AI use the concept of knowledge. The origin and enhancement of knowledge may be added or self-learned. Added knowledge means that knowledge comes from external sources and generally provided by databases. This is the case for cellular automata, expert systems and multi-agent systems. Some authors call this distributed artificial intelligence.

Self-learning AI also need a basic, added, knowledge to initialize the model but the model produces and enhances the knowledge by itself: neural networks, cognitive and endomorph multi-agent systems.

The development of AI is closely related to that of computer science. Among fundamental research, we note the publication of Alain Turing (1950), considered a founder of AI *Computer machinery and intelligence* and the important advances performed by Marvin Minsky *Matter, minds and models* (1965) and *Society and mind* (1987). Since the 1980's an important effort has concerned the relationship between modelled components, which become more autonomous.

- Cellular automata (CA)

The development of cellular automata (CA) is built upon the advances by Ulam and Von Neumann (Von Neumann 1966), Burks (1970) and Gardner (1970, 1971).

A CA is a system that has components that are interacting at the local level according to elementary rules to simulate a complex and dynamic system over space and time. Space (the cellules), their state and time are discrete (Wolfram 1985, Jen 1990). Langlois and Philipps (1997) complete this definition with a description of AC structural and functional proprieties.

- The structural proprieties define the topology of the cellular grid, which is generally a raster grid. Most of them have two dimensions (raster image) linear or volumetric applications or n-dimensional AC's are possible. The structural proprieties also depend on the form of cellules, usually square or hexagonal, and, consequently, on the number and quality of cellular connections (contiguity and number of neighbours). Like the filter techniques, the grid border management is also a critical aspect. GIS implementation of AC commonly does not allow toric grids. So border pixels are excluded or surrounded by virtual pixels. Another possibility is to anchor the active matrix into a wider, passive, environment; a solution often selected in fire simulation models. Finally, we can distinguish between AC's that only consider the direct vicinity and AC's handling with larger spatial interactions, usually weighted by distance.
- The functional proprieties are a list of discrete states that a cellule may realize and transition rules. They are also called evolution rules of the automaton. These rules, rather stochastic than deterministic, configure the state that the cellules become during the simulation (Mezzadri-Centano 1998).

The AC characteristics may be illustrated by the famous game of life invented by Conway (Gardner 1970), thought to be the ancestor of AC.

Conway's AC had a toric matrix with square pixels that may be dead or alive depending on very simple transition rules. The initial conditions are random.

The cellular interaction needs, at least in theory, a parallel processing (Tosic and Agha 2003, 2004a, 2004b). With sequential computers parallelism is simulated by either synchronic or asynchronic activation. The more cellule categories (possible states) there are, the more complex AC modelling becomes. Objective conflicts in space colonisation need a form of arbitration like random decision, probabilities or refereeing based on extended vicinity characteristics. So a somewhat realistic AC application needs an immense computational volume. Zeigler (1976) already intended to optimize AC processing.

AC's applications in environmental geography are very numerous, therefore we will only mention a few examples. Elmozino and Lobry (1997) and Dubé et al. (2001) use AC for forest simulation. Jacewitz (2002) and Wu and Marceau (2002) employ AC to answer ecological questions and Engelen (2003) for LUCC. But it is in urban geography that AC has become a major modelling approach, which takes advantage of theoretical advances like the studies of Forrester (1969) and Tobler (1979). Langlois and Philipps (1997) give an overview of AC applied to urban dynamics that may be updated by the publications of Batty and Xie (1999) and Yeh and Li (2001).

- Multi-Agent Systems (MAS)

In plain text, multi-agent systems (MAS) may be described as a sophisticated extension of a cellular automaton responsible for socializing the cellules. MAS, also called distributed artificial intelligence, have more individualised components, which are within in systemic interaction. The components, called agents, are autonomous and organised according to social rules. Ferrand (1997) states that the agents are endowed with a quantitative and qualitative state and transitions (both discrete). Simultaneous interactions (parallel processing) occur between them (internal or social), but also with external stimuli (data input or system environment processes), which are also called perceptive interactions. The social agent structure is based on behaviour rules and outcome that may be explicit (like for AC) or emerge from the simulation (Briot and Demazeau 2001). In the latter case, they call them reactive agents, which require memory and knowledge about the other agents. Some authors call them cognitive agents (Franc and Sanders 1998, Bousquet and Gautier 1999).

The computer implementation usually uses object languages and a wide range of scripts are available today.

MAS is also useful for a large range of applications: simulation of complex systems (Savall et al. 2001), LUCC (Parker et al. 2001, 2003), generalisation of urban topographic maps (Ruas 1999, 2002), landscape and farming simulation (Poix and Michelin 2000). MAS are also often used in participatory modelling (Castella et al. 2005, ComMod 2005).

The limiting factors are the great amount of processing time and difficulties in validation of modelling results. As early as 1997, Ferrand deplored the lack of tracking in MAS.

- Neural networks (NN)

Neural networks (NN) are inspired by the workings of the human brain and characterised by parallel data processing and the ability to enhance its knowledge itself. Most of them are synchronic and deal with discrete time. Each elementary neuron calculates a single output depending on the input information. A neuron may receive information from several upper neurons. Depending on signal force, transfer function and activation sill, an upper neuron is activated or not (Fig. 1.3). The neurons are connected hierarchically as a network that works like a black box. The training of a neural network is a critical point. Using a training data base the network is configured, reflecting the initial conditions of the simulated system, so as to optimize the network by a set of weights. NN became very popular in the last few years because they are general, non-linear estimators that may be used in many disciplines (Villa et al. 2007). At the end of the 1990's, they were often applied in recognition tasks and signal processing, predicting applications based on time series (Bishop 1995, Parlitz and Merkewirth 2000, Lai and Wong 2001).

The origin of neural networks is old as the work of James (1890), which presented the idea of the associative memory. Hebb (1949) returned to this concept as a training model for NN: Hebb's law. Rosenblatt (1958) designed the first neural computer, called perceptron, it was applied to the recognition of forms and was later enhanced by Widrow and Hoff (1960). Hebb's law is important in the understanding of the independent learning ability of neural networks. Hebb (1949) said that than an axon connecting neuron A with neuron B by a synapse is often excited, thus the quality of this connection becomes different so that the signal flow becomes easier. In artificial neural networks, this repetition effect is simulated by a weight, which is changing during the training period. Consequently, the training of the network is supervised. The second important point is that of the connecting structure of the network: its topology. Simple networks (like Hebb's one) have only two layers. All neurons of the input layer are connected with all neurons of the output layer. There are no connections between neurons belonging to the same layer. Today, researchers usually design multilayer networks with at least one hidden layer. This multilayer perceptron preserves the hierarchical connecting design and was used in statistics as early as the 1960's (Davalo and Naim 1969).

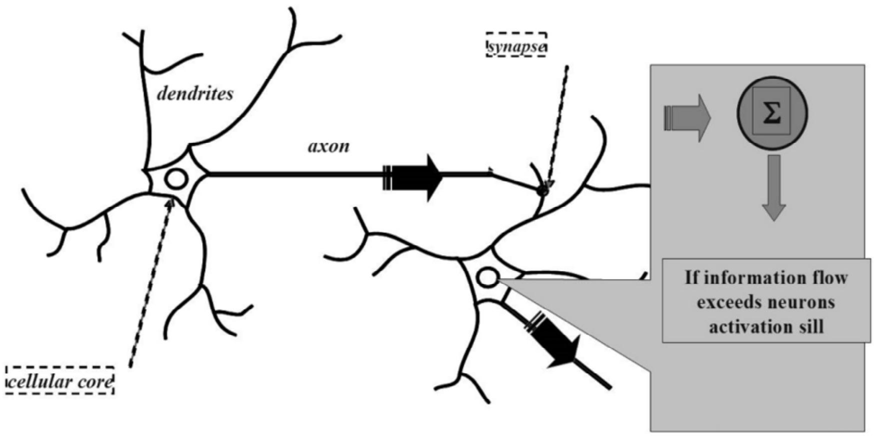


Fig. 1.3 Architecture of a neural network

Since the 1980's, NN applications have really taken off with the introduction of powerful computers. In geography and environment research, we notice a delayed use of NN in comparison with other methodological approaches (end of the 1990's).

1.2.1.4 Fuzzy logic

The concept of fuzzy logic may be introduced as an extension of classic Boolean logic with the aim of handling non-binary data and especially occurrences of data uncertainty or phenomena of partial truth. This means that the logical evaluation gives a result neither entirely false nor entirely true. A famous illustration of this concept is the perception of temperature classes (Fig 1.4). Fuzzy logic deals with reasoning that is approximate rather then precisely deduced from classical predicate logic. The concept of partial truth or degrees of truth is often confused with probabilities. Fuzzy truth expresses a membership to an imprecisely defined set, not likelihood or conditional membership.

The fuzziness of geographical data is related to the imprecision in the location and boundaries and also to uncertainty and gaps in attribute data. The origin of fuzzy logic is associated with Lotfi Zadeh's research, particularly his sub-set theory (Zadeh 1965) and his theory of possibilities (1978). The first one led to the membership function (e.g., Fig. 1.4), the second theory on the possibility function is associated with the fuzzy command. Real variables are transformed into fuzzy variables belonging to their fuzzy set membership function. Among others Tong-Tong (1995) furnishes an introduction to the fuzzy logic concept.

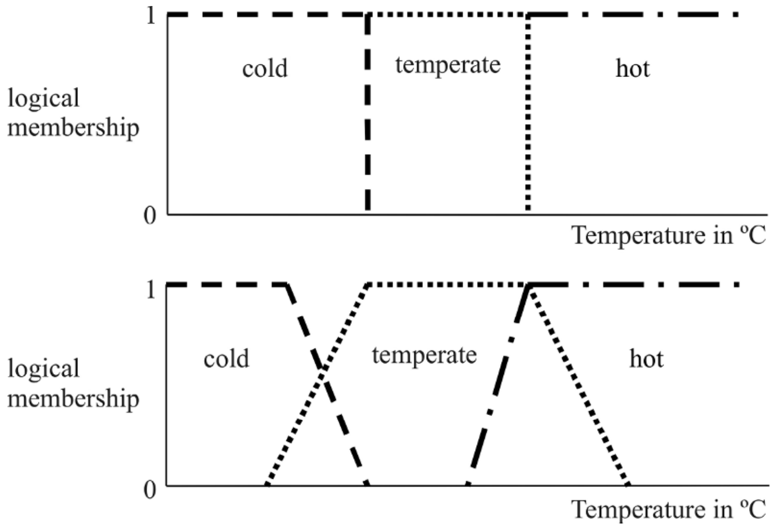


Fig. 1.4 Subset theory and membership functions in Boolean logic (above) and fuzzy logic (below)

A great deal of research has been developed based on fuzzy systems to solve problems related to geo-processing (e.g., Bouchon-Meunier 1995, Dragicevic and Marceau 2000). According to Saint-Joan and Desachy (1995), fuzzy systems deal with imprecise and uncertain information in a more efficient way than algebra map systems based on Boolean logic. Many authors point out some advantages in the use of fuzzy inference systems to solve problems associated with the environment (Centeno and Góis 2005, Schultz et al. 2006). In decision support, the integration of heterogeneous data creates a trade-off between favourable and unfavourable conditions. Fuzzy logic also allows a standardisation of the original data units in order to process them together. Using fuzzy logic, the aim can be focused onto specific regions of interest. Fuzzy reasoning can be used as validation tool, reducing the abrupt spatial difference between false and true. Petry et al. (2005) provided an up to date and complete overview of the methodological aspects in fuzzy modelling and its usefulness for geographic problems.

1.2.2 Modelling tools

The practical implementation of modelling concepts and methodological approaches may be undertaken using two different methods. The first one consists in using modules included in available GIS software. In opposition the second method uses a specific model designed with general tools such as computer languages, macro languages or more general statistic programs like SPLUS or Matlab. Halfway between these methods some program platforms exist, offering a wide range of scripts and libraries. In this section, we succinctly describe the characteristics of the most well-known GIS software that include modelling tools.

Among GIS software, ESRI products (ArcInfo, ArcView, ArcGis) are commonly used. Recent editions of ESRI software include a lot of modelling tools. Some of them are not included in the basic software but in complementary modules. This is the case of the Land Change Modeler, a software extension to ArcGis available since summer 2007, which is developed by Clark Labs first for their own GIS software: Idrisi, a universally used GIS and image processing software. Particularly, its last edition (Idrisi Andes) offers a multitude of modelling tools:

- LCM (Land Change Modeler): LCM is the new integrated modelling environment of Idrisi Andes (Eastman 2006) including tools for analysing the past land cover change, modelling the potential for future change, predicting the phenomena evolution, assessing its implication on biodiversity and ecological equilibrium and integrating planning regimes into predictions. The first step is a LUCC analysis and performing of LUCC budgets. The second step is the modelling of transition potentials. To do this, the dynamics are split into sub-models (transition form one land use/land cover category to another). Each sub-model is described by relevant criteria. The quantitative variables can be included into the model either as static (unchanging over time) or dynamic factors. The dynamic variables change over the training and simulated period and are recalculated for each interaction during the course of prediction. The transition potential maps may be calculated by using a multi layer perceptron or by logistic regression. Then, the established knowledge about the land cover transitions is used to forecast prediction, a simulation step performed either by Markov chain analysis or by an external model. The spatial allocation of predicted transition amount may be influenced by dynamic variables, infrastructure changes and zoning. The results may be used for ecological sustainability and land planning scenarios.
- GEOMOD: Geomod (Pontius et al. 2001) is a LUCC simulator modelling the transitions from one land use to another (e.g., from forest to non-forest). To do so, GEOMOD needs as start-up information the beginning and ending time of the simulation, the coverage with the initial state of the two categories, the land surface area changing in use, land use change drivers and a stratification map. A suitability map may be produced from driver information or supplied (external), particularly by multi-criteria (MCE) and multi-objective evaluation (MOLA) modules.

These are decision support tools also frequently used with CA_MARKOV (see below). The stratification map allows the division of the study area into several regions. Each region only allows one transition direction. GEOMOD includes the possibility of restricting possible transitions, by simple filter, to the neighbourhood of occurring land use at the start time. GEOMOD is designed to predict the location of LUCC, not the quantity of the changing area.

- CA_MARKOV: This tool is an integrated tool calling for Markov chains analysis (MCA) for time prediction and Multi-Criteria Evaluation (MCE), Multi-Objective Evaluation (MOLA) and cellular automata to perform a spatial allocation of simulated land cover scores. MCA of second order is a discrete process and its values at instance t+1 depend on values at instances t0 and t-1. The prediction is given as an estimation of transition probabilities. MCA produces a transition matrix recording the probability that each land use/land cover class might change into each other class and the number of pixels expected to change. MCE is a method that is used to create land use/land cover specific suitability maps, based on the rules that link the environmental variables to land use/land cover and its dynamics during the training period. These rules can be set integrating statistical techniques with a supervised analysis performed by the modeller. The suitability maps are used for spatial allocation of predicted time transitions. A multi-objective evaluation module and a cellular automaton are performed to resolve objective conflicts between land use/land cover classes or categories and to improve the spatial contiguity in the final prediction map.

GRASS (Geographic Resources Analysis Support System) is freeware and open source software, which is used particularly in erosion and rainfall-runoff modelling, hydrological modelling and landscape analysis. Detailed information is available online on the GRASS homepage.

CLUE (Conversion of Land Use and its Effects) was developed by Wageningen University in the Netherlands. CLUE, also freeware, is a dynamic and multi-scale LUCC model tool basing on concepts like connectivity, hierarchical organisation, system stability and resilience and a large range of driving factors. The prediction step is performed by statistical regression. More information about the concept and applications of CLUE can be found in Verburg et al. (2002).

LTM (Land Transformation Model), also freeware, is a software designed by HEMA (Human-Environment Modelling and Analysis Laboratory) belonging to the Department of Forestry and Natural Resources of Purdue University in Indiana, United States. LTM combines GIS and remote sensing tools with neural networks and geostatistics to forecast land use changes.

DINAMICA, freeware, is developed by a research team of the Remote Sensing Center of the Federal University of Minas Gerais, Brazil. The latest release, DINAMICA EGO (Environment for Geoprocessing Objects), aggregates traditional GIS tools with specific simulation modules designed for complex spatial phenomena. The model, from calibration to validation, follows a data flow in the form of a diagram; a friendly graphical interface permits the creation of models by connecting algorithms via their ports, likely the Macro Modeler in Idrisi. DINAMICA offers the possibility to divide the test area into sub-regions, characterised by different environmental dynamics, and apply a specific approach for each one of them (Rodrigues et al. 2007). The calibration step produces a probability map of occurrence for each transition, using the weight of evidence method. DINAMICA uses two complementary transition functions: the Expander and the Patcher. The first process is dedicated only to the expansion or contraction of previous patches of a certain class. The second process is designed to generate new patches through a seeding mechanism. The combination of DINAMICA's transition functions presents numerous possibilities with respect to the generation of spatial patterns of change. Model validation is based upon the fuzzy similarity, which takes into account the fuzziness of the location and category within a cell neighbourhood (Hagen 2003).

SLEUTH, developed by Clarke (Dietzel et al. 2005) at UC-Santa Barbara, is a software with two components: the Clarke urban growth model (UGM) and The Deltatron Land use/Land Cover model (DLM). SLEUTH uses cellular automata and is principally applied to urban growth modelling.

Land Use Scanner and Environment Explorer are modelling software developed in the frame of the LUMOS consortium – a platform for land use modelling in the Netherlands bringing together public agencies, research centres, university and private enterprises in the Netherlands. The Land Use Scanner calculates future land use change on the basis of land use scenarios (demand on space) suitability maps and attractiveness criteria. The Environment Explorer is a multi-scale dynamic model to perform land use scenarios for the Netherlands. Viet (2006) gives more detailed information about the Environment Explorer, Kuhlmann et al. (2005) about Land Use Scanner.

MOLAND (Monitoring Land Use/Cover Dynamics) is a research project carried out at the Institute for Environment and Sustainability – Land Management and Natural Hazards Unit form the Joint Research Centre (IRC) of the European Commission. Based on cellular automata, its aim is to provide a spatial planning tool for assessing, monitoring and modelling the future development of urban environments (EUR-JRC 2004). A particular focus is the analysis of fragmentation in urban landscapes.

The call on additional predictive models or specific computer software became a common practice to resolve particular modelling aspects mainly in physical geography. We also notice a ramification of spatial distribution modelling tools (Bioclim, Domain, ENFA, GARP, MaxEnt) that may be connected, during the modelling process, to GIS based modelling tools (See Chap. 11). MaxEnt (Maximum Entropy), applied generally to geographic distribution questions (Phillips et al. 2006), is a representative example for new modelling tools trying to preserve as much of the uncertainty of the original data as possible.

As mentioned, a lot of models are self-made and designed without using standard available GIS software. Typically they call on already written scripts for statistical software or computer languages. The following case studies (See Part B) give a survey about the range of possibilities to proceed in this way.

1.2.3 Model validation

Model validation clearly is a critical point. Even if it occurs as the last step in the modelling chain, it has to be placed in the general modelling context.

Whatever the methodological approach is, the general modelling procedure begins with the definition of the model objectives and the initial hypotheses. The next step consists in collecting the relevant and available data, their description and definition (metadata) but also the knowledge about system behaviour and the underlying model and the simplifying restrictions. Often a graphic representation is used to guarantee a synoptic overview of this conceptual process. The following steps are the computer implementation of the model, its initialisation, running and the validation of performed results.

The model credibility depends on its validation. Following Coquillard and Hill (1997) referring to the definitions of the Society of Computer Simulation (SCS 1979), this general term may be split into three tasks:

- *Verification* - First, the modeller has to make sure that the model works accurately: correct computer code implementation, the right module interaction and insertion into the computing environment. This step is also called the internal validation. Heuvelink (1998) focuses on error propagation in environmental modelling with GIS.
- *Calibration* – The purpose of this step is to test the conformity of the global model behaviour related to the objectives. For simulation models (models evolving with time), the calibration also signifies the initialisation of the model with data and knowledge coming from a training period or training dates. In the case of predictive modelling, this means that the

model is able reproduce former and actual system states on the base of delivered information. Artificial intelligence based models also call this step model optimization by machine learning. It has to be mentioned that most of the common validation techniques are also applicable for calibration. Some authors combine verification and calibration and call model calibration the process of model design such that it is consistent with the used data for model elaboration (Verburg et al. 2006a).
- *Validation* – The aim is to improve the robustness and acceptability of the model. In the strict sense of the word, validation is the evaluation of model results accuracy. Therefore used data don't have to be known by the model. In the following paragraphs, we focus on model validation as measurement of model accuracy and correctness of model results.

Rykiel (1996) distinguishes between 'operational' (measurement of model output performance) and 'conceptual' validation. He calls the latter one the procedure to ensure that postulations underlying the conceptual model are correct or justifiable and that the model is reasonably represented compared to the model objective, the simulated system. Obviously, Rykiel's definition about conceptual validation matches with Coquillard and Hill's acceptance of verification and calibration.

A first validation may be visual. It's a more intuitive comparison method, the main feature is the resemblance between model output and the validation data, e.g. simulated land use and observed land use. However, the visual approach only gives a first impression and model accuracy has to be otherwise validated, generally statistically. Among validation methods we can distinguish principally between two branches:

- Full validation: a validation by a comparison with the real data (observed reality) is possible. A large panel of statistical tools may be used to appreciate the correctness of the model output: comparison matrix (pixel by pixel, ROC and Kappa indices, fuzzy location, spatial shape and pattern), comparative analysis of LUCC-budgets etc.
- Partial validation: a comparison between model outputs and real data is impossible. This is the situation if the model is simulating a future system state, which is impossible to validate completely for an obvious lack of real data. The validation may be tried by comparison (e.g., with an experts knowledge), by repetitiveness (stability of model outputs), by convergence (of outputs from different models).

1.2.3.1 Full validation techniques

The validation is based upon a comparison between the modelled output and real data. A classical example is a similarity test between a simulated land use and real land use at the same date. Both documents have the same nomenclature and resolution (or scale for vector map outputs). A basic validation consists in pixel by pixel assessment: a comparison matrix showing the overall prediction score and categorical error rates. Various statistical indices are available; the most well-known is the Kappa index of agreement. Pontius (2002) developed a statistical tool, implemented into Idrisi Andes, combining an assortment of Kappa indices measuring the agreement of a pair of maps in terms of quantity and quality (location). ROC (Receiver Operating Characteristic) is another statistical measurement of agreement in terms of location (Hanley and McNeil 1982). ROC differs from Kappa location index by comparing a likelihood image (e.g., a suitability image) of a land use category and a Boolean image showing where this category really occurs. To do so, ROC ranks in descending order the categorical suitability by user defined thresholds. The occurrences of each resulting class are compared to the binary real map of location. Consequently, ROC is also an excellent calibration tool because it allows for the measurement of how well a suitability map, expressing the training knowledge, matches with the initial and model known conditions (Pontius and Schneider 2001).

Most models better predict stability as change. An interesting model validation approach focuses on changed pixels: real changes (between the model's known state and a future state, unknown to the model) and simulated changes. Applied to LUCC, Pontius et al. (2004) calculate a LUCC-budget splitting changes into gain, loss, net change and swap. Swap means the changing of location for the same amount of occurrences. The comparison of real and modelled LUCC-budgets permits a more detailed understanding of model errors.

Nevertheless, the mentioned validation approaches are based on a pixel by pixel comparison and don't take into account spatial pattern, their distribution and shapes (White et al. 1997). Spatial analysis measurements are the norm in landscape ecology (Forman 1995, McGarigal and Marks 1995) and may complete the panel of validation tools.

Fuzzy logic represents a different way to escape a strict cell to cell validation. Fuzzy logic permits answering the question about the degree of agreement in location more flexibly and should be used in cases of low spatial confidence or multiple resolution data. The fuzzy comparison method developed by Hagen (2003) was incorporated in some GIS based modelling tools such as DINAMICA. The adjustment uses a declining exponential function comparing the cells classes' distribution to the pixel in the centre of the filter. Barredo and Gómez (2003), using the MOLAND (Monitoring Land Use/Cover Dynamics) model, presents a Fuzzy Kappa measure which is more gradual than the classic cell to cell comparison.

1.2.3.2 Partial validation techniques

It appears clearly that future land use/land cover, simulated as a scenario or prediction, can not be validated by classical comparison techniques using, real, but not yet available data. However, a conceptual validation and the assurance of the model's robustness may provide useful information about the model's validity. Robustness can be tested by measuring the output stability during iterative model running. The exploration of error effects in model results derived from uncertainty of input data, data weighting and transformation also provides useful information about model performance. Gómez Delgado and Barredo (2005) describe a method, which assesses the risk when using model outputs. Gómez Delgado and Tarantola (2006) propose a sensitivity analysis with the aim to test model stability. They use several indices measuring model result's variability relative to changes of the input parameters. An additional and commonly applied validation approach consists in confronting model outputs with expert opinions.

1.3 Presentation of following case studies (Part B)

The following series of contributions (See Part B), written by researchers working in Brazil, France, Italy, Mexico and Spain, attempt to show a large, but not exclusive, display of what geomatic models using GIS can provide in modelling environmental dynamics. The professional fields of the authors stretch from geography, geomatics, ecology, environmental sciences, urban development and land planning, computer science to mathematics. All of them belong either to university communities or research centres.

1.3.1 Themes and objectives

The thematic applications of the performed simulation models shown in the following pages all deal with environmental dynamics, although they are as various as the notion itself. Some authors focus on modelling of concrete environmental dynamics like deforestation and reforestation, fire risk, expansion of intensive forms of agriculture, loss of biodiversity or urban growth while other proceed to a more general analysis and simulation of land use/land cover changes related also to landscape changing.

The outcome of each contribution may be another criterion helping us to understand the set of used models and to try to classify them. One objective is what today is called participatory modelling, that is, including the opinion and knowledge of the involved (local) communities and co-operating with local participants in building prospective tools for exploring paths for sustainable development at the local scale (Guerrero et al., Cuevas and Mas, Godoy and Soares-Filho, Monteil et al.). Several articles have the aim to provide decision support for environmental management and land planning (Aguilera et al., Barredo and Gómez, Benito and Peñas, Valenzuela et al.) or with the aim to provide operational solutions (Galtié). In comparison, some papers clearly aim to make more fundamental research in model comparison and validation (Follador et al., Paegelow et al., Selleron and Mezzadri-Centeno), while others intend to reconstruct former landscapes (Camacho et al.).

In a more general sense, almost half of the presented works have a practical objective (instantaneous time modelling, decision support, participatory modelling), while the second group insists more on methodological aspects about modelling methods, simulation and scenario significance and validation.

1.3.2 Time scales

Used timescales in modelling provide one criterion more to make a typology of the following case studies.

The contribution of Galtié is based on a short timescale including actual and recent annual (last decade) data. The aim is to derive an instantaneous and quasi real-time updated level of risk, which can be used in fire risk prevention and the fight against fire. Actual data reflect the state of the main components of risk (land cover, land use, etc.). A decade training period is used to determine the terms for the component's combination and calibration (explanatory variables).

The majority of the presented work use a medium timescale: from a few decades to a century. All eleven of these contributions intend to create prospective simulations, which typically used two or three earlier decades for the training data. Some of them use more historical data, describing the modelled variable in relation to the speed of the involved dynamics. The simulations or prospective scenarios also span to a few decades (up to 2040 in Barredo and Gómez). Sometimes the simulated date belongs to the recent past. This means that the training data didn't include the most recent date, which is only used for model validation. Inside this medium timescale group, a finer classification may be obtained by focussing on the type of modelled dynamics. Low speed dynamics and/or regressive land cover dynamics are considered by Paegelow et al. and Monteil et al. The latter work may also be regarded as a transition between short and medium timescales because it uses annual training data.

But fast and progressive land use/land cover dynamics form the largest group (9 chapters). Urban growth, loss of biodiversity, agricultural intensification and deforestation are high speed processes that require a better understanding through modelling because they are directly related to global problems and what we call nowadays sustainable development.

Finally, the contribution of Camacho et al. deals with a long time span in order to perform an approximation of the historical land use. It's also the only modelling used in a retrospective way.

1.3.3 Modelling approaches and used models

When we refer to methodological modelling approaches and used models – some authors use only one approach which belongs clearly to one modelling type (e.g., cellular automata, Markov chain analysis, etc.), while others used a combination of several methods and a third group employs numerous models in order to compare them – we have another criterion, with which to classify the following works.

The contributions of Follador et al., Paegelow et al. and Selleron and Mezzadri-Centeno are based on several models with the aim to compare model outputs (simulated land use/land cover) and to enhance their validation. In concrete terms, these authors use functions included in commercial GIS software like Idrisi Kilimanjaro or Andes, in freeware software like DINAMICA and/or algorithms that they developed themselves. Applying different modelling approaches to the same study area(s) and data base(s), has the objective to improve the model's outputs by comparison and to better identify critical points and, in this way, to get more information about model ability and model generalisation.

Paegelow et al. compare a so called "combined geomatic model" (Markov chain analysis, multi-criteria and multi-objective evaluation and a cellular automaton) based on Idrisi Kilimanjaro functions with self-developed algorithms like polychotomous regression and neural network based models. Follador et al. apply the same "combined geomatic model" and made a comparison with the Land Change Modeler (implemented in Idrisi Andes), a self-made neural network (PNNET: Predictive Neural NETwork) and DINAMICA EGO. Except for PNNET, these models call on MCA (Markov chain analysis 2nd order) for computing time transition probabilities.

Another case is the work done by Benito and Peñas. The two methodological approaches – a simulator of land use change, GEOMOD implemented in Idrisi Andes, and a spatial distribution model, MaxEnt –run together and prove that their combination improves the predictive capability compared to the GEOMOD based modelling approach alone. More concretely, MaxEnt is performed to generate a greenhouse-distribution model jointly with GEOMOD to simulate greenhouse growth over the distribution model.

The other authors use one main modelling method which is, often, split into several, more or less, complex modelling steps. Here we find practical applications for commercial GIS software modules, especially Idrisi. Guerrero et al. make use of GEOMOD (Pontius et al. 2001) and Camacho et al. employ an optimisation method (Briassoulis 2000) exploiting multi-criteria and multi-objective evaluation technique.

For the research utilizing only one model, the cellular automaton based algorithms are dominant. Godoy and Soares-Filho as well as Cuevas and Mas employ DINAMICA EGO, a generic type of cellular automaton developed by Soares-Filho et al. (2002), which may be described as a spatio-temporal model for the analysis and simulation of land use changes.

Barredo and Gómez employ the MOLAND model, a cellular automata (CA) based model (White et al. 1999, Barredo et al. 2003 and 2004) that integrates various criteria in a probabilistic approximation to perform urban scenarios. In standard CA, the fundamental idea is that the state of a cell at any given time depends on the state of the cells within its neighbourhood in the previous time step, based on a set of transition rules. In the MOLAND model, a vector of transition potentials is calculated for each cell from the suitability, accessibility, zoning status and neighbourhood effect. Then, the obtained deterministic value is modified by the stochastic parameter using a modified extreme value distribution.

Aguilera et al. (modelling of greenhouse expansion), Valenzuela et al. (urban growth modelling) and Galtié (WUI fire risk modelling) implement a modelling method halfway between the use of existent modules and a self developed approach. The first two approaches, basically cellular automata, are implemented in the Macro Modeler of Idrisi Andes; the third one uses ArcGis software. Although they employ a software interface, the models of these authors are complex and specifically designed and therefore they have to be regarded as proper development as well.

Monteil et al. present a spatialised multi-agent model, the SMASH model (Spatialised Multi-Agent System for ASH colonisation), implemented using the CORMAS platform (Bousquet et al. 1999) and coupled to the vector data that were produced with ArcView software. SMASH illustrates a “companion modelling” approach for building a simulation model supporting analysis of prospective changes. It emphasises the role of reflexive character and the variety of individual behaviour of human participants on land-use change, which is currently regarded as an important feature to account for prospective studies (Greeuw et al. 2000). In the companion modelling approaches, the spatial multi-agent system (MAS) is developed in a participatory process.

With regard to Selleron and Mezzadri-Centeno, they compare a cellular automata and a fuzzy logic based model using specific algorithms developed in C++ by the authors themselves.

1.3.4 Data Bases: Raster or vector, origin and nature of variables

Most of the modelling issues presented below use databases in a raster format.

In the research of Monteil et al. the initialisation of the agent attributes is carried out by starting from the vector data layers, resulting from a geographical information system (GIS), developed on their study area with ArcView 3 software. This link between the vector representation in the GIS and the matrix representation in the spatialised multi-agent model thus requires a conversion between these two modes of representation (rasterisation of the vector layers). Procedures of import-export exist in the ArcView extension Spatial Analyst to rasterise a vector layer into a matrix of numerical values saved in the text format. Also CORMAS can import such files to initialise attributes of the cells.

Godoy and Soares-Filho also carried out a spatial data base, afterwards it was employed to realize a land use change analysis in the form of a transition matrix, first in vector format. The reasons are available data origin and data standardisation. This step is followed by data conversion because DINAMICA operates in a raster format. Guerrero et al. use vector representation of data as well in ArcView to perform a land use/land cover change analysis.

These examples illustrate that obviously many original data bases are in the vector format. All of them are then converted into images because every used model takes advantage of easier spatial analysis in grid cell format. The vector origin is related, on the one hand, to available official GIS data, provided by public administrations. On the other hand a lot of digitized maps come from aerial photo interpretation. Aerial photographs are the basic high scale data used to create a chronological land use/land cover set such as satellite images at lower scale. Vector digitalisation is also processed to extract information from existent analogical maps.

Regardless of the method of obtaining data, it is certain that raster data bases are closer to involved models. In this context, it has to be emphasised that digital ortho-photographs and especially satellite images – already in raster format – become more and more important. For the research of Selleron and Mezzadri-Centeno, Follador et al., Aguilera et al., Cuevas and Mas, Benito and Peñas, and Guerrero et al., remote sensing data with medium spatial resolution (mainly Landsat TM and ETM+, Spot and Aster but also Landsat MSS data for earlier dates) are the principal data sources to build a chronological series for model calibration. Also remote sensing data have a high temporal resolution, which permits the periodical retrieval of information for the same area. With this background, one notices the increasing use of available online images and maps; Google Earth, to name the most famous example is only one of a quickly growing number of websites. Aguilera et al. do so to update earlier ortho-photographs.

Barredo and Gómez use the datasets from the CORINE project (EEA 1993) as input data for their model thus the resulting scenarios have the same spatial and thematic properties as CORINE. Using this European-wide dataset makes it possible to model large European areas in a single implementation of the model.

Whatever the origin of land use/land cover maps is that form the principal modelled variable, it has to be mentioned that they are related to other variables, which are capable of explaining a more or less important part of land use/land cover variability in space and time. These explanatory variables sum up the 'knowledge' the model will use to compute a scenario or simulation. Generally, authors use distance and accessibility maps and DEM (digital elevation model) related maps such as topography, slope and aspect. Zoning status, like the one of protected areas or other territorial divisions, materializing management differences, bioclimatic information but also information about any form of human activity (economic, social, institutional, infrastructural) complete the large pool of involved data able to improve model outputs. To illustrate the huge spectrum of knowledge used to define variables, we quote here just the mobilised variables by Monteil et al. In order to simulate the interactions between land use options and ash encroachment for the long term (30 years), they take into account land cover (cropland, grassland, etc.), land use (crop, meadow, urban, etc.), slope (several classes) and identification numbers (farmer, cadastral parcel, and agricultural parcel). Agricultural parcels are the basic units of the farmers in the technical management of the farmland and farmers are the principal 'players'.

Among these explanatory variables authors often distinguish between those that will not significantly change during the training period and the simulation period (static variables like topography) and a second group of criteria changing rapidly (dynamic variables like accessibility). The difficulties, linked to different resolution/scales and information density, to combine all these data are so well known that we will not go into further detail here.

The techniques employed to measure the relationship between the explanatory variables and the variable to be modelled are various, but there are also various techniques to compute the helpful variables' weights of evidence.

Most of the authors employ traditional statistical tests like the Pearson correlation coefficient, a range of regression tests (linear, multiple, logistic), but also more recent tests about the goodness in terms of location like ROC statistics (Pontius and Batchu 2003) and various Kappa indexes (Pontius 2002). The free software DINAMICA includes a module for the definition of the categorisation intervals and automatic calculation of the weights of evidence. For each transition, it produces a transition probability map using the sum of the weights of evidence related to each category of the territorial configuration variable (Rodrigues et al. 2007). To do so, the entrance maps have to be spatially independent. As in other software, the Cramer's test and the measure of uncertainty of the combined information (Bonham-Carter 2002) is undertaken. Correlated variables have to be de-correlated or to be combined into a third one that will used by the model. The relationships calculated through the weights of evidence are applied to parameterise and to calibrate the simulation model.

Frequently, these data are used to aid in the creation of suitability maps for specific land use/land cover. Dependent on thematic model application, the same method also leads to vulnerability maps or risk maps. A lot of the research presented in this book (Aguilera et al., Camacho et al., Follador et al., Paegelow et al., Valenzuela et al.) employ the in Idrisi implemented multi-criteria evaluation (MCE) or GEOMOD (Benito and Peñas, Guerrero et al.).

1.3.5 Study areas and scales

The employed scale or the chosen spatial resolution and the fact that some contributions undertake a comparison between several study areas create another criterion to characterise the following case studies. Beginning with the last point, only two research studies compare two terrains in order to conceive more general conclusions. This is the case of Paegelow et al. applying the same models to two similar mountain areas in southern Europe. Also Galtié is basing his risk modelling approach on two different terrains in the south of France in order to include a representative sample of fire risk conditions of southwestern of Europe.

The spatial resolution (grid cell size) varies from 10 to 100 meters. Some authors also employ different resolutions and, consequently, nomenclatures. The finest grid (10 meters) is applied by Godoy and Soares-Filho. Grid resolutions of 20-25-30 meters are used by Camacho et al., Cuevas and Mas, Follador et al. and Paegelow et al. Selleron and Mezzadri-Centeno, after geometric correction and data homogenisation, finally use 75 meters raster cells. Aguilera et al., Barredo and Gómez, Benito and Peñas, Guerrero et al., and Valenzuela et al., chose spatial resolutions of about 50, 80 and 100 meters.

Monteil et al. try different rasterisation methods (information at pixel centre or use of the relative majority of the area) and various grid cell sizes (from 10 to 50 meters in pixel size) to convert the original vector data with the objective to simulate agricultural land use change at the parcel level under the conditions of a southern France mountain area. They, finally, adopt a resolution of about 14 meters.

Galtié deals with three scales (French department scale, municipality scale and infra-municipality scale) to take into account the different administrative, organisational forms of the territory, with their related fire prevention and fire-fighting services and objectives like identification of basins of risks and sensitive points. In this way, he mobilises hectometric, decametric and metric data in order to include hazard and stakes forming fire risk as well as to take into account fire dynamics at all scale levels.

The dimensions of study areas are also variable depending on the type of modelled environmental dynamics. The smallest areas are about 10-20 km^2: urban area of 8.5 km^2 (Godoy and Soares-Filho) corresponds to a quarter of Belo Horizonte (Brazil), rural area of 20 km^2 (Monteil et al.) in the Pyrenees mountain (France). Most of the terrains involved form local entities or little regions (from 200 to 2,000 km^2: Paegelow et al, Follador et al, Camacho et al., Selleron and Mezzadri-Centeno, Valenzuela et al., Aguilera et al., Cuevas and Mas) while Benito and Peñas work at the province level (Almería, Spain, 7,000 km^2). Barredo and Gómez employ the MOLAND model almost to the same extent (metropolitan area of Madrid, 8,000 km^2). Guerrero et al. use an entity constituted by four sub-regions in Michocán (Mexico) that covers 6,500 km^2. Galtié, dealing with two different areas, works from the local (0.01 km^2) to the regional (2-400 km^2) and zonal (400 km^2) scales.

1.3.6 Calibration, results and validation techniques

An important aspect in all the case studies is the calibration and validation of computed results. Consequently, we also focus in this presentation on these aspects that are essential in order to contribute to developing modelling tools for environmental dynamics applicable in current management and forecast tasks.

1.3.6.1 Calibration

The calibration of performed models usually requires a training period including a chronological series of maps about the environmental dynamic to be modelled and the explanatory variables. With regard to the number of maps or images forming the training data base used to calibrate the model, a majority of the research presented here are based on two dates and the dynamics during this selected period. In other words, the performed temporal simulation – almost always undertaken by way of conditional probabilistic transition matrices – is carried out with two dates to model a posterior third date. This is evidently a difficult situation for researchers, who wish to deal with numerous training dates depending on the modelled object but often reflects the reality in terms of available data or time to elaborate them.

Some authors, like Selleron and Mezzadri-Centeno, call on three dates for the model calibration. Modelling approaches by neural networks and polychotomous regression (Paegelow et al.) mobilise all available training data for model configuration. Then the model calibration is done stepwise, from one date to the next.

The optimisation model by multi-criteria evaluation, used by Camacho et al., makes use of one calibration date, the oldest one, to process retrospective modelling.

Aguilera et al. and also Valenzuela et al. propose models that are based on one date as a reference state to simulate a later one. In these studies, the authors consider the concept of calibration as an adjustment process for the model to be as similar as possible to reality. For example, Aguilera et al. consider the calibration as a model configuration process that allows for the creation of an ex post simulation for actual conditions using known information. So they calibrate their model by generating various simulations for today and then compare them with reality. However this 'trial and error' method is quite common during the calibration step with the aim to optimise and configure the model.

The calibration of the risk models proposed by Galtié operates on two levels: at the overall model level, using a method based on experts' statements; at intrinsic aggregate model level, using a method based on crossing experts' statements, existent models, in situ observations and experimental validations.

Monteil et al., building a participatory multi-agent system model, use knowledge of local players and scientists based upon the recent past in order to calibrate the rules involved in the model.

Coming back to the most typical scenario, the length of the training period depends on the one hand, on the considered dynamic and its swiftness, and on the other hand on the time span of macro-system conditions that can be simulated for the near future. The span of calibration time varies from steps of two to three years (Cuevas and Mas, Follador et al.) to about a decade (French study area in Paegelow et al., Selleron and Mezzadri-Centeno, Barredo and Gómez, Benito and Peñas, Godoy and Soares-Filho, Guerrero et al.) to a phase closer to twenty or thirty years (Spanish study area in Paegelow et al.) and even fifty years (Monteil et al.).

A related issue is the time step between the last calibration date and the validation date although, once again, presented studies differ in length and significance. A lot of models are applied accordingly so that the simulation date corresponds to the last available (model unknown) date in order to perform a comparison with reality in terms of the goodness of the prediction and specific misclassification. The number of years separating the last model known calibration date and the date of simulation is about three to five years, respectively (Cuevas and Mas, Follador et al., Selleron and Mezzadri-Centeno) and eleven to fourteen years (Paegelow according to the two study areas). The time step is about fifteen and seventeen years for both Aguilera et al. and Valenzuela et al. using the simulation for calibration as well as for validation.

In the second group of elaborated models one of the simulations corresponds to the known model's last/actual reality map. In other words, one of the model outputs (mainly as a validation step to perform long term simulation scenarios) is useful for its validation (Godoy and Soares-Filho, Benito and Peñas, Barredo and Gómez).

1.3.6.2 Results

Most of the following case studies carry out a model output in the form of simulation maps or mapped scenarios either corresponding to the last available real situation or to the near future, with the exception of the retrospective modelling of Camacho et al. Some authors perform various scenarios depending on different dynamics or anticipating a range of possible changing (Monteil et al., Godoy and Soares-Filho).

The future projections are achieved in the following studies: Selleron and Mezzadri-Centeno (projections to 2000, 2005 and 2010), Aguilera et al. (2025), Valenzuela et al. (2018), Benito and Peñas (2010), Barredo and Gómez (2040), Godoy and Soares-Filho (2012 and 2020), Cuevas and Mas (2015), Guerrero et al. (2025). As mentioned above some of them present multiple scenarios. Aguilera et al. carry out three future simulations about greenhouse growth: stabilization, tendency growth reflecting the trajectory of the recent past, and moderate growth. Benito and Peñas also compute three scenarios about greenhouse growth and their ecological and environmental effects: linear, accelerated and slowed growth. Developing models for urban growth, Barredo and Gómez propose three simulations differing particularly in spatial location: scattered growth, rapid urban growth, compact development, from scenarios produced by the Intergovernmental Panel on Climate Change (IPCC) in the Special Report on

Emissions Scenarios (SRES). Valenzuela et al., involved in urban dynamics and urbanisation patterns, compute four scenarios varying spatially in urban patterns: aggregated, lineal, junction growth and growth in the form of planned residential barriers. Cuevas and Mas, computing a participatory land use modelling tool, show first the trend scenario following the amount and pattern observed during the training period. Alternatively, they develop a 'cattle' scenario that presumes a loss of social cohesion and an increased conversion of dry tropical forest to pastures for cattle, but also a sustainable scenario supposing implementation of protected areas and the promotion of sustainable pastoralism.

Camacho et al. calculate retrospective simulations corresponding to three dates (1571, 1752 and 1851) for which statistical data about land use are available. The computed probabilistic spatial distribution of land use can not be validated at the infra-municipality level and only the comparison with the closest land use map corresponding to the middle of the 20th century permits any conclusions about the goodness of fit.

Galtié, contributing to archive for an operational fire risk model, calculates various scale dependant risk indicators for long time periods (risk prevention) as well as for immediate time periods (operational prevision).

Monteil et al. are building a multi-agent model simulating ecological processes of ash colonisation and farmers' land management behaviour to explore scenarios of change in agricultural land use and landscape reforestation and their social and environmental consequences according to the impact of assumed changes in the socio-economical environment (public policies for agriculture; rural urbanisation) on farmer's behaviour. Preferring a participatory approach, the construction and calibration of the farmers' behaviour model are the principal results. Scenarios are still on-going and a set of visualisations (interactive maps, plots of selected indicators of the farmland and the landscape levels, dynamic crosstabs of operations and land use/land cover changes) are being worked out to support the participatory assessment.

1.3.6.3 Validation techniques

Some authors first process a visual comparison between real and simulated land use/land cover maps (Aguilera et al., Barredo and Gómez, Follador et al., Paegelow et al., Selleron and Mezzadri-Centeno). Then they use, like most of the researchers, statistical tests to quantify the prediction score in terms of the correct extent and spatial localisation. Although some model outputs are difficult to validate by these methods (e.g., fire risk or long term scenarios) and authors have recourse to expert opinion. Among the variety of statistical tools that authors apply to compare either real to simulated results or simulations with each other we have listed the following popular methods.

- Cumulated surface by category (which doesn't care about correct localisation);
- Pixel-by-pixel validation using matrices (simple to process but doesn't consider the agreement of spatial proximity);
- Correct prediction scores and residues;
- Various Kappa indices (Pontius 2002) measuring the agreement in terms of quantity and quality (location);
- LUCC (Land Use/Land Cover Change) budget focussing only on the changes (Pontius et al. 2004) and it is more difficult to predict changes than stability;
- Fuzzy logic based indices (Hagen 2003, Hagen-Zanker et al. 2005) measuring the agreement of location and overcoming the restrictions induced by hard pixel limits like pattern quantification and exclusive cell state.

To this basic list of validation instruments, some authors add more specific tools, which are needed either for a singular thematic or available by specific software. Accordingly, Benito and Peñas are measuring the spatial similarity of model outputs (greenhouse growth) by Procrustes analysis (Jackson 1995). It compares the fit between different matrices (e.g., real and modelled distribution) by linear transformation (rotation, translation, scaling) of one grid to achieve the best fit with the reference grid. The index of agreement is the sum of squared errors; the lower it is the better is the agreement.

DINAMICA EGO, employed by Cuevas and Mas, Follador et al. and Godoy and Soares-Filho offers a special, fuzzy logic based, tool measuring what we called agreement of quality or spatial similarity. Referring also to the research of Hagen (2003), DINAMICA EGO provides a vicinity-based comparison tool measuring the fuzzyness of location (Rodrigues et al. 2007).

Another way to quantify spatial similarity consists of applying ecological indices (refer to McGarigal and Marks 1995 and Botequilha et al. 2006 for an exhaustive description of these metrics) like patch number or medium patch size. Aguilera et al. also uses this as well.

Galtié implements and compares three methods of validation/calibration: crossing of produced risk values and historical and current fire occurrences, comparative analysis of results derived from existing methods and validation by experts' statements.

Monteil et al. provide their companion model based on a multi-agent system with some visualization features to facilitate validation of the conceptual model with local partners and experts (conceptual validity in the meaning of Rykiel 1996: ensuring that assumptions underlying the conceptual model are correct or justifiable and that the representation of the system in the model is reasonable for the model's intended use).

1.3.7 Outcome and originality

The previously developed criteria are helpful to characterise the following contributions but are insufficient to give an entire comprehensive view of them and to classify them. Therefore we index the following research examples with regard to their originality and their outcome. These are the aspects that emphasise the best of the scientific and methodological contribution of each work and may be their best study to date. As a result we group the thirteen articles into five chapters.

They are only a sample of the variety of methodological approaches, and thematic applications for environmental dynamics and objectives for simulation. Most of them are at the crossroads for these criteria and this makes it difficult to clearly order them in accordance with fundamental notions like the nature of the model, the modelled variable or the principal aim that motivates the research. However, some proximities or associations clearly appear and allow the ordering of the selected examples into some sets.

- *Model comparison applied to deforestation and reforestation*

  A first series of four articles deals with deforestation (in Central and South America) while European mountains are characterised by an important spontaneous reforestation. The first article clearly has a thematic objective: reducing carbon emission related to tropical deforestation while the three following tend towards methodological comparison and model validation.
- *Decision support and participatory modelling*

  Decision support as a practical application of geomatics evidently tends to offer innovative tools to assist environmental management. The first article of this set deals with fire risk to improve risk prevention while the two other's on top of that explore the participatory approach in modelling often related to the concept of sustainable development.
- *Retrospective modelling*

  Contrary to all other examples, the authors here explore a multi-criteria approach applied to model historical land use.
- *Multi objective conflicts and environmental impact of intensive agriculture*

  Leaning on the example of greenhouse expanding on the Andalusian coast, the authors focus on two more general problems: the concurrence between different land uses on a limited space and the environmental impact of this form of development.

- *Urban environment and urban growth*

Finally, three articles illustrate environmental problems in urban space and urban growth related to land use conflicts. Two contributions are applying different models to simulate urban land use change while the third is exploring land use scenarios in urban regions related to climate change scenarios.

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GIS based modelling software

ArcGIS http//www.esri.com/index.html
CLUE http//www.cluemodel.nl/
Dinamica http//www.csr.ufmg.br/dinamica/
Environment Explorer http//www.lumos.info/environmentexplorer.htm
GRASS http//grass.itc.it/index.php
Idrisi http//www.clarklabs.org/
Land Use Scanner http//www.lumos.info/landusescanner.htm
MOLAND http//moland.jrc.it/the_project.htm
LTM http//ltm.agriculture.purdue.edu/default_ltm.htm
SLEUTH http//www.ncgia.ucsb.edu/projects/gig/v2/Dnload/download.htm

PART B

CASE STUDIES

Model comparison applied to deforestation and reforestation

2 Land use / Land cover change dynamics in the Mexican highlands: current situation and long term scenarios

Guerrero G, Masera O and Mas J-F

Abstract
This paper examines the land use/land cover change dynamics in the Purepecha Region of the Michoacan State, Central Mexico. This region is representative of the Mexican Highlands in both its socioeconomic and ecological aspects.The vegetation consists primarily of pine-oak forests and pine forests. There are large areas used for agriculture and permanent crops –particularly avocado orchards-. The region is undergoing a complex pattern of land use/land cover change, including a rapid process of forest degradation and deforestation as well as the abandonment of agricultural areas leading to forest regrowth. We use remote sensing techniques to determine the regional land use/land cover change transition matrix for the period 1986-2000, and discuss the land use/land cover change dynamics. We then apply the GEOMOD model (Hall et al. 1995) to build long-term scenarios in the region. With this tool we identify the most important drivers for the deforestation process and build vulnerability maps on potential deforestation sites within the region in 2025.

Keywords: Land Use/Land Cover Change, GEOMOD, Purepecha region, Spatial Models, Deforestation

2.1 Introduction

Mexico has been classified as a megadiverse country. Because the country suffers from one of the highest rates of deforestation in the world (Velázquez et al. 2002a), the situation for forests in Mexico is critical (Masera 1996). Based upon the comparison of LU/LC maps for the entire Mexican territory between 1976 and 2000, the deforestation rates were evaluated as 0.25 and 0.76% per year for temperate and tropical forests, respectively (Mas et al. 2004).

The State of Michoacan, in the Central Mexican Highlands, is no exception. The state's temperate forests reach 1.5 million hectares, 40% of which have been degraded and show secondary vegetation. Twenty percent of the temperate forests in the Michoacan State are located within the Purepecha Region; this region has environmental and socio-economic conditions representative of the Mexican highlands. Timber harvesting is intense, and migration has accelerated in recent years bringing about structural changes in economic activities, which have created complicated processes of land use change (Alarcón-Chaires 1998).

Land use and land cover change processes represent a complex dynamics that depend on the type of cover, the ecological interactions, physical environmental, socioeconomic activities and other meteorological phenomena (Lindenmayer and Franklin 2002, Kaimowitz and Angelsen 1998). This chapter describes the land use change dynamics in the Purepecha Region and emphasizes the understanding of the deforestation process. We used the model GEOMOD2 to simulate land use/land cover change (Pontius et al. 2001), and to examine those factors that have a direct relationship with the regional deforestation process.

2.2 Text areas and data sets

The study area is located in the western center of Mexico in the state of Michoacan. Because most of the Purepecha population (name of the dominant ethnic group) lives in the central and northern regions of Michoacan, the area is denominated as the "Region Purepecha" (Fig. 2.1). It comprises 19 municipalities covering an area of 652,000 hectares. The region accounts for approximately 11.1% of the state's area, with a population of approximately 732,000 inhabitants (18.3% of the state total) dispersed among 927 settlements. The population density is of 1.12 inhabitants/ha. In Michoacan State, as well as in the Purepecha Region, emigration is very high; approximately 150,000 inhabitants from Michoacan immigrated to United States between 1987 and 1992 (Mendoza 2003). The migratory process has accelerated in recent years, particularly to the United States (Rivera 1998). Michoacan is the main producer of avocado worldwide. Since 1997, due to the end of the restrictions of exportation to United States, production notably increased. For 2000, the Tancitaro and Uruapan region produce almost one million tons of avocado (Hinojosa et al. 1999).

The region is mountainous; elevation ranges from 620–3,860 masl. Due to recent volcanic activity, andosols are the dominant soil type. The climate is temperate sub-humid with an average rainfall between 800 and

1,100 mm mainly concentrated in the summer, and average temperatures between 11°C and 14°C. The rough topography of the region results in a wide variety of microclimates. Michoacan presents a great variety of vegetation types. According to the National Institute of Statistics, Geography and Informatics (INEGI), the vegetation in the region Purepecha consists primarily of pine-oak forest, pine forest, agriculture and permanent crops.

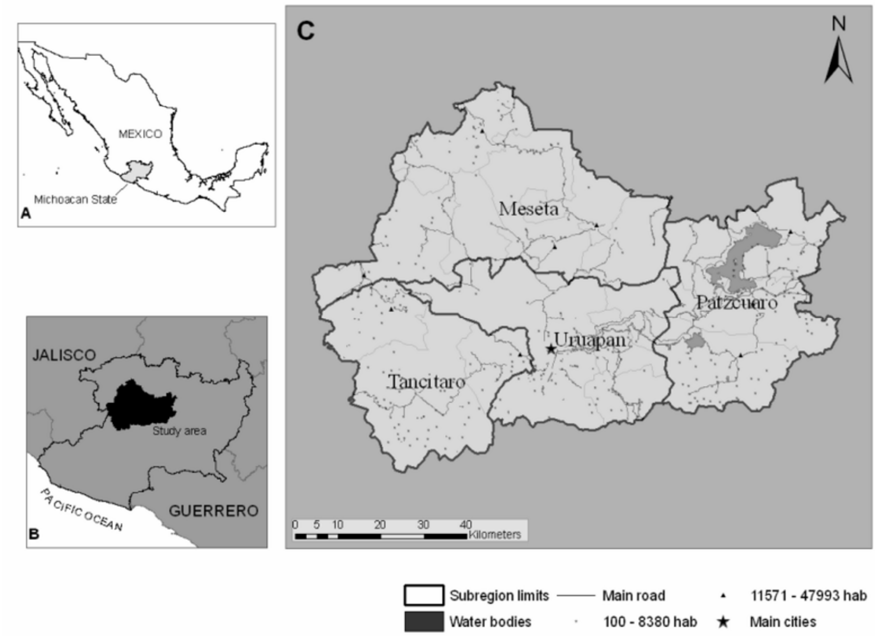

Fig. 2.1 Location of the study area. The area is located in the western center of Mexico in the state of Michoacán (A and B). The study area includes the Paztcuaro and Zirahuen lakes and was subdivided into four sub regions: Meseta, Patzcuaro, Uruapan, and Tancitaro (C)

2.2.1 Image classification

A classification of two Landsat images was carried out that corresponds to the years 1986 and 2000. The images were taken in the same months (February-April). The first one is part of the Landsat Thematic Mapper TM series, and the second one belongs to the Enhanced Thematic Mapper Plus ETM+ series. The interpretation of remotely sensed images was realized by a maximum likelihood supervised classification, using the IDRISI32 software. We created spectral signatures using training site data of fourteen vegetation types. For ten land-use categories we used 88 field validation points, for the remaining four categories the INEGI land use and cover and National Forest Inventory map were used (Palacio et al. 2000, INEGI 1980).

Table 2.1 Land Use/Land Cover classes in the Purepecha Region

Land use/Land Cover used in the National Forest Inventory (NFI 2000)	Land Use/Land Cover used in this study	Major Land Use/Land Cover clusters
Agriculture Rain-fed agriculture	Agriculture	Man Made Land Cover
Rain-fed agriculture with permanent and semi permanent cultures	Orchards	
Irrigation agriculture	Irrigated agriculture	
Oak Forest Montane cloud Forest	Oak Forest	Forest
Pine Forest	Pine Forest	
Pine-oak (Oak-pine) Forest	Pine-Oak Forest	
Fir Forest	Fir Forest	
Pine Forest with secondary vegetation Oak Forest with secondary vegetation Oak-Pine Forest with secondary vegetation	Forest with secondary vegetation	Forest with secondary vegetation
Subtropical Shrubs Subtropical shrubs with secondary vegetation	Scrubland	Scrubland/Grassland
Induced Grass land	Grassland	
Forest Plantations	Forest Plantations	Forest
Area without vegetation	Area without vegetation	Man Made Land Cover
Human settlements	Human settlements	
Water bodies	Water bodies	Water bodies
Tropical deciduous and subdeciduous forest Hygrophilous vegetation	Without classification	Without classification

We used the National Forest Inventory (NFI) (Palacio et al. 2000) in order to identify the same vegetation types. For the aim of this study, the 21 classes in the NFI, were regrouped into 15 classes (Table 2.1). We also grouped these 15 categories into five major land use/land cover clusters to better examine the overall dynamics of the regional land use change process. The first cluster included all primary forests LU/LC classes. The second cluster included secondary forests LU/LC classes. The third comprised all man-made LU/LC classes such as crops, orchards and human settlements. The fourth included all grasslands and the scrublands with or without secondary vegetation. The fifth included only the water bodies (Velázquez et al. 2002b).

2.2.2 Land Use/Land Cover Change Analysis

The land use/land cover change (LU/LC) analysis was performed using the ArcView3.2a software. An overlaying analysis was performed in order to assess pathways of change and locate sites where these changes occurred. Four processes of LU/LC change were identified: deforestation, degradation, recovery, and revegetation. Deforestation occurs when primary and/or secondary forests change to a man-made land cover. Any transformation from a primary land cover cluster into a secondary land cover cluster indicates degradation. Recovery includes changes from a secondary land cover cluster into a primary land cover cluster. Revegetation comprises changes from a man-made land cover into a secondary or primary land cover cluster.

Data Collection and Preparation

The methods used to estimate and simulate deforestation in the GEOMOD model are detailed in Hall and Dushku (2002) and Pontius (2006). The model requires as input the following mapped information: 1. Land use/land cover maps for two points in time used as the primary inputs; 2. A political map with the sub-regions used to highlight different patterns of land use change at a sub-regional level; 3. A selection of multiple potential candidate driver maps that conditioned changes to clear forest for agriculture or other human-dominated land use (e.g. elevation, soil type, precipitation, roads, hydrography). In our case, all digital map data required by the model was collected, corrected for projection differences, and converted to grid data layers of the same origin and extents. These consist of 914 rows by 1,245 columns, with a grid cell resolution of 100 by 100 meters. Then reclassified each land use/land cover map, the soils map, and the sub-regions map to represent land (1) and non-land (0) in order to create a 'MASK' that would ensure that information was available for analysis on all input maps. We did this by overlaying the binary maps until only the non-zero cells coincided. The final mask, therefore, included only those areas that were consistently identified as "land" in all maps. Then the distance from roads, towns, rivers and lakes was calculated. In the initial analysis each candidate driver map was classified into categories representing ½ kilometer distance from each of these potential physical features. After a first calibration these were reclassified to represent much smaller distances. Table 2.2 shows the final set of candidate driver maps, it includes the 5 "distance from" maps. The land use/land cover maps were reclassified to include only two classes. The land use type 1 for this study represents "only forest with primary vegetation". The land use type 2 represents human-impacted land use categories and includes secondary forests (Brown et al. 2007). The final set of candidate driver maps includes six maps, for the most significant see Table 2.3; all were then converted to ASCII format as required.

Table 2.2 Category delineation for candidate spatial pattern drivers used in the simulation with the GEOMOD model

Driver	Range of values	Units	# Classes	Class Width
Elevation	622-3836	Meters	20	200
Slope	52	Grades	10	1=0°, 2-9=5°, 10=10°
Aspect	0-360	Grades	10	1=plano, 2=0-22.5°, 3-9=45°, 10=22.5°
Soils	12	Nominal	12	1
Precipitation	700-2,000	Millimeters	7	1-3=100mm, 4-5=200mm, 5-7=300mm
Temperature (Dry season)	12°-33°	Grades	7	3°
Temperature (Raining season)	6°-36°	Grades	10	3°
Sub-regions	4	Nominal	4	1
Dist. From towns	8,528	Meters	30	284
Dist. From roads	4,709.56	Meters	24	200
Dist. From all water sources	15,368	Meters	32	500
Dist. From perennial water Source	20,976	Meters	42	500
Dist. From perennial streams	22,483	Meters	30	750

2.3 Methodology

2.3.1 Conversion rates

Conversion rates were assessed based on forest cover data, using a lineal formula:

$$\mathrm{D}R = \left[\frac{\mathrm{A}_1 - \mathrm{A}_2}{\mathrm{n}}\right] \tag{2.1}$$

Where DR is the deforestation rate (area/year); A_1 and A_2 are, respectively, initial and final forest areas, and n is the interval (years) during which the change in forest coverage is evaluated.

2.3.2 Long-term scenarios

In order to simulate the future evolution of the deforestation in the study area for the period 2000-2025, we used the GEOMOD model, which uses spatially distributed data. GEOMOD was developed by researchers at SUNY College of Environmental Science and Forestry (Hall et al. 1995) and uses digital raster maps of bio-geophysical attributes and socio-economic factors such as infrastructure, as well as digital maps of existing land use, to extrapolate the known pattern of land use/land cover from one point in time to other points in time.

2.3.3 Model calibration and validation

GEOMOD begins by categorizing each potential pattern driver map into categories or classes and adding the number of cells of each class that exist in the entire geographic region being analyzed. The model then adds how many cells of each of these categories lies in areas deforested between the first and second points in time. Then GEOMOD calculates the proportion of this sum for each class versus the sum of all cells of that exist in the region. This proportion indicates the degree to which land had been deforested in the past and is assigned to all forested cells of that class to indicate their "vulnerability" of being deforested in the future. We use individual driver maps and multiple combinations of calibrated driver maps to show areas of highest overall likelihood of deforestation, GEOMOD uses this map of "vulnerability" or "risk map" to simulate deforestation for a second point in time (see Fig. 2.6). The results were validated comparing the simulated 2000 deforestation map with the actual 2000 deforestation map to determine which combination of drivers yielded the most accurate prediction, the goodness of fit test for each simulated map produced is based on both the percent of cells simulated correctly and the positional agreement measured through the Kappa Index of Agreement (Pontius 2000). Since GEOMOD is interested in the more accurate spatial precision, we have used the Kappa for location or K location statistic, to measure goodness of fit. Kappa for location measures the degree to which a simulated map agrees with a reality map with respect to location; i.e., it estimates the success rate between the percentage of success of the model and the success due to chance alone (Pontius 2000). A kappa value of 0 indicates that GEOMOD cannot predict the landscape at the year 2000 better than at random (i.e., without information). Simulated maps do not necessarily match pixel-by-pixel with observed maps, however, they can present similar spatial patterns and land cover distributions. A fuzzy similarity index was used for comparing both maps. This index is based on the concept of fuzziness of location, in which a representation of a cell is influenced by the cell itself and, to a lesser extent, by the cells in its neighborhood (Hagen 2003) (see Chap. 8).

2.4 Results

2.4.1 Analysis of real LUCC between 1986 and 2000 for model calibration

2.4.1.1 Image classification

Fig. 2.2 shows the LU/LC map for the Purepecha Region for the year 2000. We also obtained the area of each LU/LC class (Table 2.3).

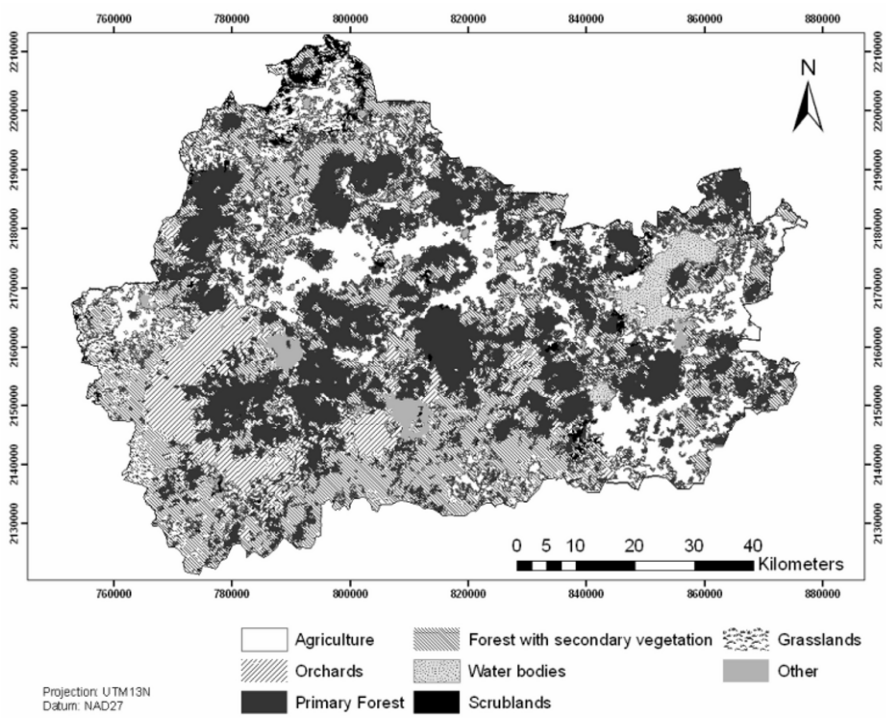

Fig. 2.2 Land Use/Land Cover map for the Purepecha Region in 2000

Table 2.3 Extent of Land use /Land covers classes in the Purepecha Region (ha and % of total area)

LU/LC class	1986		2000	
	Ha	%	ha	%
Pine Forest	102,013	17.71	82,310	14.35
Pine-Oak forest	86,926	15	85,449	14.89
Oak forest	11,996	2.0	9,609	1.67
Fir-forest	7,729	1.34	7,384	1.29
Forest Plantation	580	0.13	768	0.2
Secondary forest	95,541	16.59	150,864	26.2
Scrubland	8,159	1.41	10,052	1.75
Grassland	12,440	2.16	14,463	2.52
Area without vegetation	5,961	1.03	3,771	0.6
Human settlements	7,219	1.2	8,655	1.51
Agriculture	187,792	32.6	132,425	23.08
Irrigated Agriculture	7,435	1.29	5,071	0.88
Orchards	28,011	4.86	51,120	8.91
Water bodies	11,994	2.08	11,832	2.06

2.4.1.2 Land use cover change processes

Table 2.4 shows the land use/land cover change matrix for the period 1986-2000 for the five clusters. The last column shows the area (in hectares) for each cluster in the year 2000, while the last row shows the area of each class in the year 1986. From the 573,621 ha included in the study area, 27% of primary vegetation, 10% of secondary vegetation and 29% of man-made land classes showed no change during the period.

The process of land use change in the Purepecha Region is very complex with a net average loss of 4,232 ha of forests per year. 68% of total deforestation resulted from the transformation of primary to secondary forests. These last are very dynamic and play an important role within the region. In absolute terms, secondary forests increased 54,000 ha during the period, due to both the degradation of primary forests and also to the revegetation of abandoned agriculture lands. Approximately 16,000 ha of secondary forests were converted to agricultural lands, particularly to avocado orchards. As described by Velázquez et al. (2002b) this process shows that secondary forests are basically a transitional phase for the change from primary forests to non-forests land classes.

Table 2.4 Land cover change matrix for the Purepecha Region 1986 - 2000 (ha)

2000 (t_2)	1986(t_1)						
	Forests	**Scrubland/Grassland**	**Water bodies**	**Man-made**	**Sec Forest**	**Total**	**%**
Forests	156,915	428	19	10,287	17,870	185,521	32.34
Scrubland/ Grassland	436	9,852	61	10,057	4,109	24,515	4.27
Water bodies	0	5	11,686	79	60	11,831	2.06
Man-made	11,764	5,388	155	167,063	16,597	200,965	35.03
Sec Forest	39,984	4,926	73	48,912	56,894	150,789	26.29
Total	209,098	20,599	11,994	236,398	95,531	573,621	
%	36.45	3.59	2.09	41.21	16.65		100.00

Transition probabilities among the different clusters are shown in Fig. 2.3. It can be seen that forests and agriculture are the most stable classes with 75% and 71% of their respective area remaining as such in the study period. On the other hand, secondary forests and scrublands are very dynamic with only 60% and 48% of their respective area remaining in the same class during the 14 year of the study period. Secondary forests recover to primary forests or are degraded to agriculture roughly in the same proportion (17% and 19% respectively). Scrublands also degrade to man-made classes (26%) or recover to secondary forests (24%). Approximately 6% of total primary forests are deforested completely and another 19% are degraded to secondary forests.

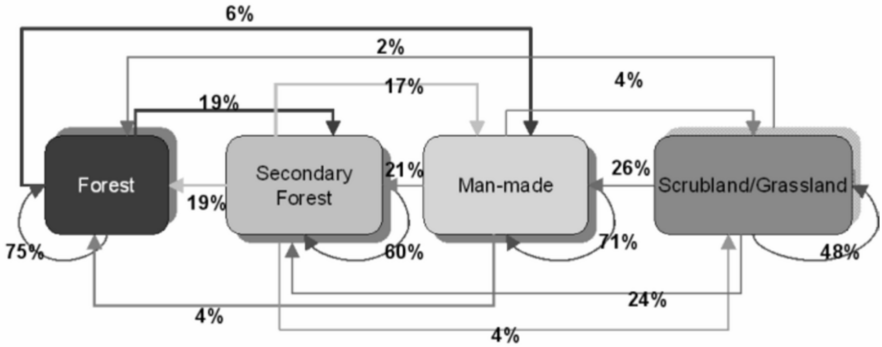

Fig. 2.3 Flowchart showing the transition probabilities among the different LU/LC classes in the period 1986-2000

The conversion rates between 1986 and 2000 are shown in Fig. 2.4 for all the land classes considered in the study. The bars above zero represent the types of cover which decreased during the period, whereas the bars under the zero indicate the increase of cover. All the primary forests lost areas, with the oak forest the one with the fastest deforestation rate. Rainfed agriculture also lost area at a high rate (2.5% per year). On the other hand, avocado orchards increased at a very fast rate (4.4%/yr) as well as forests with secondary vegetation (3.3%/yr).

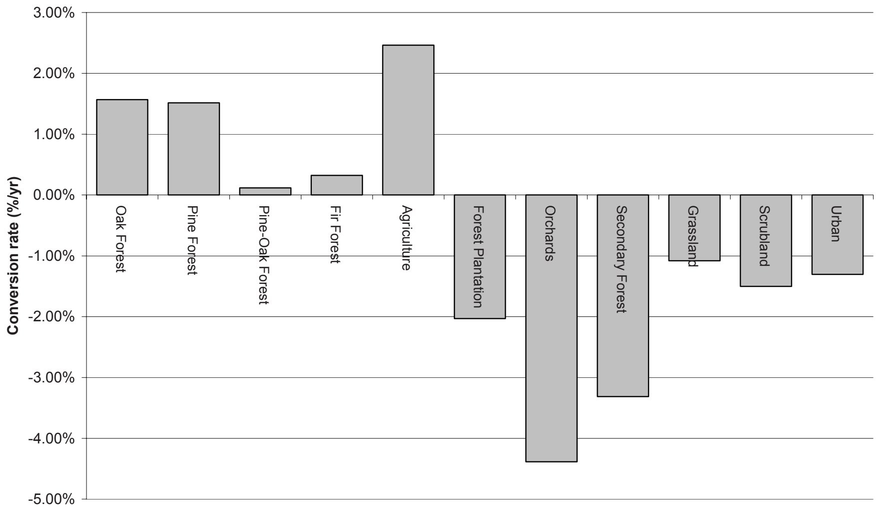

Fig. 2.4 Conversion rates associated to the different LU/LC classes

2.4.1.3 Land Use/Land Cover Change Dynamics

Several processes have contributed to the land use/land cover change dynamics within the region. These processes can be better understood dividing the region into 4 main sub-regions: Tancitaro, Patzcuaro, Uruapan, and Meseta (See Fig. 2.1). In Tancitaro, the deforestation process dominates the LU/LC change dynamics, particularly due to the establishment of avocado orchards. In fact the area devoted to avocado plantations increased 128% in Tancitaro between 1986 and 2000. Almost 8,000 ha of primary pine forests and 9,400 ha of secondary forests were lost to this cause. In Uruapan the deforestation and degradation were also the most important processes.

The opposite processes (revegetation and recovery) are particularly important in the Meseta and Patzcuaro Lake sub-regions. The total area of shrubs and forest with secondary vegetation has increased in these two sub-regions due to processes of land abandonment. Degradation is also present, particularly due to the conversion of pine primary forests to forests with secondary vegetation.

The extent of deforestation, degradation, recovery and revegetation within the region is displayed cartographically in Fig. 2.5 showing the critical areas where environmental loss prevails.

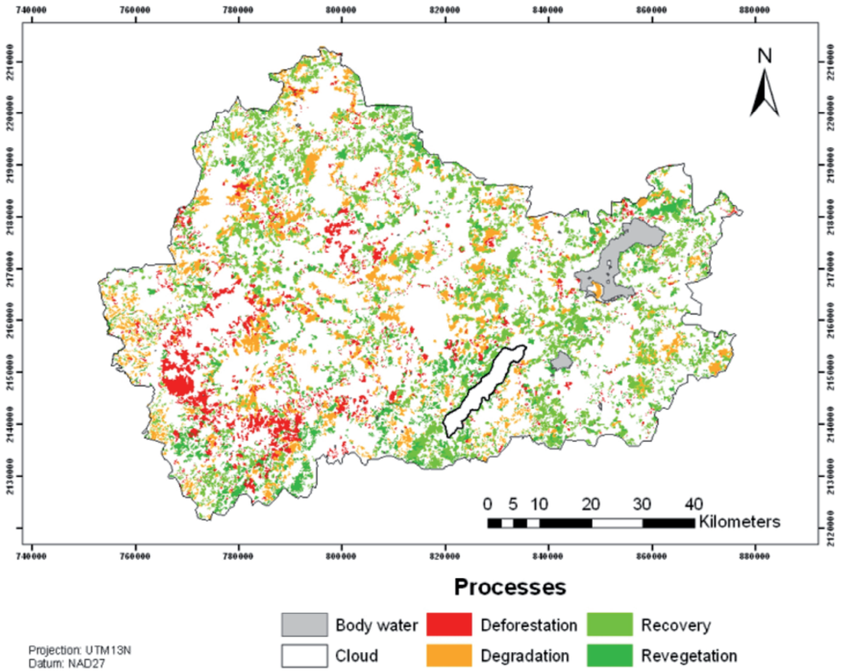

Fig. 2.5 Land use cover change processes (deforestation, degradation, recovery and revegetation) in the Purepecha Region (1986-2000)

2.4.2 Land use/Land Cover Change modelling

2.4.2.1 Long-Term Scenarios

As mentioned above, we used the GEOMOD2 model to simulate the spatial distribution of future deforestation in the region from the year 2000 to 2025. To understand those factors that explain the spatial distribution of forest clearing for human uses in the region, we analyzed four sub-regions. Then we reclassified each land use map in two land use types: as type 1 all primary forests and all other land used types included secondary forest and man-made vegetation type as type 2. Finally, we calculated the deforestation rate for each sub-region (Table 2.5).

Table 2.5 Deforestation rates for each sub-region

Sub region	Forest cover 1986 (ha)	Forest cover 2000 (ha)	Deforestation rate (ha/year)
Uruapan	52,640	40,097	896
Tancitaro	42,258	28,470	985
Patzcuaro	44,036	35,977	576
Meseta	72,206	53,239	1,355
			3,812

GEOMOD was run first with each of the eleven selected drivers, followed by the multiple combinations of driver maps with the addition of drivers, one driver at a time. The addition of each driver improved our ability to replicate the 2000 landscape for the entire region. The success of each driver is measured by the Kappa for location. Different pattern drivers exhibit more or less ability to improve on projections depending on the sub-region analyzed; however the best Kappa for the entire region (0.177) was a combination of four driver maps, because they were the most significant determinant of deforestation pattern. We used this combination of drivers to make the long term scenarios in Fig. 2.6.

As seen in Table 2.6, the individual most successful driver for the entire region and Uruapan sub-region was distance to localities, for the Tancitaro sub-region the most successful driver was precipitation, followed by elevation, and slopes; in the Meseta sub-region the best individual driver was slope. In the Patzcuaro sub-region, the combination of drivers was the most successful.

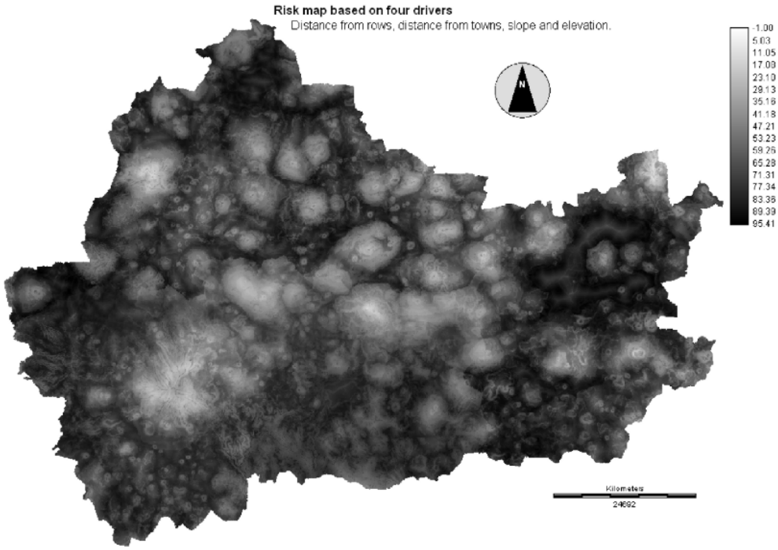

Fig. 2.6 Deforestation vulnerability map based on analysis of empirical areas of deforestation versus four candidate drivers maps

Table 2.6 Final set of candidate driver maps. The cells colored in dark gray, gray, and light gray indicate the three drivers (from high to low, respectively) giving the highest Kappa location index

		REGION		URUAPAN		TANCITARO		PATZCUARO		MESETA	
1	Distance from towns	88.800	0.128	88.880	0.216	86.760	0.131	91.680	0.068	87.910	0.095
2	Distance from roads	88.660	0.118	87.740	0.136	86.780	0.132	91.880	0.091	88.080	0.108
3	Elevation	88.590	0.112	87.900	0.148	88.980	0.277	91.480	0.047	86.770	0.009
4	Slope	88.480	0.103	86.840	0.073	85.560	0.118	91.880	0.091	88.258	0.121
5	Temperature (Rainy season)	88.328	0.091	87.715	0.134	84.769	0.235	91.070	0.006	86.648	0.007
6	Temperature (Dry season)	88.290	0.088	87.470	0.117	88.030	0.214	91.300	0.033	86.810	0.013
7	Precipitation (Rainy season)	88.220	0.083	86.180	0.026	89.190	0.291	91.110	0.005	86.924	0.083
8	Distance from water sources (rivers and lakes)	88.049	0.070	87.921	0.148	86.939	0.142	91.110	0.005	86.610	-0.022
9	Distance from permanent streams	87.970	0.064	87.850	0.144	86.800	0.134	91.040	-0.003	86.576	-0.005
10	Soils	87.910	0.059	86.780	0.068	86.342	0.103	90.790	-0.031	87.525	0.066
11	Distance from lakes	87.912	0.059	86.780	0.068	86.342	0.103	90.790	-0.031	87.520	0.066
12	Aspect	87.690	0.022	85.650	-0.011	85.410	0.042	91.360	0.033	87.750	0.083
Combinations											
13	Drivers 1 and 2	88.9424	0.1391	88.651	0.1999	86.929	0.1418	91.691	0.0693	88.3667	0.1287
14	Drivers 2 and 3	88.9124	0.1368	88.865	0.215	89.1425	0.2871	91.7384	0.0746	86.819	0.0128
15	Drivers 1, 2 and 3	89.2123	0.1601	88.879	0.216	88.7982	0.2645	91.8794	0.0904	87.79	0.0855
16	Drivers 1, 2, 3 and 4	89.4284	0.177	88.999	0.2244	88.5129	0.2458	92.1072	0.1159	88.3514	0.1276
17	Drivers 1,2,3,8 and 10	89.0298	0.1459	88.141	0.1639	88.1407	0.1639	91.7371	0.0744	87.7232	0.0805

We used the annual rate of deforestation and the final risk map to simulate the future (see Fig. 2.6). Assuming linear deforestation rates, 95,000 ha of forests will disappear in the 25 year period. This figure represents a loss of 24% of the forests by 2010 and up to 60% by 2025. The maps with the simulated deforestation process for the years 2000, 2005, 2010, 2015, 2020 and 2025, show those places more likely to be deforested. The most vulnerable forests are located in the surroundings of the Tancítaro Peak, close to the city of Uruapan and within the Meseta sub-region (Fig. 2.7). Within the different forest types, pine-oak forest loose 56% of their total area by the year 2025, oak forests 54%, pine forests 46% and fir forests 31%.

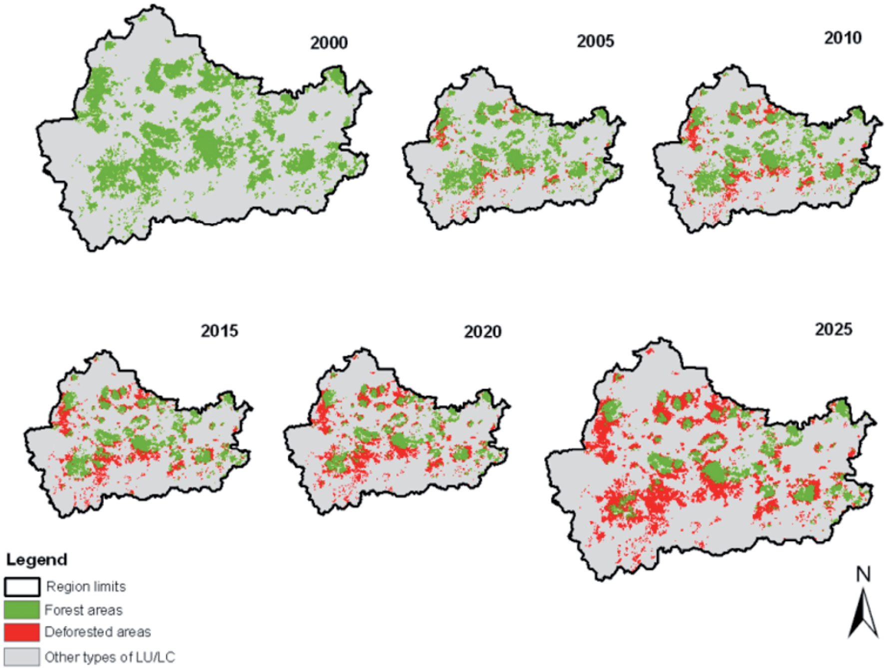

Fig. 2.7 Simulated maps of forest cover change between 2000 and 2025

2.5 Validation and discussion of results

2.5.1 Simulations

The success in the simulation process was measured by the Kappa statistics, measuring the different drivers individually and grouped. The driver with the highest Kappa was total rainfall during the rainy season (Kappa 0.291) within the Tancitaro sub-region. This latter sub-region also showed the most agreement between simulated and actual maps, and was the area with the highest deforestation rates within the Purepecha Region, particularly due to conversion of forests to avocado orchards.

In general, both within sub-regions as well as within the entire region, the percentage of cells successfully simulated was high (84-92%), but the Kappa statistics was low (-0.031 to 0.291). In fact, it has been found that low Kappa indicates that the deforestation pattern (exact location of clearings) is difficult to predict, at least using the present approach and variables. Hall (2002) has found a similar result in regions where little net change is detected in the time period analyzed, as is the case with the Purepecha Region.

On the other hand, we found that the model increased the predictive power when several drivers were grouped together. Specifically, the group of drivers: distance to villages, distance to roads, elevation, and slope was the most successful in our simulations. Mas (1996) reports that these last three drivers are usually important in the analysis of deforestation processes, as they are closely interconnected (e.g., at higher slopes less density of villages or roads).

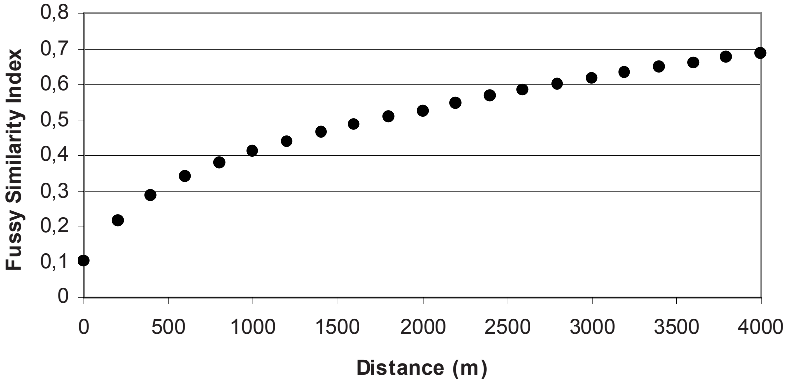

Fig. 2.8 Fuzzy Similarity Index as a function of distance (positional fuzziness)

Fuzzy similarity index was calculated using distance from 0 to 4,000 m. Based upon a null distance, this evaluation corresponds to an evaluation in which only exact coincidences of changes between the simulated and reality maps are considered as correct. In juxtaposition, based upon large distance, the evaluation tolerates positional shift between the simulated and the real patches of deforestation. Fig. 2.8 shows the fuzzy similarity index as a function of positional fuzziness. When increasing the positional fuzziness, the index is greatly augmented, which shows that the model is roughly able to identify the location of change.

2.5.2 Land Use /Land Cover Change Dynamics

As stated before, the pattern of land use change was complex, with many transitions among land classes and a few net changes between 1986 and 2000. One of the most important changes is the reduction of the area under rainfed agriculture, and the increase of forests with secondary vegetation.

This is the result, on the one hand, of the abandonment of agriculture fields on sloppy areas due to migration of local farmers, and their gradual re-vegetation. This process has been documented by several authors (Velázquez et al. 2002, López 2003, Alarcón-Chaires 1998). On the other hand, secondary forests have also increased as a result of the degradation of primary forests, which are subject to a non-sustainable forest harvesting regimes (Masera et al. 1996). Deforestation has also been important, mostly through the conversion of both primary and secondary forests to avocado orchards (a process that also affected rainfed agriculture) in those regions suitable for this commercial crop. This process is due entirely to economic reasons, as avocado plantations greatly increases the farmer's income per hectare relative to traditional crops (such as maize) (Ruiz 2003).

Because revegetation processes in the region are not linked to specific government policies, but mostly to migration due to lack of local economic opportunities, it is difficult to predict its future faith. On the other hand, evidence points out at a continuing of the degradation and deforestation of primary forests, as no integrated forest management plan has been successfully implemented within the region (Linck 1988, Masera et al. 1996, Klooster 2000, Klooster and Masera 2000).

2.6 Conclusions

Spatially-explicit models like GEOMOD are useful tools to evaluate the main drivers associated to LU/LC change processes. These models, also allow for the specification of the location of future projected deforestation (Menon et al. 2001). Plus, GEOMOD has demonstrated that it is reasonably easy to understand and to apply it in diverse projects (Menon et al. 2001). However, several constraints still limit the predictive power of the GEOMOD model. The model can simulate only one land use change process at a time, which limits capturing the complexity of the land-use change dynamics. In our case, only the deforestation proccess was modelled, setting aside other proccess of interest within the Purepecha Region, such as recovery, degradation and revegetation. We suggest that spatially explicit models must include at least more than one LU/LC change dynamic, in order to achieve a better diagnosis of areas more vulnerable to deforestation. At a methodological level, the simulations performed in this study can be greatly improved by using a third time period to validate the deforestation predictions.

In the future, it will be important to develop simulation models that incorporate the dynamic interactions among the different drivers. Specifically, it will be important to model the dynamic-temporal and spatial-processes associated with the decisions of the regional economic agents.

This approach will help isolate the effect of each of the exogenous variables, and to model their response given changes in the variables and parameters incorporated in the model. More importantly, it will be possible to perform predictions about the land use change patterns under different socio-economic, political and demographic conditions.

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3 Tropical deforestation modelling: comparative analysis of different predictive approaches. The case study of Peten, Guatemala

Follador M, Villa N, Paegelow M, Renno F and Bruno R

Abstract

The frequent use of predictive models for analyzing of complex, natural or artificial phenomena is changing the traditional approaches to environmental and hazard problems. The continuous improvement of computer performance allows for more detailed numerical methods, based on space-time discretisation, to be developed and run for a predictive modelling of complex real systems, reproducing the way their spatial patterns evolve and pointing out the degree of simulation accuracy. In this contribution we present an application of several methods (Geomatics, Neural Networks, Land Cover Modeler and Dinamica EGO) in the tropical training area of Peten, Guatemala. During the last few decades this region, included in the Biosphere Maya reserve, has seen a fast demographic raise and a subsequent uncontrolled pressure on its own geo-resources. The test area can be divided into several sub-regions characterized by different land use dynamics. Understanding and quantifying these differences permits a better approximation of a real system; moreover we have to consider all the physical, socio-economic parameters, which will be of use for representing the complex and sometimes random human impact. Because of the absence of detailed data from our test area, nearly all the information was derived from the image processing of 11 ETM+, TM and SPOT scenes; we studied the past environmental dynamics and we built the input layers for the predictive models. The data from 1998 and 2000 were used during the calibration to simulate the land cover changes in 2003, selected as reference date for the validation. The basic statistics permit to highlight the qualities or the weaknesses for each model on the different sub-regions.

Keywords: Predictive Models, Space-time discretisation, Remote Sensing, Neural Networks, Markov Chains, MCE, Dinamica, Risk management, Deforestation, Peten, Guatemala

3.1 Introduction

3.1.1 Overview

The human activities in tropical forest areas create an increasing consumption of resources, often driven by a demographic rise or by large-scale industrial, mining or agricultural projects. The frequent use of simulation methodologies to understand these environmental impacts and their long terms consequences represents an important tool for a rational management of hazard problems. The continuous improvement of computer performance allows for more detailed numerical methods, based on space-time discretisation, to be developed and run for a predictive modelling of complex real systems, which reproduces the way their spatial patterns evolve.

We know that a model is an abstraction that simplifies the studied phenomena, considering only its principal components and properties (Coquillard and Hill 1997). The modeller should make several decisions, which demand a deep knowledge of the model and the links between model and reality (La Moigne 1994), in order to define the objectives coherently with the available data (Matheron 1978 and 1989). To better understand the complex land cover properties and the socio-economic factors, which influence the human activities, interdisciplinary cooperation among different research areas is required and an integrated use of several tools and methodologies. After an exploratory analysis (*what, where, when*), the next step is to study the causes and rules that characterize a phenomena and its evolution (*how, why*); the level of understanding is valued comparing the first raw model outcome with a set of experimental data, pointing out the limits of our approach and often determining some parameters previously ignored (Kavouras 2001).

To improve the data sets, particularly where field measurements are not possible (large regions with hard environmental conditions; developing countries with political instability; research projects without time and money consumption possibilities), we can take advantage from remote sensed information. GIS represents a powerful tool for integrating multiscale data from ground-based and satellite images. The spatial scale of investigation may vary with the type of land cover as different parameters vary in different ways across the space (Moore et al. 1993); choosing the right support size depends on our objectives and on spatial frequencies of an environmental system. Moreover, we have to consider the computer processing power, because a large size matrix (larger number of rows and columns due to downscaling) may demand a very long computing time and often this represents a serious obstacle for running numerical methods. In this contribution we use a pixel size of 20m by 20m, which satisfies both processing capabilities and accuracy of spatial pattern representation (Hengl 2006) providing a finer definition of land cover and partially solving the mixed-pixel problems (Atkinson 2004, Foody 2004).

Another important question during the model development and calibration is the choice of a temporal scale, as every land cover change presents a particular space-time structure. This temporal lag must be representative of the main dynamics during the studied period but it strictly depends on data availability and on specific planning problems. If we want to project the ecological and socio-economic consequences into the immediate future we can adopt higher temporal resolution than strategic planning addressing longer terms goals (Kavouras 2001). In this contribution we adopted a lag of approximately two years, using the data sets from 1998 and 2000 to reproduce the landscape evolution in 2003, selected as a reference date for the validation.

With reference to the space-time working scale, care must be taken when different support sizes are at stake (Chiles and Delfiner 1999). Typically, the data are defined on a "support", often comparable to points in space or instances in time; on the contrary the target model could be defined on larger "support", for instance temporal average values. A similar situation applies when several satellite scenes with different resolution must be processed together. Several consequences apply in such cases, because frequencies distributions, dispersions and spatial correlations for the same variable change when the support size changes.

3.1.2 Description of Predictive Models

Four predictive methods are presented here; they simulate the land cover changes in the La Joyanca region occurred from 2000 to 2003, using different theoretical approaches: the Predictive Neural Network is an optimized-automatic method; the Geomatic and the Dinamica Ego models aggregate an automatic time prediction (Markov chains analysis) with a supervised spatial allocation of predicted pixels, based on modeller-expert opinions; the Land Change Modeller adopts the same Markov chains analysis but an automatic Multi Layer Perceptron for the spatial allocation of simulated land cover scores. We chose these approaches because of their simplicity, their easy adaptability to different problems and data, and for their low cost (PNNET and Dinamica EGO are freeware; Idrisi Andes has an accessible price for academic personal).

The basic statistics of predicted results and the analysis of residuals demarcate the limits and the potentialities of each model in the different subregions of the test areas, characterized by different environmental dynamics.

3.1.2.1 PNNET: Predictive Neural Networks

Here we adopted a Multi-layer Perceptron (MLP), which is a feed forward Neural Networks (NN) composed of three layers. The input layer is the layer, in which the number of neurons is dependent on the amount of input data, e.g., thematic maps and environmental criteria. The output layer is the layer in which the number of neurons depends on our goal, i.e. predicted land cover maps. Finally, the intermediate hidden layer in which size was decided by performing a cross validation of NN to optimize the models. Several NN with different topology but the same Input layer were trained using a supervised learning algorithm (error-back propagation); and the best NN was selected on the basis of statistical criteria (i.e., root mean-squared error) to minimize the difference between the real and the predicted output (Joshi et al. 2006, Lee et al. 2006, Villa et al. 2007). The *nnet* function (Venables and Ripley 1999) was loaded in the R© computing environment for the training process; the R© language was used to compile our three programs to produce a predictive land cover map, which is freely downloaded from:

http://nathalie.vialaneix.free.fr/maths/article.php3?id_article=49:

3.1.2.2 Geomatics model

This method comes from the integration of Markov chains analysis (MCA) for time prediction and Multi Criteria Evaluation (MCE), Multi Objective (MOLA) and cellular automata to perform a spatial allocation of simulated land cover scores. MCA of second order is a discrete process and its values at instance *t+1* depend on values at instances *t0* and *t-1*. The prediction is given as an estimation of transition probabilities. MCA produces a transition matrix to record the probability that each land cover class might change into another class (or any of the other classes) and the number of pixels expected to change. MCE is a method that is used to create land cover specific suitability maps based on the rules that link the environmental variables to the studied phenomena (deforestation). These rules can be set to integrate statistical techniques with a supervised analysis by the modeller. The suitability maps are used for spatial allocation of predicted time transitions. A MOLA and cellular automata are performed to integrate the predicted land cover maps and improve the spatial contiguity.

3.1.2.3 Land Change Modeller: the new Idrisi Andes model

This model aggregates a Markov Chains analysis (MCA) for time prediction, Multi-layer Perceptron (MLP) and a zoning based on incentives-constraints for a spatial allocation of simulated land cover scores. We have to use only continuous quantitative variables (PNNET can use both quantitative and qualitative variables, coded in disjunctive form). After the sample size definition, we set the number of neuron in the hidden layer and stop the model when the accuracy rate is approximately 90%. MPL can repeat the training multiple times to achieve the desiderate error score. The classification produces two transition potential maps, which express for each pixel its potential for both deforestation and reforestation. The change prediction step integrates the amount of changes, calculated in MCA, with the potential maps for the modelled transitions to produce both hard and soft classification. The last one points out all the zones with different probability to change, showing the more vulnerable spots. During this phase we can introduce an incentive-disincentive for each transition, to influence its potential map on the basis of our environmental system knowledge (e.g., future government planning, forest reserves).

3.1.2.4 Dinamica EGO: Environment for Geoprocessing Objects

Dinamica EGO is the new simulation model of environmental dynamics developed by the Remote Sensing Laboratory (CSR) at Federal University of Minas Gerais (UFMG), Brazil. This powerful freeware (http://www.csr.ufmg.br/dinamica/EGO) aggregates the traditional GIS tools with several operators for simulating spatial phenomena. The model, from calibration to validation, follows a data flow in form of diagram; a friendly graphical interface permits the creation of models by connecting algorithms (*functors*) via their ports. We note that it is possible to divide the test area into sub-regions, characterized by different environmental dynamics and apply a specific approach for each one of them (Rodrigues et al. 2007). The calibration calculates the matrix of transition rates (net rates) for a time period (initial-final landscape); and a probability map of occurrence for each transition is produced using the Weight of Evidence method. The absolute number of pixels to be changed was divided between two transition functions, *Expander* which analyses the expansion or contraction of precedent patches for a given category, and *Patcher* which generates new patches (e.g., new cleared areas). The validation produces a fuzzy similarity map (a comparison within a determined zone of influence for each cell) between real and predicted outcomes; this method considers not only the pixel by pixel agreement (hard comparison), but also the probability to find the correct value in the pixel neighbourhood.

3.2 Test areas and data sets

3.2.1 La Joyanca training site, Peten, Guatemala

Our test area is located on the border between Guatemala and Mexico; it is included in the Biosphere Maya, the largest continuous tropical forest of Central America (Fig. 3.1). Our studies were focused around the La Joyanca site, Peten; which is a part of "*Bosque Humedo Subtropical*" (de la Cruz 1982) with a mean annual temperature of 25°C, precipitation average fluctuating between 1,160 and 1,700 mm/year, and a semi-evergreen tropical forest cover. The topography is generally lowland with an elevation from 50 to 250 m above sea level (IGM, Instituto Geográfico Militar Guatemala, Mapa 1-DMA, E754, 2067I).This region is characterised by hilly landscape with small escarps; the soils are comprised of evaporitic limestone and microgranular dolomite (Arnauld 2000). The first historical occupation of Peten, with its nearly complete deforestation, began during the Classic period of the Mayan Empire and ended with its collapse and thus subsequent reforestation (Geoghegan et al. 2001). During the last decades this region has known a new progressive demographic raise, due to the immigration of Ladinos and native people from the south of Guatemala running away from poverty and looking for new lands. The human impact became evident after 1988 with the first settlements on the northern border of Rio San Pedro; in the following years a fast deforestation through the traditional slash and burn technique for agriculture and mainly for ranching activities, created a dangerous situation for environmental sustainability (Follador and Renno 2006).

3.2.2 A poor data set

Remotely sensed images represent an important, cheap and minimally time consuming font of data. Because of the absence of detailed maps and numeric attributes for our test area , nearly all information were derived from image processing of 11 ETM, TM (Path 20, Row 48) and SPOT (Path 606 and 607, Row 315)[1] scenes (41 layers), from 1988 to 2003, acquired with irregular periodicity depending on clouds cover and data availability.

Their preprocessing included the Relative Radiometric Correction (DOC) to reduce the atmospheric scattering within the 1998 SPOT image (the ETM+ scenes were already corrected); the water bodies *Laguna Tuspan* e *Agua Dulce* were chosen as reference. A binary map was created to mask the clouds, their shadows, the water and perennial wet lands as they

[1] Project ISIS, Selleron © CNES 2003

are considered of no interest for deforestation dynamics. The statistical study of pixel values (ND) permits the calculation of the more informative data set reducing between band correlation and data volume; we use the OIF, Optimum Index Factor, based on ratio between the standard deviation and correlation index of NDs, to choose the best color composite for each date. The analysis of the scattergram displays the probability ellipses for training regions (forest, cleared areas), highlighting the importance of red, near infrared (NIR) and medium infrared (SWIR) bands for this study. We calculated the Normalized Vegetal Index (R-NIR) and the Normalized Infrared Index (NIR-SWIR) to reduce the data set volume and to highlight the cleared and hydric stressed zones. In the end an inter-medium image called NDIm (Normalized Difference Index medium) was used as input for our RGB change detection method for the time-series 1998-2000-2003 (Follador and Renno 2006, Bruno et al. 2006). The RGB (NDIm) displays the past land cover dynamics with different colors, corresponding to different values of NDIm in the studied period. This represents a first tool for improving our knowledge of the key variables and their relationship with the phenomena evolution. In particular, we pointed out the difference between the expansion of precedent large patches (ranching activities) in *Bajio* region and the generation of new small scattered cleared areas into the tribes' communitarian concession on the highlands (*selva alta*); here the native people deforest small polygons which are periodically disused permitting a secondary forest return. Due to a more sustainable use of lands, new small crops were planted nearby.

A supervised classification was applied to the more informative RGB for each date. We aggregate the MaxLikelihood Algorithm, which considers the pixel by pixel probability of membership into each category and the ICM (Interacted Conditional Models, developed with Spring Freeware: http://www.dpi.inpe.br/spring), which is a vicinity-method which analyses the spatial distribution of the nearest pixels. The results display 4 classes: high forest (*Foresta Alta*), low wet forest (*Bajio*), perennial wet land (*Cibal*) and disturbed areas (cleared areas, nude soil, crops, roads, etc.), after reducing to binary forest-milpa during the simulation. The word milpa traditionally identifies mixed crops of maize, beans and pumpkin (Effantin-Touyer 2006), generally obtained from the forest zone by the slash and burn technique; here we use "milpa" to represent the whole loss of original closed tropical vegetation. The accuracy was very good (Kappa >0.9) for the last two categories but we have great difficulty (25%) separating *Foresta Alta* e *Bajio*, due to a partial spectra overlap. To improve this result a texture analyses using geostatistical tools (variogram) will be necessary (Atkinson et al. 2000, Chica-Olmo et al. 2000).

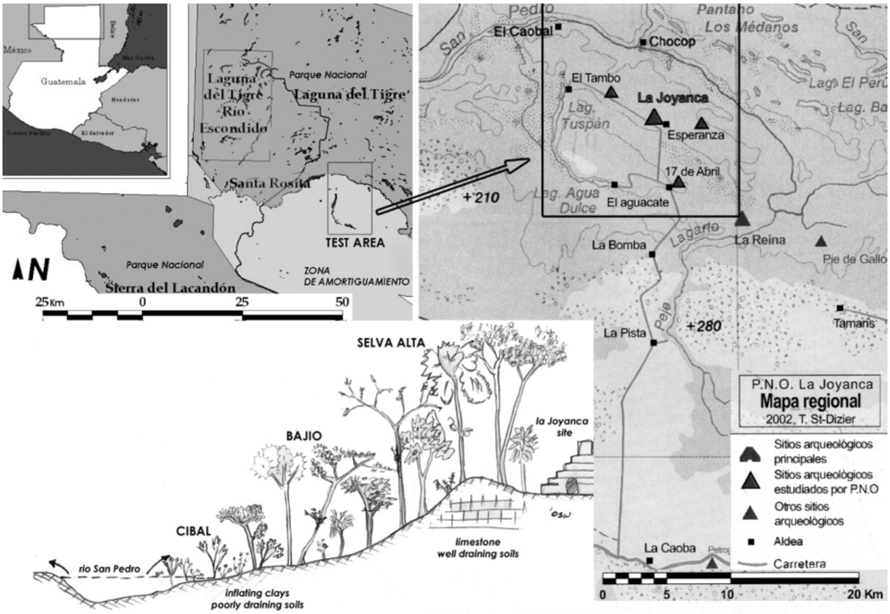


Fig. 3.1 Training area in Peten, Guatemala. The selected rectangle was approximately marked by UL (W90°38'08" - N17°19'22"), LR (W90°31'27" - N17°08'44"). Image sources: IGN and CONAP. Drawing: Follador Marco

To integrate the image processing and GIS spatial operators, we have built the environmental criteria with a strong link with the landscape trajectory. Several distance maps were calculated and a DEM was derived from the radar image. No qualitative information is used.

3.2.3 Phenomena evolution and driving processes

There is a visible change in driving processes between the training period 1988-2000 and the simulated period 2000-2003 (Fig. 3.2). From 1988 to 1998 the deforestation dynamics was clearly concentrated on the north side of Rio San Pedro, which for a long time represented the main way of access into the region. These lands are at a higher elevation than the southern ones which are periodically flooded during the rainy season. The cleared areas presented as regular geometric forms and they are mainly used for maize crops and pasture. The clearing progression was occurred as the expansion of previous patches and secondarily by the generation of new small deforested polygons. From 1998 to 2000, the human impact in the central and southern zones became evident with the first settlements and roads; the subsequent disturbance developed as enlargements of villages and axes' perimeter. The clearing process on the northern side of *Rio San Pedro* maintained the above-mentioned characteristics. Into the communitarian concession, the deforestation was limited to the high lands (limestone substrate), which are more suitable for agriculture activities, and are plotted as small irregular polygons.

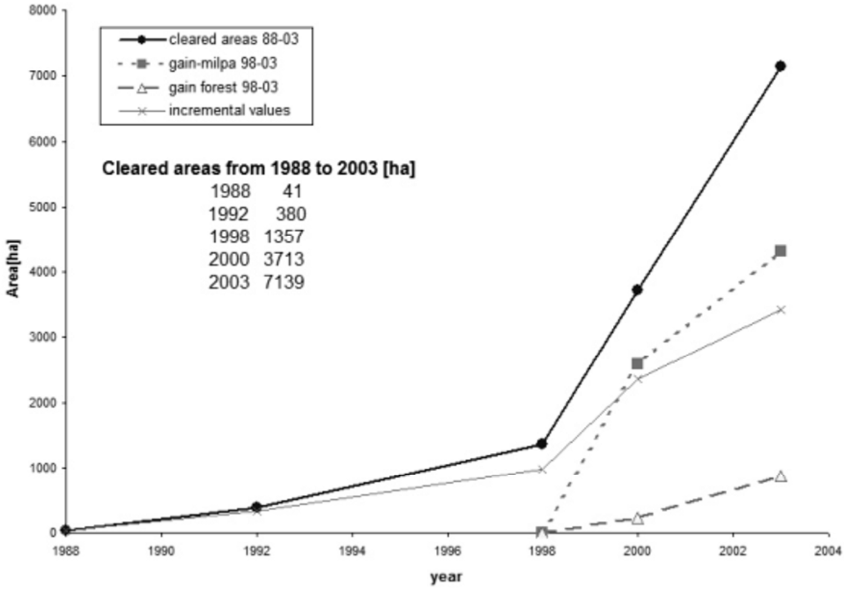


Fig. 3.2 Deforestation trend from 1988 to 2003. Gains of forest and disturbance (milpa) during the simulated period. Data derived from image processing of Spot and ETM scenes

Since 2000 we have recognized an abrupt change from previous disturbance trends, partially due to the narcotraffic interest in the northern lands and the subsequent difficulty of movement in these areas. The deforestation quickly increased in the southern regions around the settlements, along the road buffers and near the lakes. At the same time we show the generation of newly cleared, irregularly scattered areas, the farmers and immigrants slash and burn small parts of forest in unsuitable zones (wet lands or lands with hard environmental conditions) looking for new possibly productive areas. The locations of these patches are random and depend on people's arbitrariness; "*l'évolution est créatrice et non plus seulement logique*"[2] (La Moigne 1994). It's impossible to well quantify and localize these land cover changes.

[2] The phenomena evolution is not only logical but also creative.

The transition matrixes were calculated using the 1998 and 2000 data sets; they don't match the fast rhythm of deforestation from 2000 to 2003, due to the strong change in social-environmental conditions (above-mentioned) between the training and the simulated periods. Therefore the number of pixels expected to change from forest to cleared areas was underestimated. The model performance will be poor if the driving processes change over time and the training data don't match the real complexity of land cover dynamics (Pontius and Chen 2006). When the results are not satisfactory it's very difficult to point out whether the model structure itself is weak or if our environmental knowledge is too limited. However the results offer at least new general information about the modeled system, allowing for improvements for a further analysis. "*Il y a des moments où nous devons simplement agir, en toute connaissance de notre ignorance des conséquence possibles, et nous devons toujours nous donner la possibilité de reconnaitre nos erreurs passées et de changer le cours de notre action*"[3] (Arrow 1974).

3.3 Methodology and practical application to the data sets

3.3.1 PNNET approach

In order to model the deforestation, we considered the following regression problem: the map is divided into several squared pixels; for each of them, the target variable is bimodal and its value depends on the following question. "Will this pixel be forest at the next date $t+1$?" The variable is coded in a disjunctive form: [1 0] for a positive answer and [0 1] for negative answer. To address this question, we use several predictive variables:

- the land cover pixels at date t, coded in a disjunctive form (*temporal process*);
- the frequency of forest and no forest pixels in an influence zone at date t (*spatial process*): for each pixel we define an influence zone, which is a square-shaped neighborhood centered on the pixel and whose size, V, has to be chosen. The frequency of forest (and no forest) pixels in the influence zone is calculated by a decreasing function of the distance from the central pixel;
- *environmental criteria* at date t: dynamic (distances from cleared areas and distances from developing roads, both in 1998 and 2000) or static

[3] Sometimes we have to work knowing our ignorance about the possible consequences; this allows recognizing our past errors and changing our future activities.

(distance from Pipeline, from Rio San Pedro, from lakes, from villages, from the southern river and DEM). The model can take into account both numerical and categorical variables (coded in a disjunctive form). For our study we didn't consider any categorical variable.

We modeled this regression problem by a single layer perceptron (Fig. 3.3); it comprises 14 neurons as inputs: land cover pixels (2 neurons), frequencies in the influence zone of forest and no-forest (2 neurons) and environmental variables (10 neurons) at date *t*. It has one hidden layer with *k* neurons (where *k* is chosen by the user for more – large *k* – or less – small *k* – flexibility) and an output layer with 2 neurons showing the probabilities of membership to each land cover class (forest or no forest) at date *t*+1. Finally, the studied pixel is allocated to the class with which it has the highest likelihood of membership.

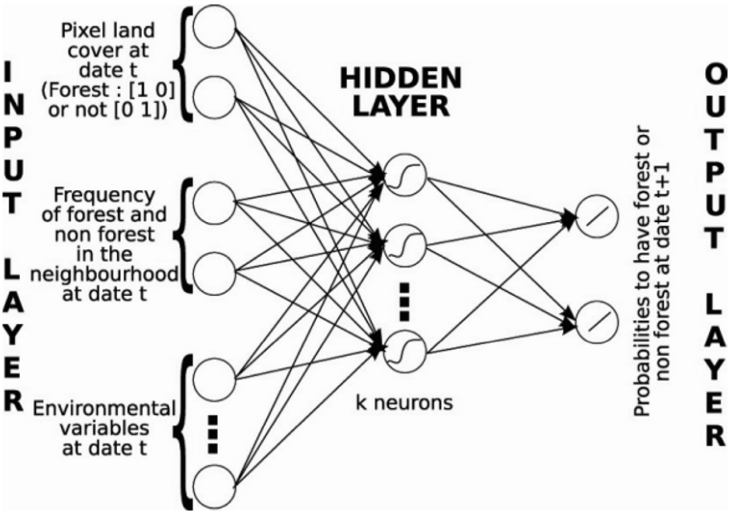


Fig. 3.3 PNNET, single layer perceptron topology

We recall that the link between the input and the output layer is made by:

$$p_w^j(x) = \sum_{i=1}^{k} w_{ij}^2 \, g\left(x^T w_i^1 + w_i^0\right) \tag{3.1}$$

where x is the vector of the input variable, $p_w^j(x)$ is the jth output depending on weights w, w_i^1 is the vector of weights between the input layer and the ith hidden neuron, w_i^0 is the bias of the ith hidden neuron and w_{ij}^2 is the weight between the ith hidden neuron and the jth output. The weights are chosen during the training step on a representative data set, in such a way as to reduce the error between the real and NN predicted values. The activation function g is the sigmoid function:

$$g(z) = 1/(1+\exp(-z)) \tag{3.2}$$

We considered three land cover maps derived from remoted sensed data acquired in 1998 (Spot2, W606-315, 1998_02_24), 2000 (ETM, 20-48, 2000_03_27) and 2003 (ETM, 20-48, 2003_05_07). Each map had 979 rows and 601 columns with a spatial resolution of 20m by 20m; this size and the number of environmental variables are too large to run them simultaneously by the R^{Ø} programs presented below. So we were obliged to reduce the dimension of the data set, using a simplification: we decided to consider only the "frontier pixels" to perform the training step and the prediction. We called a frontier pixel a pixel which has at least one different land cover in its influence zone. We note that this sampling doesn't completely represent the real characteristics of the original data sets because of its limited dispersion. The methodology used to visualize the neural network performances included three steps (Fig. 3.4):

- a *training step* which optimizes the network weights, for a given k (number of hidden layer neurons) and a given V (size of the influence zone);
- a *validation step* which selects the optimal k and V;
- a *test step* which compares the predicted land cover map with the real map in 2003.

More precisely, the training step used about 10% of the frontier pixels of the 1998/2000 maps as inputs/outputs (training set) and lead to the determination of the optimal weights w given in Eq. 3.1. For each couple of input/output pixels $(x_i, y_i)_{i=1..n}$, w is chosen to minimize the mean squared error between the predictive values ($p_w^j(x_i)$, Eq. (3.1) constructed from inputs x_i , and the real values y_i^j :

$$E = \sum_{i=1}^{n} \sum_{j=1,2} (p_w^j(x_i) - y_i^j)^2 \tag{3.3}$$

This optimization step was performed via the usual optimization algorithms (gradient descent types); to overcome the local minima difficulties we repeated the optimization step 10 times with various training sets, randomly chosen respecting the proportion of forest / no forest pixels in the entire 1998 map. Finally, we select the perceptron with the minimum mean squared error. Once a perceptron for each value of k and V has been optimized, we determined the best values for the two parameters k and V by a validation step. About 30% of the frontier pixels in the 1998 and 2000 maps were randomly chosen with respect to the proportion of forest / no forest pixels in the entire 1998 map; they were different from those used in the training step. The input pixels (from 1998 map) were used in each optimal perceptron to produce a predictive land cover map which was compared to the desired output (real pixels from 2000 map). Once again, we selected the perceptron with the minimum mean squared error. For our case study we have chosen $k = 5$ and $V = 3$.

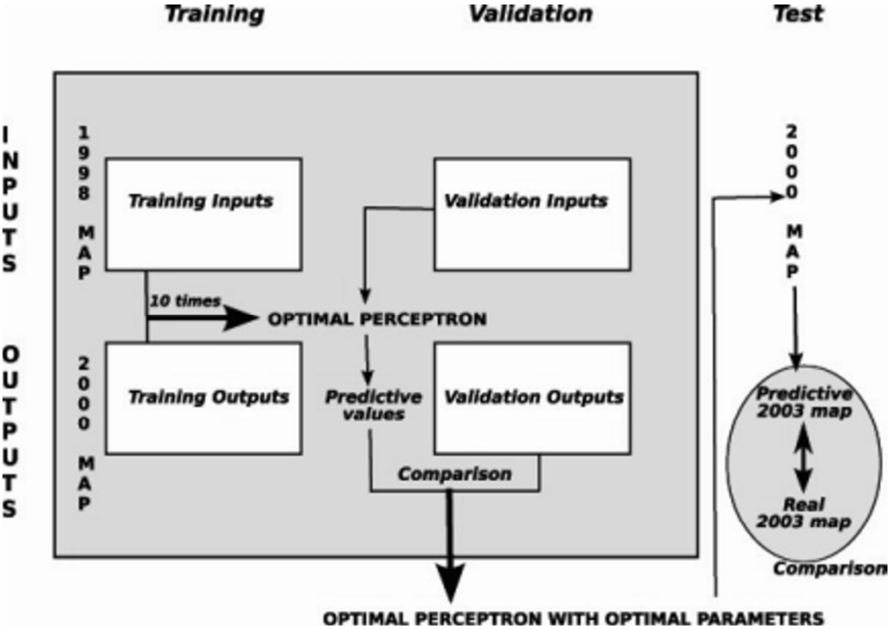


Fig. 3.4 PNNET approach for LUCC modelling

Finally, we used the whole frontier pixels of the 2000 map as an input data set for this optimal MPL to construct a predictive map for 2003. The test step offers a measure of overall divergence between the networks' and real land cover map (Fig. 3.4). At the end we added cellular automata (contiguity filter) to increase the spatial contiguity of land cover classes; in fact the row output presented many isolated pixels and a low isometric form of the patches, probably due to the "frontier pixels" approximation, which limits the number of predicted cells.

3.3.2 Geomatics approach

Unlike pure mathematic models, geomatic prediction models applied to environmental dynamics include human performed geographic analysis to carry out the relationship between land cover dynamics and potential explanatory criteria. Among the multiple methodological approaches for predictive simulation in geomatics (Coquillard and Hill 1997), we used a combination of three modelling tools: a multi-criteria evaluation (MCE) to perform suitability maps for each category of the variable to be modeled, Markov chain analysis for prediction and, finally, in integrating step using MCE suitability scores for spatial implementation of Markovian conditional probabilities. This latest step arbitrates using multi-objective evaluation and cellular automata for realistic landscape patterns (Paegelow and Camacho 2005).

The prediction model is stochastic, dealing with discrete time and finite states of land cover (modelled variable). To do so we use the available GIS software components implanted in Idrisi 32 Kilimanjaro, a GIS and Image processing software system developed by the Clark Labs (Eastman 2001) and a restrictive list of criteria so that the methodology would be easy to apply to other terrains. The calibration will be performed by modelling a known land cover state from the last available date. Therefore we use the training data from two earlier land cover layers and known and relevant environmental and social criteria. Validation will be obtained by comparison with a later, known – but not used for predictive modelling – land cover state. The chosen approach may be considered as a "supervised" model with manual establishment of a knowledge base in comparison to "automatic" approaches like neural networks. It is derived from the aggregation of several available GIS tools:

- Multi-criteria evaluation (MCE) – Spatial allocation

The knowledge about former dynamics is essential to attempt the prediction of the future evolution or to build prospective scenarios (decision support). Therefore any model has to be supplied with values of initial conditions. In this contribution to initialize the model and to improve our knowledge about phenomena behavior in space and time, we considered two earlier land cover maps as training dates (1998 and 2000). MCE is a method that is used to create land cover specific suitability maps, based on the rules that link the environmental criteria (independent variables) to the studied phenomena (deforestation, reforestation). These rules can integrate statistical techniques (PCA, logistic regression, Cramer test) with a supervised analysis of modeler. The suitability maps are used for spatial allocation of predicted time transition values.

The criteria can be split up into Boolean constraints and factors, which express a land cover specific degree of suitability and variable in space. The constraints will simply mask space while the factors may be weighted and can swap with one another. Because each factor is expressed in proper units they have to be standardized to become comparable. Standardization signifies the recoding of original values (degrees, meters, per cent) into suitability values on a common byte scale reaching from 0 to 255 (highest suitability). Based on statistical tests, recoding is processed by different ways: manual or by fuzzy functions. After the standardization, the factors are weighted by pairs using Saaty matrix (Saaty 1977) and performing the eigenvector. A second set of context-depending weights permits for the selection of risk and trade off levels.

- Markov chains – Time transition probabilities

To perform land cover extrapolation, we use Markov chain analysis (MCA, 2^{nd} order), a discrete process with discrete time periods which values at instance t_{+1} (2003) depending on values at instances t_0 (2000) and t_{-1} (1998). MCA produces a transition matrix recording the probability that each land cover class might change to each other class in the next time period and the number of pixels expected to change. The algorithm also generates a set of conditional probability maps for each land cover showing the probability that each land cover would be present at each pixel after a specified number of time units. They are calculated as projections from the 2000 land cover map.

- Integrating step based on multi-objective evaluation and cellular automata

The spatial allocation of predicted land cover time transition probabilities uses MCE performed suitability maps and a multi-objective evaluation (MOE) arbitrating between the set of finite land cover states. Finally, we add an element of spatial contiguity by applying a cellular automaton (contiguity filter); it decreases the suitability of isolated pixel and favors the generation of more compacted patches. The algorithm is iterative so as to match with time distances between t_{-1} - t_0 and between t_0 - t_{+1}.

3.3.3 Land Change Modeller approach

LCM is the new integrated modelling environment of Idrisi Andes, the new Idrisi version developed by Clark Labs (Eastman 2006), for studying landscape trajectories and land use dynamics; it includes tools for analyzing the past land cover change, modelling the potential for future change, predicting the phenomena evolution, assessing its implications on biodiversity and ecological equilibrium and integrating planning regimes into predictions.

- Land Cover Change analysis

The first step permits us to analyze the past land cover change between 1998 and 2000, which were chosen as training dates. We can easily calculate the gains and losses, the net change for each class and the surface trends for each transition.

- Land Cover Change modelling

The land cover change modelling allows us to define 2 sub-model (forest to cleared areas-deforestation and cleared areas to forest-reforestation) and explore the explanatory power of environmental criteria (using the Cramer test). The quantitative variables can be included into the model either as static or dynamic factors. The static ones are unchanging over time (e.g., distance from pipeline, distance from Rio San Pedro) and express the basic suitability for each transition. The dynamic variables change over the training and simulated period (distance of clearing areas, distance from developing roads) and are recalculated for each interaction during the course of prediction. Once the criteria were set, we calculated two transition potential maps using the Multi Layer Perceptron (MPL) tool. These express for each pixel the potential it has for both reforestation and deforestation. The MPL is more flexible than logistic regression procedure and allows one to model non-linear relationships. For the training process, it creates a random sample of transition cells and a sample of persistent cells; it uses half the samples to train and to develop a multivariate function (adjusting the weights) that predicts the potential for change based on the value of environmental criteria at any location, and the second half of sample to test its performances (validation). The number of training pixels will affect the accuracy of the training result: a small sample size may not represent the population for each category, while too many samples may cause an over training of the network. We construct a network aggregating an input layer with 10 neurons, an hidden layer with 4 neurons and the output layer with 2 neurons (suitability for deforestation and reforestation); we used a learning rate of 0.000121 and a momentum factor of 0.5. After 5,000 interactions, we achieved an accuracy rate of approximately 87%. The next classification phase performs the neural network classification, which produces the transition potential maps for deforestation and reforestation.

- Land Cover Change Prediction

The quantity of change for each transition was calculated using the Markov Chains Analysis (MCA, above mentioned), from the 1998 and 2000 classified images and specifying the 2003 end date. We created both hard and soft maps; the first ones are definitive maps in which each pixel belongs to a certain class. The soft ones are a group of images showing the degree of membership of each pixel to each possible class and yield a map of vulnerability to deforestation, pointing out possible hot spots. We use 3 recalculation steps during which the dynamic variables are updated. At the end we added the planning interventions tool, creating a disincentive for deforestation (1.5 multiplicative factor for southern areas) in the north side of Rio San Pedro (affected by narcotraffic interests, which limit the freedom of movement; the roads in the southern part will be the main vector of penetration in this test area, replacing the Rio San Pedro) and an incentive for reforestation in the central highlands (communitarian zone) where nomad agriculture permits a more sustainable use of natural resources.

3.3.4 Dinamica EGO approach

Dinamica uses a cellular automata approach to reproduce the landscape dynamics and the way its spatial patterns evolve. The simulation environment aggregates several steps which are easily built by connecting algorithms (*functors*) via their port, using a user-friendly graphical interface or XLM language. We resume here the main stages from the calibration to the validation of predicted output and the adopted parameters:

- Amount of change estimate

The first easy model allows calculating the amount of change for each transition through the Markov Chains Analysis of second order (comparing two land use/cover map in different dates); we used the 1998 classified map as the early image and a 2000 map as the later map for computing the transition matrix.

- Weights of Evidence Method – Change allocation

A probability map of occurrence for each transition is produced using the Weight of Evidence (WOE) method. This is a Bayesian approach to highlight the relationships between environmental criteria and land use/cover change; for example we want to know whether an individual layer provides useful information to identify the location of deforested areas. In general, if a map layer is to provide useful information, then the pixel data from cleared patches should have its own characteristics different from those of the data from forest zones. We can use the likelihood ratio function, which is a ratio between two frequency distribution functions, to point out these differences (Chung et al. 2002). A suitability map for milpa and forest can be generated based on the likelihood ratio function calculated from all the layers. We use a Bayesian method to estimate it.

The favorability for one transition (e.g., deforestation D), given a binary map describing a spatial pattern C, can be expressed by the conditional probability:

$$P\left\{D|C\right\} \equiv \frac{P\left\{D \cap C\right\}}{P\left\{C\right\}} \equiv P\left\{D\right\} \frac{P\left\{C|D\right\}}{P\left\{C\right\}} \tag{3.4}$$

Algebraic manipulation allows for the representation of this formula in terms of odds which are defined as a ratio of the probability that an event will occur to the probability that it will not occur (Bonham-Carter 1994):

$$O\left\{D|C\right\} \equiv \frac{P\left\{D|C\right\}}{P\left\{\overline{D}|C\right\}} \equiv \frac{P\left\{D\right\}P\left\{C|D\right\}}{P\left\{\overline{D}|C\right\}P\left\{C\right\}} \equiv \frac{P\left\{D\right\}}{P\left\{\overline{D}\right\}}\frac{P\left\{C|D\right\}}{P\left\{C|\overline{D}\right\}} \equiv O\left\{D\right\} LS \tag{3.5}$$

LS is the likelihood ratio and it is also called the sufficiency ratio. We take the natural logarithm of equation to define the positive Weight of Evidence W^+ which is calculated from the data:

$$Logit\left\{D|C\right\} \equiv Logit\left\{D\right\} + W^+ \tag{3.6}$$

This method can be extended to handle multiple predictive maps and to relate a change with respect to several geographical patterns. However, it will be necessary to have some restrictive hypotheses for the analyzed area as well as some prior odds ratio for each transition. In the end, the conditional probability for deforestation, given a group of environmental criteria for each pixel, is expressed by:

$$P\left\{D|C_1 \cap C_2 \cap C_3 \cap C_n\right\} \equiv \frac{e^{\Sigma W^+}}{1 + e^{\Sigma W^+}} \tag{3.7}$$

The WOE model allows for the categorization of the continuous quantitative variables, evaluating the correlation of explanatory maps and displaying the weights of evidence with respect for each type of environmental criteria. The output is saved as a text file.

- Land Use/Cover Change prediction

The simulation model allows for the reproduction of the spatial pattern evolution taking into account a large number of parameters specified in the used containers, such as:

Select percent Matrix: expresses the percentage of pixels for each transition that will be modified using the expander function; this process expands or contracts the previous patches of a certain class (e.g., previous cleared areas). The (1 – Expander %) percentage is treated with the Patcher function, which creates new patches through a seeding mechanism. We have chosen a percentage of 50% for deforestation and 70% for reforestation.

Select transition parameter matrix: this matrix takes into account three parameters for expander and Patcher functions. The mean patch size describes the mean size (hectares) of new pixel groups that will be modified for each transition. To increase this value models a less fragmented landscape with large patches for every class. The second parameter is the patch size variance, which determines how much the patch size can vary regarding the medium value; increasing this number leads to a more diverse landscape. Finally, the isometry determines the degree of aggregation of the patches (values >1 permit a better cohesion of cells groups). We have chosen a mean size of 2 and 4 ha, variance values of 1 and 2 ha and an isometry of 1.1 and 1.3, respectively for deforestation and reforestation.

3.4 Results

Four 2003 land cover maps were produced using the above-mentioned, predictive models (Fig. 3.5). We have semplified the complexity of land use/cover change only considering two transitions: deforestation and reforestation. The different simulation models were employed to project future landscape evolution under the same scenario. A scenario describes possible future situations based on different hypotheses about socio-economic, demographic, political, ecological, etc., conditions (Hauglustaine et al. 2004, De Castro et al. 2007). We have drawn our scenario using the information observed in the last few years of training period (1998-2000).

3.5 Validation and discussion of results

To understand how well the applied model outputs match with reality, many statistical methods measuring the agreement between two categorical maps have been developed in the last years. However they didn't offer an exhaustive answer to validation problem, particularly to analyzing the spatial allocation of disagreement. Our first approach is to perform a visual examination between the reference image (real 2003 land cover map) and the models output; we can quickly obtain a general idea about model performance, highlighting possible strong incongruencies in terms of quantity and location.

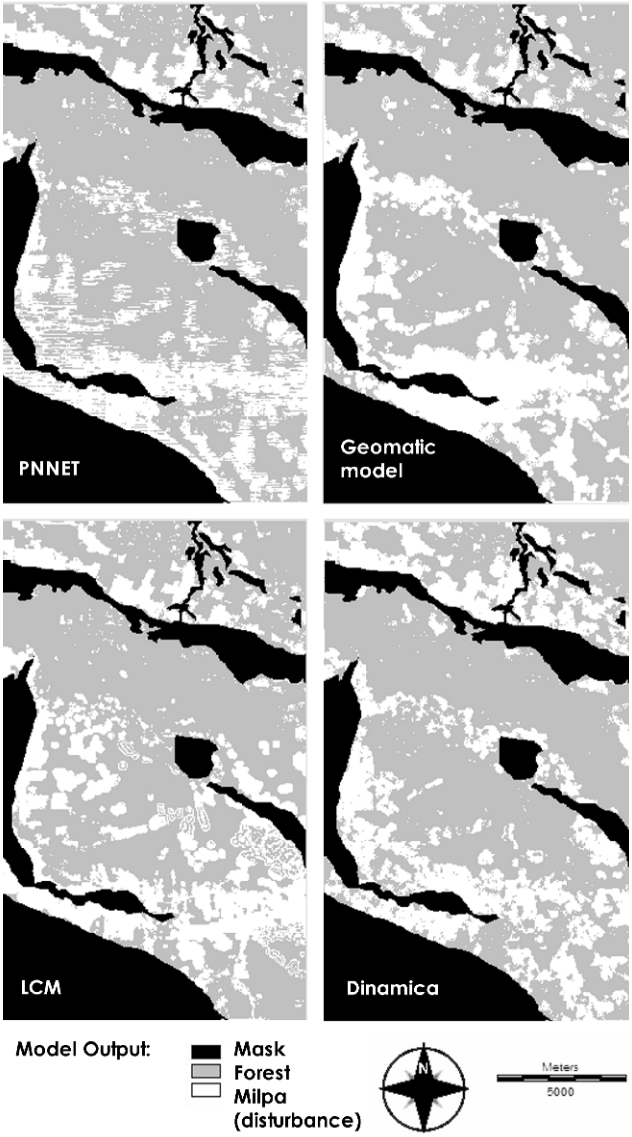


Fig. 3.5 Outputs of predictive models. Simulated Land Cover in 2003

We stress that the PNNET model underestimates the amount of deforestation in the southern zone (Fig. 3.6); the performance improves the central and northern regions. The spatial allocation of cleared areas is quite realistic, but their form is sometime fragmented, probably due to frontier pixel approximation.

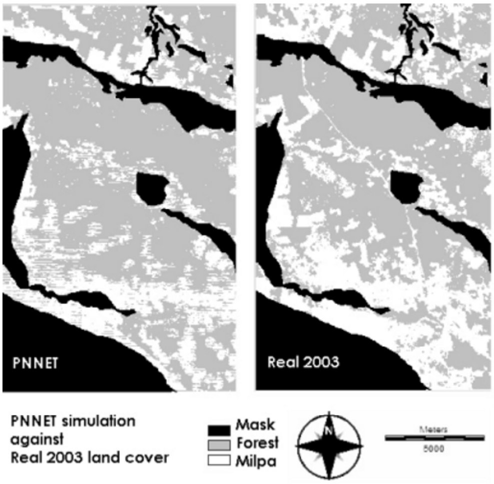


Fig. 3.6 PPNET output vs. real map in 2003

The geomatics model improves the number of deforested pixels in regards to PNNET output; we note an overestimation of cleared areas around the La Joyanca site (image centre) and a compact aggregation of the same ones in the southern and central zones (Fig. 3.7).

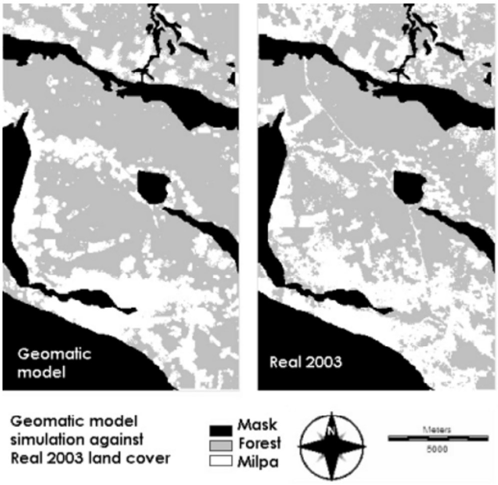


Fig. 3.7 Geomatic model output vs. real map in 2003

The Land Cover Modeler produced the worst spatial distribution of cleared areas with several deforested spots scattered in the central region. Some of them present a unrealistic structure with a concentric alternation of forest-milpa (Fig. 3.8).

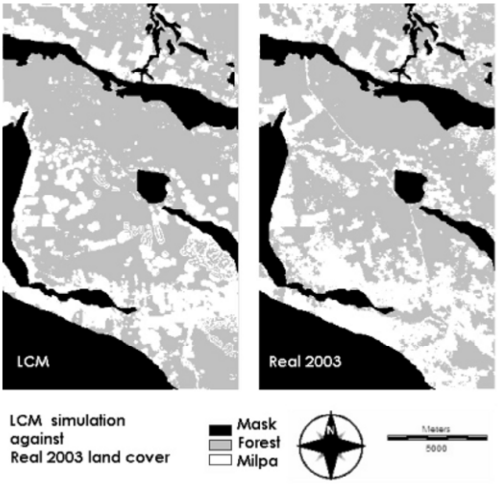


Fig. 3.8 LCM output vs. real map in 2003

In the end we visually examined the Dinamica Ego output; we saw an underestimation of deforestation in the southern area and an overestimation in the northern one. The form of cleared spots is more realistic in regards to the other models output, especially nearby at the La Joyanca site (Fig. 3.9).

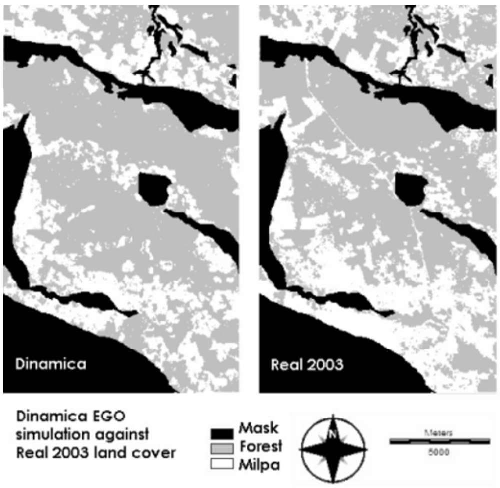


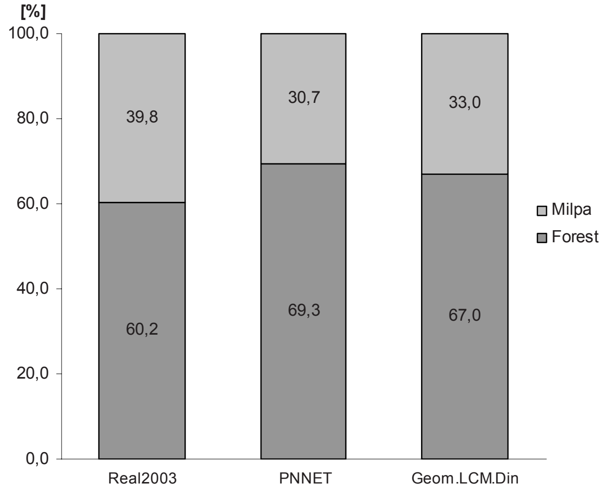
Fig. 3.9 Dinamica output vs. real map in 2003

For each simulated map we calculated the number of predicted pixels, to create a first glimpse on quantity agreement (Fig. 3.10); the PNNET shows the lower predicted value for the last three models, which uses the same

MCA (Markov Chains Analysis 2nd order) for computing the number of pixels for each transition. All models have poor predictive power because the driving processes of LUCC (Land Use/Cover Change) change over time; the deforestation during the training period 1998-2000 doesn't match the faster phenomena evolution (or persistence) from 2000 to 2003. It partially depends on the progression of a new deforestation front from the southern region, which is not included in our test area, but which became evident in 2003 on the southern side of the *Laguna Agua Dulce*.

So we denote a quantity disagreement of about 9% on total area for the PNNET predicted map and about 7% for other models, with an evident underestimation of deforested patches and an overestimation of forest.

Two land cover maps could have the same percentage of forest/milpa but a different spatial allocation of these quantities. The analysis of location disagreement is more complex: it results from swapping locations between forest and non-forest cells (Pontius 2002). It's very important to separate the change in quantity from the change of location for a better understanding of environmental dynamics and to improve the model's weaknesses.



	Forest [pixels]	Milpa [pixels]	Tot. [pixels]	Forest [ha]	Milpa [ha]	Forest (%)	Milpa (%)
Real2003	270,080	178,492	448,572	10,803.2	7,139.6	60.2	39.8
PNNET	311,019	137,553	448,572	12,440.8	5,502.1	69.3	30.7
Geom.LCM.Din	300,767	147,805	448,572	12,030.6	5,912.2	67.0	33.0

Fig. 3.10 Agreement of quantity - numerical and graphical representation

A cell-by-cell cross-validation (Table 3.1) is a very simple methodology but it is quite limited because it doesn't take the spatial proximity into account. So we can point out a large number of misclassified cells even if the correct classification is found in their neighborhood (Pontius and Pacheco 2004). The cell-by-cell validation highlights that all models present a poor performance for the Milpa with a medium value of 54.5% of agreement; this percentage increases for the forest class to 82.25%. Considering this table we can conclude that the Geomatic model performs better for deforested patches (58%) and the PNNET for the forest prediction (85%).

Table 3.1 Pixel-by-Pixel validation – Simulated maps vs. real 2003 land cover map

	Forest (pixels)		Milpa (pixels)		Total (pixels)	
Real 2003	270,080		178,492		448,572	
	Correct	Mis	Correct	Mis	Correct	Mis
PNNET	230,656 (85%)	39,424 (15%)	98,129 (55%)	89,363 (45%)	328,785 (73%)	119,787 (27%)
Geomatic	226,902 (84%)	43,178 (16%)	104,627 (58%)	73,865 (42%)	331,529 (74%)	117,043 (26%)
LCM	215,852 (80%)	54,228 (20%)	93,589 (52%)	84,903 (48%)	309,441 (69%)	139,131 (31%)
Dinamica	216,848 (80%)	53,232 (20%)	94,580 (53%)	83,912 (47%)	311,428 (69%)	137,144 (31%)

We calculated now the LUCC budget (Table 3.2) to point out the gains and losses for each category (we only consider the milpa class because the map is binary) and the amount of change from 2000 to 2003 in regards to real dynamics.

Table 3.2 LUCC budget. Percentages on total number of pixels (448,572)

Milpa	GAIN%	LOSS%	TOT. Change %	abs (net change) %	SWAP (Tot-abs)%
REAL2003-REAL 2000	24.01	4.92	28.93	19.10	9.83
PNNET2003-REAL2000	9.97	0.00	9.97	9.97	0.00
GEOM2003-REAL2000	14.02	1.76	15.78	12.26	3.52
LCM2003-REAL2000	13.37	1.12	14.49	12.26	2.23
DIN2003-REAL200	15.05	2.79	17.84	12.26	5.59

For real evolution of deforestation (real 2000 vs. real 2003) we recognize an important total change (29%) that doesn't appear in the LUCC-budget of 2003 simulated situations. In particular PNNET shows the lowest value (10%), due to the absence of reforestation dynamic from 2000 to 2003 (0% loss for Milpa or, if you prefer, 0% Forest gain); PNNET only predicts the evolution of clearing processes considering that there will be no forest re-growth in the old deforested patches. Dinamica demonstrates the highest value for total change (18%) and a ratio Swap/Net-change (0.46) closest to the real one (0.51), showing the best land cover dynamics approximation.

The other models, particularly the neural networks, underestimate the land cover change predicting instead persistence.

We intersect now the simulated land cover maps and the real one, to analyse, study the consistency between models (Table 3.3). The correctly predicted area by the four models is about 53%, which represents a poor consistency in comparison with an individual prediction rate of about 70%. This significant difference is due to the theoretic approach (automatic, semi-automatic, supervised) of considered methodologies for the spatial allocation of predicted pixels. For each intersection the forest prediction is better than the milpa prediction, due to the persistence and large area of this category in opposition to the fast and fragmented evolution of clearing phenomena. The best three model combination is the PNNET-Geomatic model-LCM, with an improvement rate of 6.25%. When we separately use the PNNET or Geomatic methods with the other ones, we obtain a poorer improvement. This consideration is seen during subsequent analysis, where the higher value (13.57%) is obtained by the intersection between the PNNET and Geomatic model, thus indicating a good consistency. Less improvement is created by the LCM and Dinamica (4.83%). Finally, we analyse the contribution of single simulated output; we note that the Geomatic model performs the best prediction (73.9%) followed by the PNNET (73.3%) with an improvement of about 21% as to the four model outputs. The last one shows a better ability in forest prediction (85.4% of real forest), while the Geomatic model performs better for the Milpa (58.62% of real disturbance).

Table 3.3 Prediction rates by crossing the models outputs. Total improvement values are calculated as to all models performance

		Accurate predicction scores %			
		Milpa	Forest	Total	Improvement
Intersection of 4 models		13.2	39.04	52.24	-
Intersection of 3 models	1) PNNET∩Geom∩LCM	15.59	42.89	58.48	6.24
	2) PNNET∩Geom∩Din	14.96	42.88	57.84	5.60
	3) PNNET∩LCM∩Din	14.31	40.32	54.63	2.39
	4) Geom∩LCM∩Din	13.84	40.1	53.94	1.70
Intersecction of 2 models	1) PNNET∩Geom	18.51	47.31	65.82	13.58
	2) PNNET∩LCM	17.3	45.28	62.58	10.34
	3) PNNET∩Din	16.64	45.24	61.88	9.64
	4) Geom∩LCM	17.39	44.54	61.93	9.69
	5) Geom∩Din	17.09	44.6	61.69	9.45
	6) LCM∩Din	15.26	41.8	57.06	4.82
Single model's prediction	1) PNNET	21.88	51.42	73.3	21.06
	2) Geom	23.32	50.58	73.9	21.66
	3) LCM	20.86	48.12	68.98	16.74
	4) Din	21.08	48.34	69.42	17.18

We have seen that for each method, the correct prediction score is linked to the nature of the classes and to their spatial patterns evolution. We have seen that the PNNET performs better for forest prediction and the Geomatic model for milpa prediction. Now we have shown that these performances depend on the number of land cover changes between 1998-2000-2003 (Fig. 3.11). The neural network shows the highest prediction score (93%) for the areas with land cover persistence (mainly closed forest areas), but it has the lower value for the more dynamic patches. The Geomatic model and Dinamica perform better for the zones with 1 or 2 land cover changes (mainly cleared areas with partial forest regrowth). All methods show a good ability to demonstrate persistence prediction driven by the simplicity of this phenomenon; unfortunately our attention is focused, however, on deforestation processes, which are more complex and interdependent on several factors. The models perform similarly on the areas which changed only one time (only 50% of real amount) but we have a strong difference in model behaviour when land cover changes occur multiple times, with better prediction scores for Geomatic model (23%) and Dinamica (21%). We note that these values are very small as regards to real amount of change.

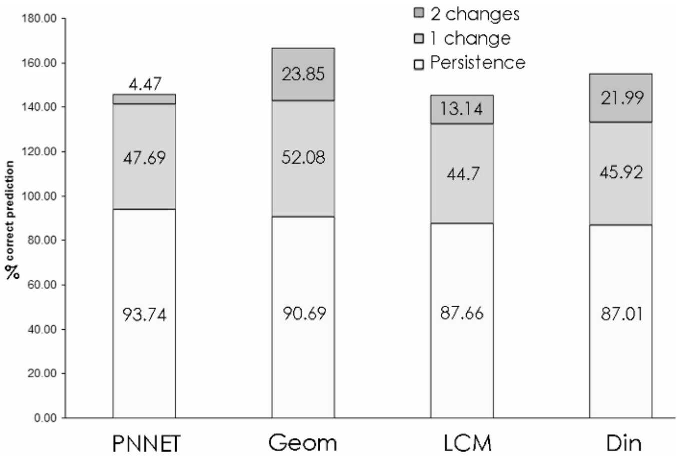


Fig. 3.11 Prediction scores (%) depending on the number of Land Cover Changes – graph and table

We have explained that the pixel-by-pixel agreement is a simple but limited method to value the quality of the fit of validation, because it doesn't consider the spatial proximity of agreement. We want to do a comparison within a neighborhood context, as two maps that do not match exactly pixel-by-pixel could still present similar spatial patterns and the correct classification could be found in the adjacent cells. To address this issue, we used the

Dinamica EGO vicinity-based comparison method (Rodrigues et al. 2007), based on the fuzziness of location, in which the pixel value is influenced by itself and by the cells in the neighborhood window. The choice of the neighborhood depends on the pixel size and on our objectives; we use the default window size (5x5 pixels), we consider this an acceptable error in the spatial allocation of predicted cells within the first 100m, because our goal is to point out the more vulnerable zones and the future trends of deforestation. When the support size is larger or the studied problems require a detailed spatial map (e.g., landslide risk map) we have to reduce the window size or give up this validation approach. The fuzzy similarity map shows the spatial match between simulated and real images; it varies from 0 (no match) to 1 (perfect match); the intermediate values are calculated using a decay function within the window size. Using the fuzzy theory, we can work with different degrees of membership and not just with a Boolean analysis 0 (error) and 1 (correct match) like in the pixel-by-pixel cross validation. We remark a smaller number of cells classified as erroneous, with a medium improvement of 6% (Table 3.4). The Geomatic model shows the smallest value (5.25%) due to the use of a/the contiguity filter in the last step of simulation, which down-weights the suitabilities of pixels distant from existing areas of each class creating more compact patches. The PNNET method output instead, with its fragmented form of cleared areas due to frontier pixels approximation, improves its accurate prediction score from 73% (cell-by-cell validation) to approximately 81% (improvement of 7.86%). The fuzzy method reflects better the quality of the-fit of general patterns between simulated and real maps, such as emerged in the visual examination.

Table 3.4 Pixel-by-pixel agreement vs. fuzzy validation. We used the Fuzzy validation approach developed in Dinamica EGO

	Cell-by-cell Error (Pixel)	Fuzzy Error (Pixel)	Improvement (Pixel)	Improvement (%)
PNNET	119,787	84,083	35,704	7.96
Geomatic	117,043	93,482	23,561	7.25
LCM	139,131	113,178	25,953	5.79
Dinamica	137,144	109,768	27,376	6.10

3.6 Conclusion and outlook

It is difficult to compare the performances of numerous methods because we have to consider many different aspects during the LUCC modelling. Often the model is focused on a specific test area and a specific problem, usually with large amount of data information; so it has a good performance in these conditions but it can't be applied when the data base is not robust or when the training characteristics change. Here we tried to present four methods which are simple to use, which can run with easily available data (without excessive time and money consumption) and which can be adapted to different regions and problems.

We have noticed that all models have a poor predictive power due to the changing of driving processes of LUCC over time. The spatial patterns evolution, observed during the training period (1988-2000), doesn't match the deforestation trends in the simulated one (2000-2003). So it's difficult to separate the capability of the model from the complexity of landscape and quality of the data. All simulated maps present the same difficulties to reproduce the clearing phenomena in the southern zone, with different degrees of approximation; the land cover change in this region is too complex to be completely predicted because the human free will can strongly and quickly modify the original landscape. We have produced four predictive maps under the same scenario; this scenario describes a future with the same demographic increase and socio-economic hypothesis observed in the last years of training period (1998-2000).

The analysis of quantitative agreement highlights an underestimation of cleared areas both for PNNET (77%) and other MCA models (82%). A pixel-by-pixel validation shows very similar performances, reducing the correct prediction score for deforested patches (55% of real ones); the PNNET has higher value (85%) for forest prediction and the Geomatic model for the Milpa (disturbance) prediction (58%).

The LUCC budget from 2000 to 2003 shows the limits of the PNNET approach; it doesn't predict forest regrowth during this period and as a consequence its swap value is null. The Dinamica EGO better approximates the real dynamics from 2000 to 2003 with a ratio swap/net change (0.46) closer to the real value (0.5). The analysis of model performance versus the number of land cover changes during the 1998-2000-2003 period shows similar scores for Geomatic and Dinamica models, which have the best predictive power on the more dynamic areas (numerous changes), while PNNET performs better for persistent forest zones.

This contribution wants to point out the potential of predictive modelling for integrating the traditional approaches to environmental and hazard problems. At the same time, we want to comment that the model performance and its utility depend on our geo-system knowledge and on the quality of data, often more than on the model's conceptual foundation. The objectives are clear to address an exhaustive question: do we want to better understand the observed object or to understand the long term effects of specific government planning or industrialization? Taking into account its goals, the modeler often prefers to work in a simplified environment with very uniform dynamics and clear relationships; it's an ideal situation to run a model and obtain a good result, but its utility is quite limited. When we analyze a phenomena's complex evolution, we have to consider all interconnections between the natural and artificial dynamics; the early raw model output could be quite poor, yet it helps us to improve our knowledge of hidden relationships between the studied phenomena and the key variables. The subsequent simulation will be better for having considered this new information.

The spatiotemporal models are simplified representations of reality. Represent is also re-represent, represent again, after a selected period; we have to accept that this result will be not an exact copy of reality. The re-representation has its own legitimacy: it has memory and project; it bases its legitimacy on the coherence with the past history and the future goals (La Moigne 1994).

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4 Evaluation of prospective modelling methods: fuzzy logics and cellular automaton applied to deforestation in Venezuela

Selleron G and Mezzadri-Centeno T

Abstract
Spatial evolutions of anthropized ecosystems and the progressive transformation of spaces through the course of time emerge more and more as a special interest issue in research about the environment. This evolution constitutes one of the major concerns in the domain of environmental space management. The landscape evolution of a regional area and the perspectives for a future state raise particularly important issue. What will the state of the region be in 15, 30 or 50 years?

Time can produce transformations over a regional area such as emergence, disappearance or the union of spatial entities. These transformations are called temporal phenomena. We propose two different methods to predict the forestry development for the forthcoming years in the experimental area, which reveals these spatial transformations. The proposed methods are based on fuzzy logic and Cellular Automata (CA).

The methods are supported by the analysis of the landscape dynamics of a test site located in a tropical rain forest country: the oriental piedmont of the Andes Mountains in Venezuela. This large area, at the scale of a Spot satellite image, is typical of tropical deforestation in a pioneer front. The presented approaches allow the geographer interested in environmental prospective problems to acquire type cartographical documents showing future conditions of a landscape. The experimental tests have showed promising results.

Keywords: Spatial dynamic of environment, modelling, fuzzy logic, cellular automata, prospective maps, tropical pioneer front.

4.1 Introduction

The spatial evolution of anthropized ecosystems and the progressive transformation of spaces over time is a large preoccupation in space accommodation, environmental domains, and prospective studies. There is an underlying question that arises concerning the landscape development and the prospective of the state of a forest area in future: How will conditions of a regional area develop within the next 15, 30 or 50 years?

In fact, the time consists of hierarchical events and can produce transformations upon a terrain landscape such as emergence, disappearing, and the union of spatial entities. These transformations are called temporal phenomena (Claramunt 1994).

Simulation with digital images has become an important and an interesting topic for research related to environment monitoring (Centeno and Selleron 2001).

A sequence of digital maps of different dates allows the analysis of the landscape dynamics of a region. Images collected by satellite (SPOT and Landsat) from the forest of Ticoporo, a tropical rain country that is located in Venezuela (South America), were used to investigate different methods of spatio-temporal prediction: fuzzy logic and cellular automata.

These methods enable us to study the future evolution of the forest by analysing the forest's progression and regression zones from a sequence of n thematic maps through time. The evolution modelling of regions, for an established date, is obtained with help of the sequence of satellite images representing the terrain conditions for distinct years. Thus, sensitive factors on region evolution are considered for the prediction purpose. It allows the geographer interested in environmental prospective problems to acquire type cartographical documents showing future conditions of a landscape.

4.1.1 Fuzzy sets in spatial modelling

Many works have been developed based on fuzzy systems to solve problems related to geo-processing. According to Saint-Joan and Desachy (1995) fuzzy systems deal with imprecise and uncertain information in a more efficient way when compared with algebra maps systems based on Boolean logic. Many authors point out some advantages in the use of fuzzy inference systems to solve problems associated with the environment (Centeno and Gois 2005, Zadeh 1965, Schultz et al. 2006):

- The integration of diverse and heterogeneous sources of information in different scales of magnitude allows a formal trade-off between favourable and unfavourable conditions.
- The possibility of manipulating linguistic terms instead of mathematical formulas can facilitate the use of the systems by specialists unfamiliar with the mathematical terminology.

– The definition of a fuzzy rule base allows the reasoning process to focus on specific regions of interest.
– Smoother decision regions resulting from the fuzzy reasoning can reduce abrupt changes in the final decision-making.

4.1.1.1 Modelling imprecision

Geographical data has a number of properties, which present challenges to the modelling process. Sometimes in image analysis approaches, it is more appropriate to regard the geographical regions as fuzzy subsets of the image. This includes complex definitions of location, multidimensionality and the inherent fuzziness in many features of the regions and their relationships (Peuquet 1984). The resultant model should be able to represent a simplified approximation of reality and manage the imprecision or indistinctness, which characterizes a lot of geographical information.

The fuzziness of geographical information can be related to the representation of regions, whose location or boundaries are not known precisely and to the representation of the information, which is expressed in imprecise terms. For all these reasons, there is now considerable interest in issues of uncertainty and imprecision in geoscientific information (Altman 1994). Fuzzy set theory is an appropriate means of modelling imprecision or vagueness and there are many areas to which fuzzy sets are being applied.

4.1.2 Cellular Automata Models

The cellular automata theory was first introduced by John Von Neumann in the forties and it gained considerable popularity in the 1970's, through the work of John Conway, called "game of life"(Gardner 1970).

A cellular automaton is a discrete dynamic system whose behaviour is specified in terms of a local relation (Toffoli and Margolus 1998). According to White et al. (2000) a cellular automata model consists of:

– a one or n-dimensional space divided into an array of identical cells;
– a cell neighbourhood of a defined size and shape;
– a set of discrete cell states;
– a set of transition rules, which determine the state of a cell as a function of the states of cells in a neighborhood;
– discrete time step with all cell state updated simultaneously.

At each time step, all cells in the array update their current state according to the transition rule (representing the dynamic nature of the system)

(Wolfram 1994). The number of possible configurations for a cellular automata (considering the transition cell updated) with s states and n neighbourhood cells is s^{s^n} (Weimar 1998).

According to the classical Cellular Automata Theory, a rule is called totalistic if it only depends on the sum of the states of all cells in the neighbourhood. Another classification is to distinguish between deterministic or probabilistic rules. In the first case, the transition rule is a function which has exactly one result for each neighbourhood configuration. However, probabilistic rules provide one or more possible states with associated probabilities, whose sum must be one for each input configuration (Weimar 1998). Each cell must be in one state. A set of discrete cell states can be defined by some property linked with the simulation of the phenomenon to be modelled.

The size of the neighbourhood must be defined. The Fig. 4.1 shows three examples of neighbourhoods that can be defined in two dimensions. The choice of neighbourhood depends on the context and it influences the propagation velocity of the phenomenon to be modelled (Weimar 1998).

Cellular automata can also be implemented with rules of different range. A range of 1 means that only the nearest cells are considered as neighbour cells, and a higher range means that more nearby cells are considered neighbours, as shown in Fig. 4.2.

The characteristics of CA used in today's geographic cellular automata (GCA) models are a mixture of the original CA formalism (Wolfram 1984) and the multiple transformations required for the modelling of the geographic space (Couclelis 1997, Torrens and O'Sullivan 2001). However, GCA can be used in any context where one of the main drivers of land use change is the influence of spatial neighbors. Some studies listed above exemplify this situation since they have consistently shown that the GCA modelling framework is well suited to capture the highly decentralized, multi-criteria, and spatial dynamics of geographic space.

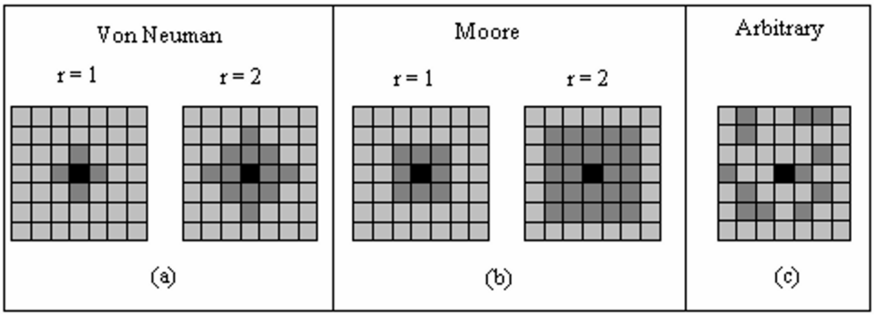


Fig. 4.1 (a) Von Neuman's neighbourhood (b) Moore's neighbourhood (c) Arbitrary neighbourhood

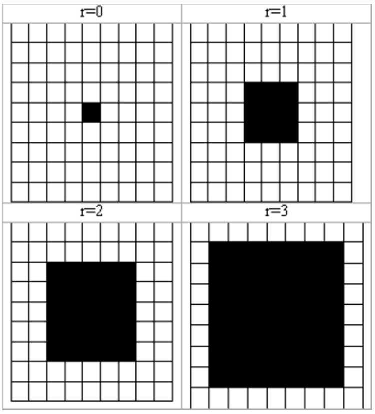


Fig. 4.2 Range of cellular automata

4.1.3 Spatio-temporal Prediction technique

Predictions are important methods of reasoning about the geographic space and they are based primarily on inferences, rather than observations (Chase and Chi 1981).

The aim of a prescriptive modelling is to represent facts, to simulate processes, to express judgements or to provide for effective descriptions of geographic phenomena, through sets of properties or constraints. The computer has to generate the potential answers to these descriptions and to present them to the users (Falcidieno et al. 1992). Prescriptive modelling attempts to answer questions such as "what should be" by simulating the effects of certain actions effecting spatial objects/phenomena/processes. Prescriptive modelling is often based on the assumption that the problem domain has been well understood it provides effective descriptions of geographical phenomena in order to help users to make in spatial decision (Centeno 1998).

The problems addressed by prescriptive models generally involve two different uses for them: exploration and generation. The first requires a selective exploration of the spatial data model using geometric, topological, geographical properties in order to satisfy the objectives. The second problem generates a simulation of geographical phenomena. The initial statement of an allocation problem is a descriptive task, which consists of an explicit specification of some geographic conditions necessary to achieve the stated objective. The set of conditions expressed by the user defines the conceptual model of the spatial phenomena; it depends on the user's requirements. The simulation of geographical phenomena can be used, for example, to foresee potential site modifications in time.

The achievement of simulation of geographical phenomena through time consists of observing the changes of the spatial entities. The sequence of events must be considered in order to study the influence of spatial processes over the entities' transformation. The past states of an entity influence its current state, the current state in turn influences the future states of this entity. In this paper, the interest lies in the techniques of simulation.

4.1.4 Related works

Some approaches described in literature use a sequence of satellite images to generate a prediction for a specific region. In Centeno et al. (1996) the prediction method uses geographical data in vector representation and it is based on the position and form study of the spatial entities contained in each map. However, this method does not take into account relevant land area features such as valleys, rivers, slopes, roads, villages or indeed regions frequently destroyed by fire. Therefore the regions are constrained to uniform morphological transformations.

In St-Joan and Vidal (1996), the proposed approach applies mathematical morphology to zones of forestry progression and regression considering shape and surface of the regions, but the prediction task is occurs without regard of important factors related to forestry evolution.

The approach of Centeno and Selleron (2001) is founded on the principle that we must make use of regression and progression zones within the forest in order to discover the privileged directions of evolution that is the growth or decline in specific areas.

Schultz et al. (2008) have developed an approach based on the work of Centeno and Selleron (2001), but the method uses genetic algorithms and genetic programming to adjust coefficients that limit the process.

The discrete nature of cell states makes CA attractive for spatial-temporal modelling in a geographic information system (GIS) raster-based environment, which describes the world as a static representation based on a discrete array of cells. GIS and CA are complementary with regards to spatio-temporal modelling as the former provides the spatial framework for geographic data while the latter contributes the temporal dimension for describing change. Furthermore, the ability to develop realistic spatial models within a GIS environment has progressed due to the increasing availability of remote sensing (RS) data.

Cellular automata have already been used in some works related to prediction using geographic data. Rothermel (1972) has developed a model that simulates and predicts surface forest fire together with a GIS terrain data. In Vale et al. (1999), a process is described to simulate a viral epidemic through time. First it defines an initial state with some characteristics in a two-dimensional space and then the evolution is modelled by CA. Jants et al. (2003) described and tested a predictive modelling system to simulate the impacts of future policy scenarios on urban land use based on four different types of urban land use change. Sullivan and Knight (2004) provide a potential model for operational fire spread prediction.

Few studies focused on the land use dynamics of rural or more natural landscapes; examples are provided by the modelling of rural residential settlement patterns in the periphery of Toronto (Deadman et al. 1993) and in the Rocky Mountains (Tehobald and Hobbs 1998), and deforestation in the Brazilian Amazonian forest (Soares-Filho et al. 2002, 2004).

4.2 Test areas and data sets

4.2.1 The "Forest Reserve" of Ticoporo and the problematic

The material used to test the prediction modelling is from the forest of Ticoporo, on the oriental piedmont of the Andes in Venezuela (Fig. 4.3).

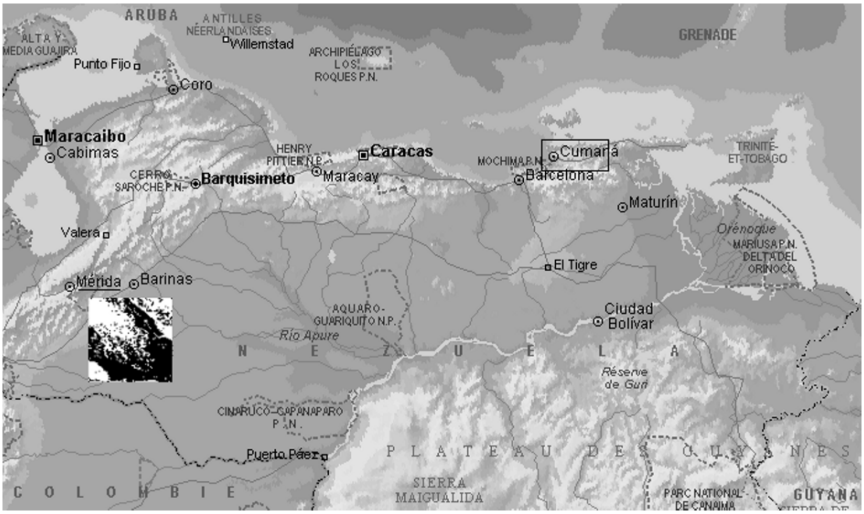


Fig. 4.3 Location of the test site of Ticoporo in Venezuela

The experimental site called *«Ticoporo Forest Reserve»,* lies on the eastern perimeter of the Venezuelan Andes, in the vast plain of Llanos crossed by the Orinoco river. This rainforest, covering an area of about 200,000 hectares, is very rich in tree species. It is very dense and has different physionomies.

It has acquired the protector status of “reserve” (Fig. 4.4), after it was already one of the last bits of the forest Llanos.

Indeed, a phenomenon of deforestation, which appeared in the early 60’s, greatly increased during the 80’s and continues to today. Its origin is the result of spontaneous movements of Andean peasants fleeing the land of the economically poor mountain region to conquer land in the plains. For them, these new “virgin” forest areas on a flat topography became a territory that allows the transformation of forest into extensive grazing pasture (land).

The phenomenon of deforestation is illegal and it has grown in an unbalanced manner in both time and space, due to several factors: the legal status of the land, the level of technology achieved and the social groups involved. Thus, at the end of the 70’s, the shape of the massif was affected by human activity and then very quickly the heart of the “reserve” was reached. The regression of the forest was driven by two very distinct forces: on the one hand, a mechanized, industrial logging (a front of methodical and mechanized cutting), this occurs at the eastern and western edges of the forest; on the other hand a deforestation by fire (an ancestral culture of burn) or by cuts in the central area.

So there are two distinct phenomena that we will distinctly separate in order to consider the modelling. First, on the eastern and western edges there is the private concessions.

If the forest is exploited, it has survived only as a biogeographic entity, because the cut trees are systematically replaced by other tree species with rapid growth and quite often this regrowth is of a single species. This part of the reserve shows significant impoverishment. Both of the logging operations are even protected by private militias!

At the center, where the second distinct phenomena occurs, it is quite different. The forest has a hybrid status –Public and Private State–. It is the prime destination of the new usurping peasants, whose aim is the systematic destruction of the forest to create new pastures. These pastures will be redeemed by the major landowners of the surrounding area, and therefore this process will in gradually increase over time.

Both types of spaces, shown in the satellite images from 1989 (Fig. 4.4), are very different: the heart of the reserve is very sparse and surrounded by the two private industrial forest-covered properties. Together these two outlaying properties form a horse-shape around the barren central region. This central area is undergoing the phenomena, which are of concern for the modelling of this work.

4.2.2 Images of the forest "Reserve of Ticoporo"

For the experience, we have three Spot images (1987, 1989 and 1994) with 20 meters resolution and one LANDSAT-MSS image (1975) with 80 meters resolution, one of the oldest images (and without any cloud cover) acquired for this site.

After geometric correction and thematic classifications of all satellite images, we performed binary maps (512 x 512; resolution 70 m.) Each satellite image contains dynamic information about the forest area with its states. The Fig. 4.4 shows an example of the experimental space on the image from 1989.

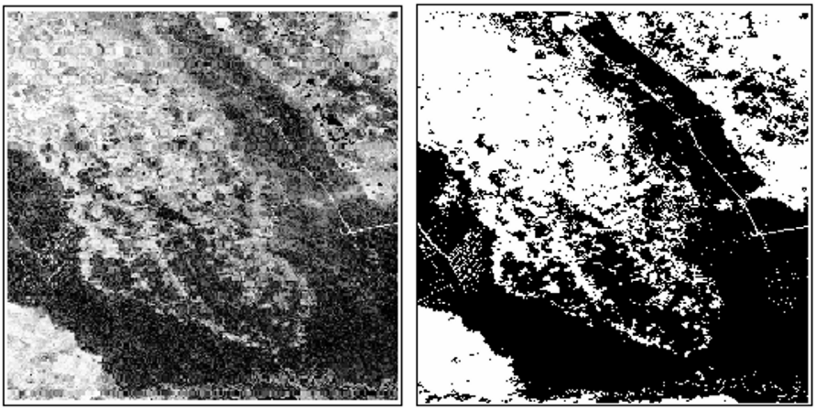


Fig. 4.4 Channel red image from 1989 (left) and threshold image from 1989 (right)

The reader sees that the original satellite image (left) contains a very large variation in hues (here translated into gray-scale) that can not possibly all be taken into account by the model. As far as the variation of shades, they mostly deal with various grades of existing pastures. The problem is centered on the process of deforestation: the transformation of the forest into pasture over time. It begins with a simplification of the basic image data through a spectral binary segmentation of the image. So we use a simplified nomenclature: "forest - non-forest". This treatment is carried out on each image using the image processing *software Er-Mapper*. Fig. 4.4 shows the results of the binarization for the year 1989, which clearly differentiates between the forest (in black), and the rest of the open space (in white).

4.2.3 Creation of a geographical mask

A geographical treatment is added to this radiometric pre-treatment. Indeed, we have two very different phenomena of deforestation and the model can not represent so many differences. Therefore, we chose to represent the space of the private industrial forest by a mask as shown in Fig. 4.5. The evolution in this area has a different behavior from the evolution of natural forest as we indicated in Sect. 4.2.1. For this reason, this region is not included in the analysis. Thus, the process of modelling, takes into account only those spaces left blank in this figure. Therefore, each image includes 128,450 hectares.

Thus, we have only one image with twelve waves (green, red and near infrared for each date). The most interesting dynamics take place in the center of the scene in quarter of 512 x 512 pixels.

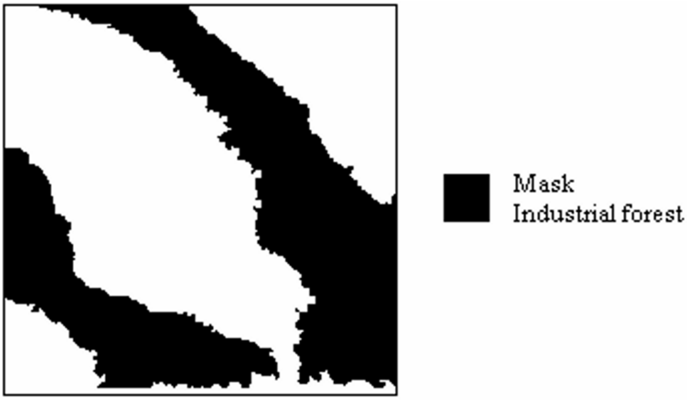


Fig. 4.5 Geographic mask of two industrial forests in Ticoporo

The Table 4.1 gives an account of the gradual statistical evolution of the forest. The table begins with the treatment of the satellite images on the test site since 1975. The total assessment corresponds to a deforestation of 40,987 hectares in 19 years, that is to say 36% of the forest cover at the beginning but with an equivalent pastoral development.

Table 4.1 Dynamical statistics about deforestation from 1975 to 1994 in the forest of Ticoporo

	1975-image	1987-image	1989-image	1994-image
Forest	113,123.85	78,193.71	70,914.27	72,136.33
Non Forest	15,326.71	50,256.85	57,536.29	56,314.23
Wood Rate	88.07	60.87	55.21	56.16
total Hectares	128,450.56	12,8450.56	12,8450.56	128,450.56

4.2.4 The forest Ticoporo Reserve: the known state and the estimation by space remote sensing

Fig. 4.6 and Table 4.1 thus account for the quantitative evolution of the forest and pastoral occupation from 1975 to 1994 by means of the binarization on the red channel of the Landsat and Spot satellites (1975) with a simplified nomenclature, “forest - non forest”.

On the basis of a rate of timbering of 88% in 1975, this corresponds to more than 113,000 hectares of tropical forest. The threshold of 56% was reached in 1994. Binary cartographic projections “forest - not forest” of Fig. 4.6 translate the changes in space dynamics from one date to another. It is immediately noted that the metamorphosis of the landscape is not homogeneous in all places, since it affects mainly the heart of the forest reserve while, simultaneously, the “two arms” of the private and protected forest fields appear relatively unchanged. Thus, from 1975 to 1994, 36% of the territory permuted into pasture, which represents an average of 2,157 hectares devastated per year, i.e., 2% of the initial capital forest.

It is important to note that if these data cover a period of 19 years, they are not very “recent”. Indeed, it was not possible to acquire new images due to cloud cover, which is almost always present in intertropical areas. Therefore, in the face of this observation, we chose to calibrate the model from the first three dates (1975-1987-1989) to make projections of space in 1994, 2000, 2005 and 2010. Thus, we reserved the last acquired image, – the real image of 1994– to validate the model to this date.

4.3 Methodology and practical application to the data sets

Through a sequence of Satellite Remote Sensing Images for n instants $t_1, \ldots, t_n$, so that $t_1 < \ldots < t_n$, this work proposes to predict the evolution of a temporal phenomenon for the time $t_n + 1$.

The method proposed in this paper is founded on the principle described in the latter approaches (see Sect. 4.1.1 and Sect. 4.1.2) provided that we make use of regression and progression zones of the forest to find the direction of evolution (appearing or disappearing). However, we achieve the prediction by coupling fuzzy set theory and out-image data. Thus, the approach adopted here seeks to yield improved results, since the prediction takes into account the zones that are more or less favourable to the evolution. Considering the following facts may aid the prediction approach:

- studied temporal events are continuous.
- geographical data are in raster representation.

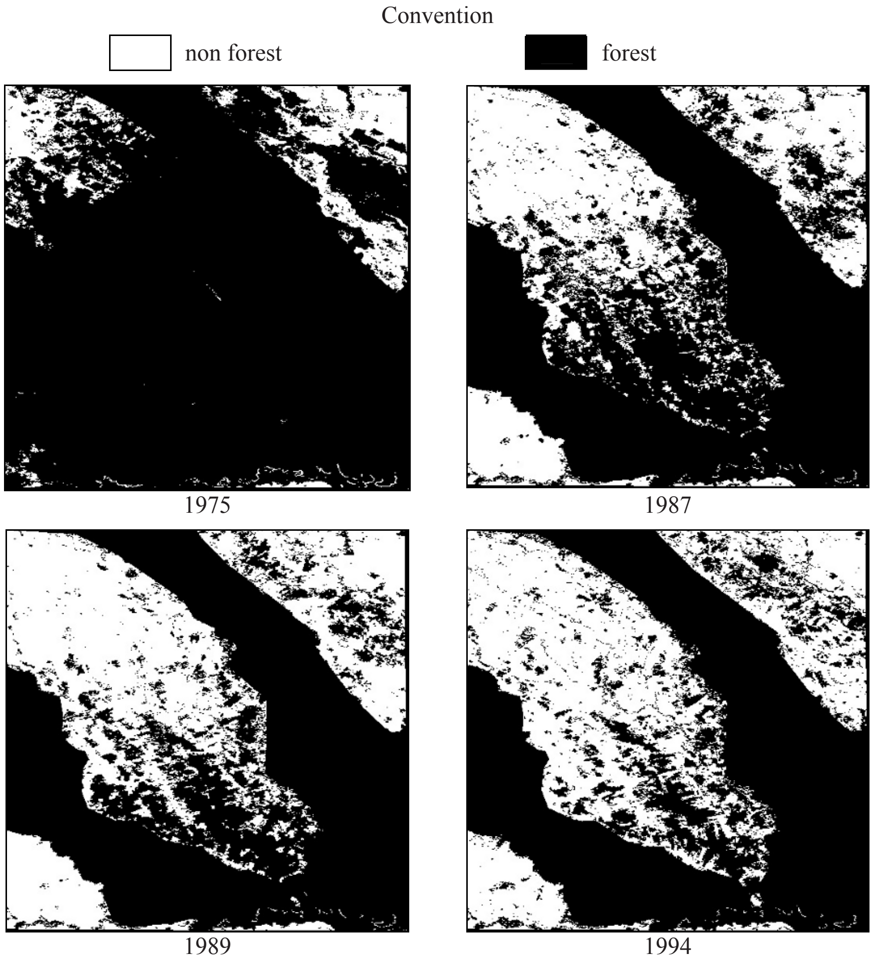


Fig. 4.6 Geographic binarization maps for each date from the forest of Ticoporo

Alpha-level sets

In fact, the resulting evolution image represents a fuzzy set that will be analyzed to determine the final shapes and positions of the regions for the predicted map. Fuzzy sets can also be defined by means of their families of α-level sets (Klir and Yuan 1995), according to the resolution identity theorem (Zadeh 1995). Given a fuzzy set *S*, its α-level sets S_α from *U* associated to $S \in f(u)$ are given by the following equation:

$$S_\alpha = \{x \in U \mid \mu_s(x) \geq \alpha\} \tag{4.1}$$

4.3.1 Problem description

We wish to predict the evolution of a temporal phenomenon for time t_{n+1} from a sequence of n thematic maps characterizing this cartographic continuous temporal phenomenon for n instants $t_1,..., t_n$ so that $t_1 \leq ... \leq t_n$.

The first step of the approach proceeds by first predicting the overall surface of the region area. What makes it possible to obtain a quantity of space permutation on the basis of fixed nomenclature: forest not - forest.

This stage contains the prediction of the overall surface value applying the analytical data in an adaptive linear adjust method. This value is calculated for the instant t_{n+1}.

4.3.2 Progression and regression maps

So, after predicting the overall surface of the region area, the next step is to obtain maps representing the progression and regression zones. Each map representing a progression or a regression zone is obtained from two consecutive images (the geographical maps taken at t_i and t_{i+1}). The regression map corresponds to the subtraction of the images taken at instants t_i and t_{i+1}, and the progression map corresponds to the subtraction of images taken at t_{i+1} and t_i. Thus, for n instants of time, there will be $n-1$ progression maps and $n-1$ regression maps. The method proposed in this work is the use of regression and progression maps of the forest to acquire the privileged directions of evolution (appearing or disappearing). Thus, the approach adopted here seeks to yield improved results, since the prediction takes into account the zones that are more or less favorable to the forest or pasture evolution.

4.3.2.1 Stages of the predictive modelling

From thematic mapping (satellite images in raster format), the basis of the proposed methods can be divided into five basic steps (Mez 1998):

1. computing of the total surface of the spatio-temporal phenomenon studied at the moment t_{n+1},
2. obtaining maps of areas of progression and regression,
3. determining the preferred directions of progression or regression through the calculation of a coefficient of evolution by fuzzy logic or cellular automata,
4. obtaining a map of evolution,
5. obtaining the projected map.

In step 3, a specific mathematical formula was applied to compute the coefficient of evolution for each pixel of the analyzed image. This coefficient of evolution shows zones more or less favorable to the evolution. In order to compute this coefficient of evolution, all progression and regression maps obtained previously are required. The more recent maps will more heavily influence results. The basic principle of the reasoning mechanism adopted here is that an area next to a progression region has a higher probability of increasing than another one that is farther from this region. The same principle is applied for regression regions. The size of the regions must also be considered, since larger regions have a higher influence on its pixel neighbors than smaller regions.

Thus, for each pixel we determine two values: one of them determines a tendency of the pixel to progress; the other determines a tendency of the pixel to regress. The variables are defined as: *p*, the number of progression zones, *n* the number of geographic maps (for *n* times), *Dk* the distance between the *pixel i,j* to the zone *k*, *Sk* the surface of the zone *k* and *T* the temporal interval between the analysed map and the time to predict. We define the coefficient of progression of each pixel by:

$$Coef_{\Pr og_{i,j}} = \sum_{t=1}^{n-1} \left(\frac{\sum_{k=1}^{p} \left(\frac{1}{D_k} S_k \right)}{T_t} \right) \tag{4.2}$$

where *p* is the number of progression zones.

In a similar way the coefficient of regression of each pixel is given by:

$$Coef_{\operatorname{Re} g_{i,j}} = \sum_{t=1}^{n-1} \left(\frac{\sum_{k=1}^{r} \left(\frac{1}{D_k} S_k \right)}{T_t} \right) \tag{4.3}$$

where *r* is the number of regression zones.

The coefficient of evolution results from a subtraction between the coefficients of progression and the previously calculated regression:

$$Coef_{i,j} = Coef_{\Pr ogi,j} - Coef_{\operatorname{Re} gi,j} \tag{4.4}$$

The resulting coefficients were normalized resulting in a fuzzy set representing the membership function of the evolution function. This set was converted into gray levels resulting in a fuzzy image. The gray values in a range of values from 0 (black) to 255 (white) identify the trends of progress or regress of diverse areas in the total region. The more favourable regions to progress are associated with the greatest coefficients and the regions that are less favourable have smaller coefficients.

4.3.3 Prediction based on fuzzy logic

In order to compute this coefficient of evolution for each pixel, all progression and regression maps are required and the most recent maps will more heavily influence the results. It is also necessary to consider the surfaces of the progression and regression zones. Probably, the zone with the biggest surface will heavily influence a pixel being equidistant from a progression zone and from a regression zone. Furthermore, an area of closer proximity to a progression zone will have a more pronounced tendency to increase than an area near a regression zone and vice versa. Thus, these principles taken into consideration in order to compute a coefficient of evolution for each pixel of the image.

Thus, for each pixel we determine two values: one of them provides the tendency of the pixel to progress; the other provides the tendency of the pixel to regress. Let *p* be the number of progression zones, *n* be the number of geographic maps (for *n* times), *Dk* be the distance between the *pixel i,j* to the zone *k, Sk* be the surface of the zone *k* and *T* be the temporal interval between the analysed map and the time to predict. We define the coefficient of progression of each pixel by:

$$Coef_{\mathrm{Pr}\,og_{i,j}} = \sum_{t=1}^{n-1}\left(\frac{\sum_{k=1}^{p}\left(\frac{1}{D_k}S_k\right)}{T_t}\right) \tag{4.5}$$

In a similar way the coefficient of regression of each pixel is given by:

$$Coef_{\mathrm{Re}\,g_{i,j}} = \sum_{t=1}^{n-1}\left(\frac{\sum_{k=1}^{r}\left(\frac{1}{D_k}S_k\right)}{T_t}\right) \tag{4.6}$$

where *r*, is the number of regression zones.

The coefficient of evolution results from a subtraction between the coefficients of progression and regression previously calculated:

$$Coef_{i,j} = Coef_{\mathrm{Pr}\,ogi,j} - Coef_{\mathrm{Re}\,gi,j} \tag{4.7}$$

This table of coefficients will be normalized in such a way that the coefficient of evolution for each pixel of the image is determined by a membership function based on the time, the pixel location with regard to progression and regression zones and the surface of these zones. Thus, the more favorable regions to progress are associated with the greatest coefficients and the less favourable regions have smaller coefficients. Thus, the influence calculated for each pixel results in a fuzzy image. Such fuzzy images can help geographers to visualize the whole temporal phenomenon that is taking place. However in the final stage of the analysis, the geographer may be interested in less fuzzy, more clearly defined data. In this case, the imprecise data can be converted to "hard" data by applying the alpha-level sets that transform the fuzzy regions into distinct regions.

The fuzzy subset obtained can then be decomposed by means of its α-level sets in order to obtain the resulting map. A gradient rather than a line represents the boundary between these regions. This gradient may be interpreted as the degree to which each pixel of an image is part of a progression region of the forest.

We have done successive applications of this discrete approximation (α-cuts) to the coefficients of the evolution image in such a way that the final surface reaches the predicted surface. The result is a distinct set containing all the pixels, whose membership grades are greater than or equal the specified value of α.

4.3.4 Prediction based on cellular automata

The steps to the solution of the problem are described as follows in Fig. 4.7.

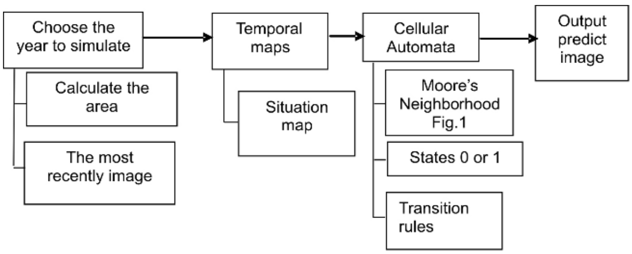


Fig. 4.7 Simulation steps using Automate cellular (AC)

The temporal GIS data was used to create a map called the situation map, which describes the forest area in accordance with their progression, regression or stability through time. The situation map was used to create the transition rules.

In this work, the totalistic rules were used, they are formed by the total quantity of neighbourhoods in some specific state.

After calculating the new value of the surface, the most recent image is used to start the prediction until the specified year.

The "situation map", in Fig. 4.9, was created to describe the forest areas in accordance with their progression, regression or stability through time. This map is formed by the combination of the temporal images (Fig. 4.8).

The Table 4.2 shows how the "situation map" was composed. It represents all the possible combinations that one pixel in the same position (i,j) with two states (0 or 1) can have when it is compared in three temporal images. The Moore's neighborhood with r = 1 was chosen.

That combination created three situations called stability, progression and regression. The digital level is indicated in the table to compose the map visualization (Fig. 4.9).

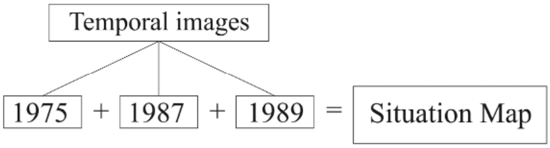


Fig. 4.8 Combination of temporal maps

Table 4.2 Composition of the situation map (0 = non forest; 1 = forest)

1975	1987	1989	Situation	Digital level
0	0	0	stability	250
0	0	1	progression	50
0	1	0	regression	200
1	1	1	stability	5
1	1	0	regression	200
1	0	0	regression	200
0	1	1	progression	50
1	0	1	progression	50

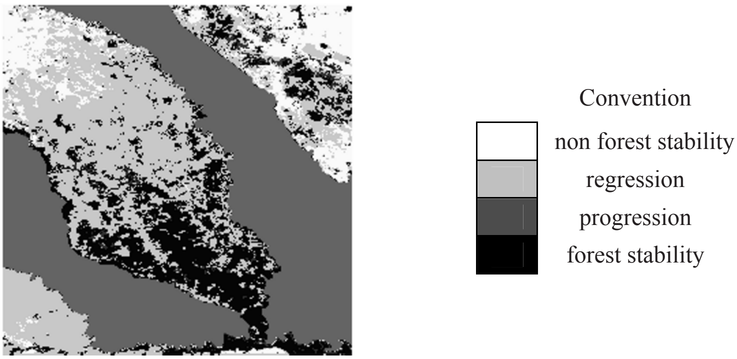


Fig. 4.9 Situation map (outside the industrial forest mask)

The forest was considered homogeneous with two states represented in the present diagram:

0 = non forest 1 = forest

The transition rules are the totalistic rules that consider the total quantity of cells in the state = 1, in the Moore's neighborhood. The situation map was adapted to different transition rules according to the zone. There are 3 zones for transition rules: stability zones, progression zones and regression zones.

Rule 1: Progression zones. If the neighbor's number equal 1 or 0 and the central pixel is 1, it will be in the next instant zero. If the neighbor's number is equal 2, the central pixel doesn't modify. If the number of neighbours is equal to 8, 7, 6, 5, 4 or 3 and the central pixel is equal to zero, it will be in the next instant 1.

Rule 2: Regression zones. If the number of neighbours is equal to 0, 1, 2, 3, 4, 5 or 6 and the central pixel is equal to 1 it will be in the next instant zero. If the neighbor's number is equal to 7 or 8, the central pixels don't modify.

Rule 3: Stability zones. In this case, there are no changes in the zones.

The practical application of both cellular automata and fuzzy logic based models consists in using specific algorithms in C++, which were developed by the authors themselves.

4.4 Results

The principal aim is to describe the evolution of the landscape of the "Reserve of Ticoporo" forest for the years 1994, 2000, 2005 and 2010. The geographic maps in Figure 4.6 are satellite images showing the recorded changes in the thresholds within the regional area at three times: 1975, 1987 and 1989. The prediction maps for the years 1994, 2000, 2005 and 2010 were obtained by applying α-level sets to the years of concern and are shown in the following figures. Since a satellite image from 1994 was provided, we have used it to validate the results.

The first three images have been processed taking into account the mask of the industrial forest. Using the methodology in Sect. 4.3.2, we have finally obtained the evolution image (fuzzy image), which shows the coefficients of evolution that combine the progression and regression data. The result is shown in Fig. 4.10, in which the darker a pixel is the more it will undergo deforestation (outside the geographic mask).

4.4.1 Space-time environment dynamics from satellite images since 1989 to 1994

Before assessing the results of the temporal projections, we give a statistical evaluation of the spatial dynamics in Ticoporo, according to the last two acquired images from the years of 1989 and 1994 (binary images indicated as "bin"). Table 4.3 shows the statistical results of evolution (in percentage) and their spatializations from Fig. 4.10. The legend of this figure translates the grayscale into four possible combinations of evolution:

regression of the forest from 89 to 94 (F89b-NF94b), progression of the forest (NF89-F94b), forest in 89 and forest in 94 (F89b-F94b), non-forest in 89 and non-forest in 94 (NF89b-NF94b).

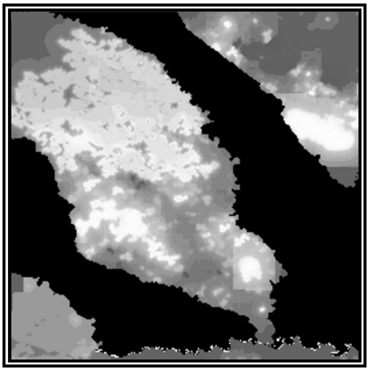


Fig. 4.10 Evolution zones of the forest

To evaluate the experimentation's results for the modelling of the landscape changes at various temporal periods, we again used the method introduced by Pontius (2004). Indeed, this method applied to research of the LUCC (*Land Uses & Land Cover Change*) program is exportable. In our case, it makes it possible to establish a rigorous statistical comparison of known and/or simulated environmental data through time. This makes it possible to estimate the relevance of the used methods for space projections. This also provides space and statistical dimensions changes to landscape changes over one defined time period. This evaluation begins from a former, known state.

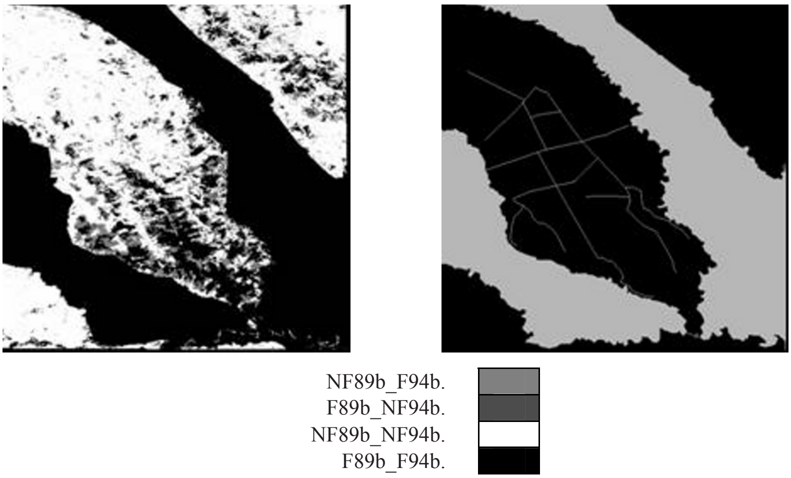


Fig. 4.11 Spatial comparison between satellite image from 1989 to 1994 (left) and the main axes of penetration (right)

On the other hand, the cartography (Fig. 4.11) authorizes a perception of spatio-temporal dynamics in the central part of the forest where more and more isolated forest scraps (F89-F94, black) appear compartmentalized. This phenomenon is all the more perceptible as the not-forests spaces in white (NF89-NF94) seem to increase toward the south through time; the demarcate white areas overall from the northwest to the southeast. The right-hand side of the figure schematizes the rectilinear axes of this penetration well.

Table 4.3 Statistical states of forest (F) and non-forest (NF) in % between 1989-1994 from satellite images

%	1989-NF	1989- F	total 1994	Gain	%	Gain	Loss	Total change	Swap	Absolute value of net change
1994-NF	**34.8**	6.9	41.7	6.9	**NF**	6.9	5.6	12.5	11.2	1.3
1994-F	5.6	**52.7**	58.3	5.6	**F**	5.6	6.9	12.5	11.2	1.3
total 1989	40.4	59.6	**100.0**							
Loss	5.6	6.9								

With Table 4.3, one obtains an evaluation and a comparison between the forest states starting from known data: dynamics between two images Spot –binarized– of 1989 and 1994. The left side of the translated table is expressed in percentages, then the proportions of Forest and Non-Forest in the time interval and the losses and the profits are added up for each date. The right side gives an account of the extent of spaces in the reserve affected by these changes (total changes) and the rate of the permutations occurring between these two environmental objects –F and NF– (Swap). The nomenclature comprises only two stations, and the “profits and losses” are relatively close.

Comparing the evolution before 1975 to 1989 (Fig. 4.6), when deforestation was extreme, and the five year interval 1989-1994 (Table 4.1; see Sect. 4.2.3), one observes an attenuation of the rate of deforestation. The cross matrix of Table 4.3 establishes the proportion of forest to pastures (NF) (52.7% per 34.8%) in 1994. 87.5% of spaces of the reserve thus remained unchanged, whereas only 12.5% permuted between these two stations of nomenclature. What corresponds in detail to a double phenomenon: a deforestation, which reaches 6.9%, while reforestation is 5.6%. The total rate of permutation remains relatively unimportant 11.2% (difference between the total change –12.5– and the absolute value of the net change -1.3-), which corresponds to 14,386 hectares. These results indicate a relative statistical stability for 1989 to 1994, which is in conformity with the cartography of Fig. 4.6 with few modifications between spaces of pastures (NF) and the forest (F).

4.4.2 Validation of the predicted model for 1994

The real image present some small regions. The method applies a filter to the image, for this reason the noise does not appear in the two predicted images.

Real Spot image 1994 (bin.) Predicted image for1994 by FL Predicted image for1994 by CA

Fig. 4.12 Comparison between the real satellite image and the predict maps for 1994 by fuzzy logic (FL) and cellular automata (CA) approaches (Forest, black; Non-Forest, white)

Fig. 4.12 juxtaposes the cartography of two space projections by fuzzy logic (FL) and the cellular automats (CA) for the year 1994 beside the real satellite image of 1994 (Spot image binarized; left). Generally, the two models implemented (FL and CA) seem to provide cartographic results that reveal a rather strong similarity. The two modeled images seem to have almost entirely eliminated the small forest islands scattered throughout the central part of the area towards the northwest (whereas the real image shows that they still exist). Both also show the increase of the new axes of pasture penetration from the peasants (linear-shaped axes corresponding to a type of deforestation), which have a very perceptible energy from the center of the image towards the south. These projections highlight the particular behavior of these peasants - principal agents of deforestation.

Table 4.4 Statistical results compared between two modellings for the year 1994

	1994-image	**1994-FL**	**1994-CA**
Forest (Ha)	72,136.33	66,602.76	64,159.13
Non Forest (Ha)	56,314.23	61,847.80	64,291.43
Timbering Rate (%)	56.16	51.85	49.95
All (Ha)	128,450.56	128,450.56	128,450.56

Table 4.4 shows a clear statistical over-estimation of deforestation for the two projections compared to the real image, as is indicated by the rate of timbering. It is nearly 52% for fuzzy logic and nearly 50% for the cellular automats, whereas in reality it is 56%. The FL simulation model overestimates by

4.31% (5,533 ha) and the AC model overestimates by 6.21% (7,977 ha) in comparison with the real deforestation. In other words, the model of the cellular automats would be a little less relevant than fuzzy logic.

However, the two projections are fairly similar to each other, for example the difference in the deforestation rate is only 1.9%, which corresponds to 2,443 hectares. These models appear to want to give a scenario of relative stability for the phenomenon of spatial deforestation considering the small gap between the two projection models for 1994.

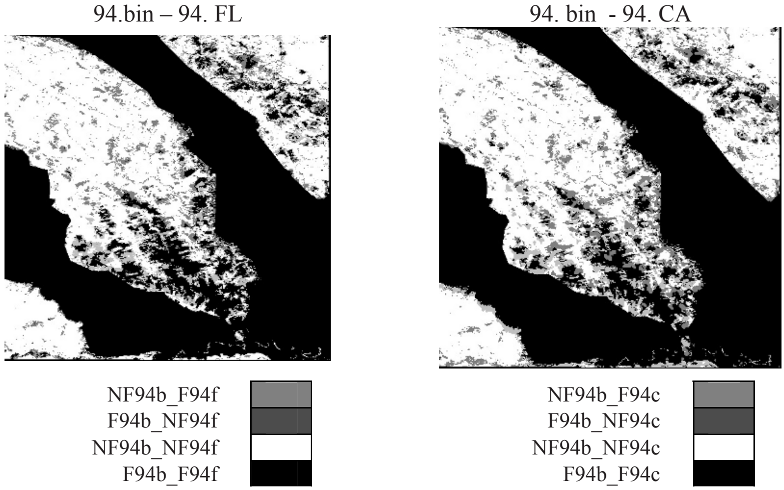


Fig. 4.13 Space-time dynamic states of Ticoporo between FL and AC in comparison with the reality in 1994

Fig. 4.13 corresponds to the cartographic projections of the two models for the year 1994 with a detailed nomenclature of the operated changes. The method used is identical to that described in the preceding paragraph (i.e Fig. 4.10). Thus, each of the two space projections includes the four possible combinations of dynamic environmental between reality (noted 94b) and projections in 1994 (noted “94 FL” for fuzzy logic and “94 AC” for the cellular automats).

The square matrix of Table 4.5 allows for the comparison of the predictive results of the two models for the year 1994 with the real image of 1994 (binary image) on the same bases of the nomenclature “Forest-1; Non-forest-0”. Statistically, the two predictive models used demonstrate relatively little difference between them with respect to the field reality. Thus for forest spaces, the difference between the predicted totals and the real totals are established at 56.5 compared with 58.3% for FL and at 55.2% compared with 58.3% for AC, that is to say a variation of prediction from only 1.8% for the FL and of 3.1% for CA. The variations for nonforest spaces are identical.

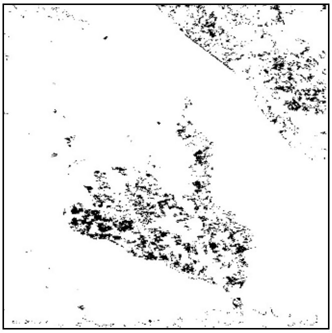
Table 4.5 Comparison of predictions and the ground reality for 1994 (FL and AC)

%	Real image 94		
1994	Forest- 1	non-forest – 0	total predicted
FL - forest-1-	51.4	5.1	56.5
FL- non forest-0-	7.0	36.5	43.5
total reality	58.3	41.7	100.0

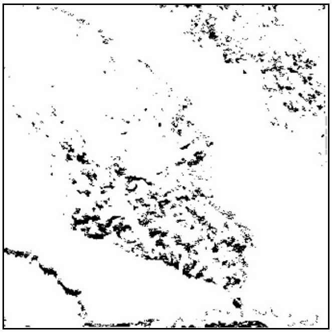
%	Real image 94		
1994	Forest- 1	non-forest – 0	total predicted
AC - forest-1-	49.6	5.6	55.2
AC- non forest-0-	8.7	36.1	44.8
total reality	58.3	41.7	100.0

Thus for forest spaces, the difference between the predicted totals and the real totals are established to 56.5 compared with 58.3% with the FL and to 55.2% compared with 58.3% with AC, that is to say a variation of prediction from only 1.8% for the FL and of 3.1% for CA the variations are identical for nonforest spaces.

Moreover, the total rates of prediction posted by FL and AC are also correspond, because they present only 1.3% of difference between them for the forest and only 0.3% for pastures (NF).



94b-94FL



94b-94CA

Fig. 4.14 Differences between the image spot of 1994 and the projections in 1994: fuzzy logic (left) and cellular automata (right-hand side)

Figure 4.14 represents the arithmetic difference, pixel with pixel, between the known reality through the binarised Spot image of 1994 and the two types of space projection for the same year. The legend's format is standard in white, a correct prediction at the same time for forested spaces and for grazing ground spaces; in black, an erroneous prediction in terms of probability for these same spaces. We can also refine these results with the method expressed spatially by Figs. 4.8 and 4.11, which define the "areas of progression and areas of regression".

In terms of the set's themes, the origin of the shift in results between the projected images and the real image (binarised) also come from the quasi-systematic removal (in both cases) of the many small scattered forest scraps, which are still perceptible in the central part of the forest reserve as in the northeast corner of the image. In other words, these discontinuous, small forest islands of variable sizes, although minority on a become pastoral space dominating, would have a probability less strong than envisaged to be destroyed contrary to the result provided by the methods of predictive modelling. This stage of the analysis, one can put forth the assumption of following explanation for the fuzzy logic model : if the principle stated in phase 1 (to predict a value of total surface by applying to the analytical data a method of adapted regression linear) seems overall true, the absence of introduction of rules of behaviours to the predictive models reduced some their capacities to be extrapolated to become it of these small forest small islands for, on the contrary, marking more that of the largest solid masses.

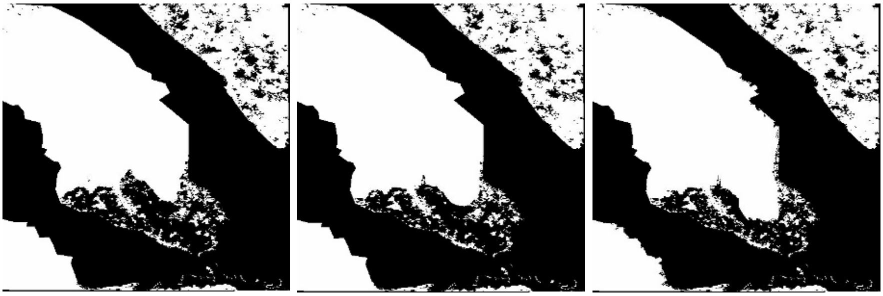
4.4.3 Prospected scenarios of fuzzy logic and cellular automata for years 2000, 2005 and 2010

The modelling on steps of selected times 2000, 2005 and 2010 uses the same databases –the binary satellite images–. The two types of projections carried out do not seem to visually confirm (Fig. 4.15) what we had previously detected with the analysis of projection over the year 1994 (see Sect. 4.4.1; Fig. 4.11). The cellular automata method over-estimates the phenomenon of deforestation compared to the fuzzy logic method. It appears that the reverse dominates. To be convinced of this, it is enough to compare the central parts of the six small images: they became completely white with fuzzy logic, therefore a projection which appears radical apparently without nuance and undoubtedly far away from reality, whereas the method of the cellular automata appears less brutal, in other words, more adjusted to the rate/rhythm of transformation of the landscape since one still distinguishes pieces isolated from forest in center-south space of the image.

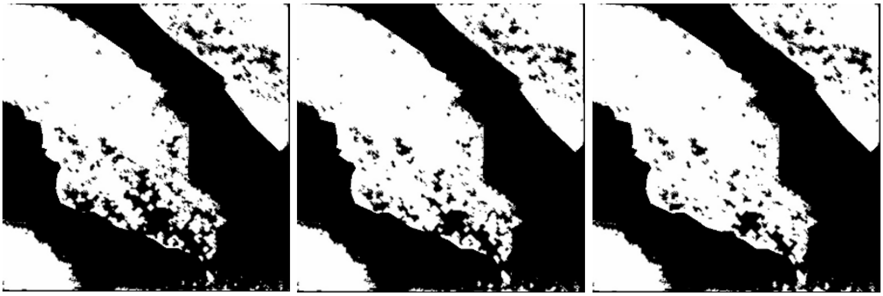
4.5 Statistical validation of spatio-temporal projections by fuzzy logic and cellular automata

4.5.1 The state of the "Reserve of Ticoporo" forest estimated to the year 2010

The validation of the model is a comparison of the results of the two projections date for date since 1994, but it is not compared with known results, because there have been no Spot or Landsat images without cloud cover since 1994.



by FL: Predicted image for 2000; Predicted image for 2005 ; Predicted image for 2010.



by CA: Predicted image for 2000; Predicted image for 2005; Predicted image for 2010.

Fig. 4.15 Resulting maps to fuzzy logic (FL) and cellular automata (CA) approaches (years 2000, 2005, 2010)

Table 4.6 and Fig. 4.16 shows the statistical results acquired for the projections for the selected years 2000 - 2005 - 2010 by the two methods: fuzzy logic ("Fuz") and cellular automats (CA). If the scores reached vary somewhat for each projected date, the two types of projection have a common point: the process of deforestation and/or creation of new spaces of pasture are continuous from 1975 to 2010. The forest permutation in pastures appears inexorably linked at the neighbourhood level to the timbering rate included/understood spreading from 42 to 46%, respectively for the cellular automats and fuzzy logic.

Table 4.6 Statistics of the space-time dynamics for the test site of Ticoporo for the years of 2000, 2005 and 2010

	2000-Fuz	2000-CA	2005-Fuz	2005-CA	2010-Fuz	2010-CA
Forest (ha)	54,821.69	59,706.99	51,779.77	56,491.12	58,986.69	54,507.11
Non Forest (ha)	73,628.87	68,743.57	76,670.79	71,959.44	69,463.87	73,943.45
Timbering Rate %	42.68	46.48	40.31	43.98	45.92	42.43
All (ha)	128,450.56	128,450.56	128,450.56	128,450.56	128,450.56	128,450.56

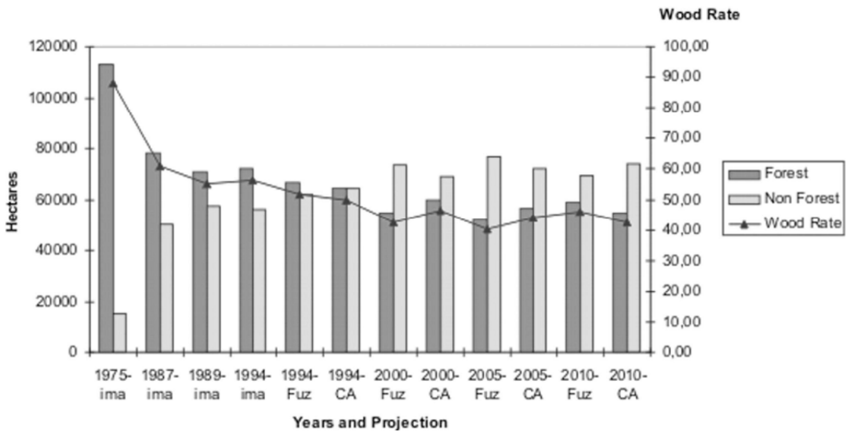


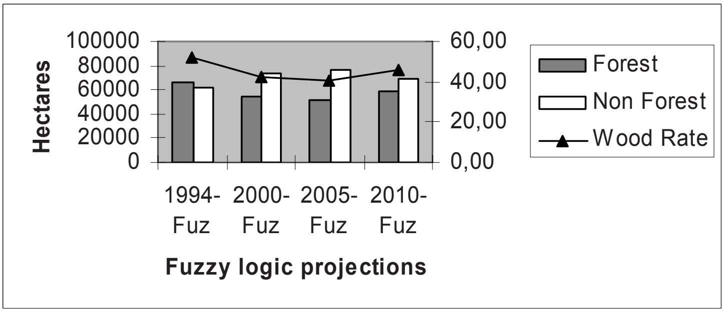
Fig. 4.16 Changes occurred with Ticoporo since 1975 to 2010 as well as the timbering rate

Table 4.7 and the diagrams (Fig. 4.15) are the result of the two types of projections in terms of deforestation scenarios. The phenomenon seems attenuated compared to the first period (1975-1994), seeing as the increase of devastation would reach 13,150 ha according to fuzzy logic or 17,629 ha according to cellular automata by the year 2010. The method of fuzzy logic seems to over-estimate deforestation for the years 2000 and 2005 compared to that of the cellular automats (24 and 31% against 18 and 28%, calculated in hectares, that is a difference in 814 ha in 2000, 429 ha in 2005), and in contrast to 2010 with respectively 22 against 34% of additional cuts compared to 1994 (an additional 280 ha for the cellular automats).

Table 4.7 State of the forest of Ticoporo until 2010. Projection Fuzzy logic and cellular automata models

since 1994	1994-FL	1994CA	2000-FL	2000-CA	2005-FL	2005-CA	2010-FL	2010-CA
Deforestation (Def.)	5,533.57	7,977.20	17,314.64	12,429.34	20,356.56	15,645.21	13,149.64	17,629.22
Average/year			2,886	2,072	1,851	1,422	822	1,102
Def. since 94 (%)			24.00	18.66	31.73	28.54	22.02	34.05
Def./year (%)			4.00	3.11	2.88	2.59	1.38	2.13

Unfortunately, interpretation cannot refine these statistical results more by comparing them with known situation on the ground of each projected date (variable space and known sets of themes), because there are no satellite images for the period of interest (not since 1994) due to cloud cover inhibiting the evaluation of the relevance of these space-time projections.



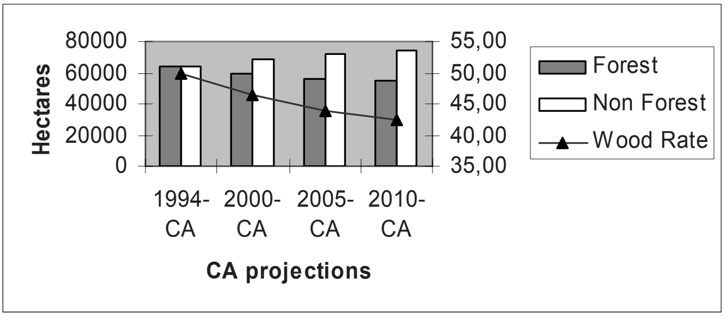


Fig. 4.17 Projections based on FL model (up) and CA model (down) from 1994 to 2010

Figure 4.17, in which the two types of projections are shown separately, shows a very different behaviour between the two timbering rates from deforestation for two consecutive periods (2000-1994; 2005-2000; 2010-2005) according to the projections: a decidedly more stability for fuzzy logic and a regular but decreasing pattern for cellular automata.

Table 4.8 Differences between the two models for projected estimations in time

CA-FL 1994	CA-FL 2000	CA-FL 2005	CA-FL 2010
-2,443.63 Ha	4,885.30 Ha	4,711.35 Ha	-4,479.58 Ha

Related to the year 1994, the projection by fuzzy logic appears to underestimate the deforestation by 5,533 hectares (that is to say -7.67 % of existing forest space in 1994), that of cellular automata still more with 7,977 hectares (-11.06 %). But compared with the 1975 forest state, the same percentages decrease to the respective values of 4.31% and 6.21%. In addition, the difference between the two projections (CA - FL for same year -1994- adds up to a little more than 2,443 hectares. It is a relatively minor difference (3.40% compared to the forest state estimated in 1994) in comparison to the same differences operated for the other years; indeed these last years would reach figures higher than 4,400 hectares (6.1% of the forest total of 1994). We also note the inversion of direction of this calculation between on the one hand, the years 2000-2005, and on the other hand, the year 2010.

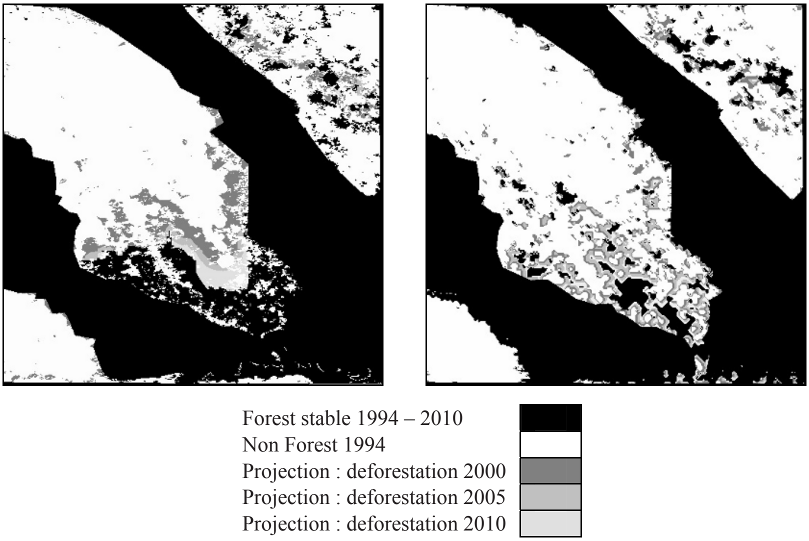


Fig. 4.18 Result of the space projections cumulated for 1994 to 2010 by fuzzy logic (left) and cellular automata (right)

This cartographic result spatially combines three temporal cumulated projections of fuzzy logic and cellular automata by superposition. This cartography will confirm that even the heart of the *forest Reserve,* which is mainly affected by this continuous phenomenon of deforestation, is well. The fuzzy logic method proceeds in a spatial way (like an areola), whereas cellular automata function much more in a staircase.

Our observations on the ground, show that the displacement of the migrating peasants, who are major participants in the deforestation, is always toward the southeast. These individuals, who are involved in the radical permutation "forest-pastures," claiming pasture land along the axes directed north-west-south-, this penetration into the surrounding forest is already well marked on the 1989 image. Logically, these projections thus appear as a continuity of the process that started around 1975.

In addition, always in the heart of the solid mass (more precisely in the south-western centre), a black, untouched area remains, of a rather imposing size. In other words, in the space of 16 years, this means that the peasants have not entirely destroyed this forest unit. The advance thus appears to be blocked by the presence of an insuperable river.

4.6 Conclusion and outlook

The predictive methods of fuzzy logic and cellular automata make it possible to answer partly the question of short-term and medium-term conditions for a tropical forest environment whose existence is radically threatened by a migrating peasant population, who use a cut and burn technique to win pasture land from the rain forest. The present method combines the remote observation of a face tropical pioneer front with the means of the processing of multi-date satellite images to fuzzy logic and cellular automata. This achieves the objectives of description, cartography, and temporal projections of the deforestation dynamics in progress for various steps of the selected times (1994 to 2010). The method is founded on the diachronic analysis of the space-time evolutions contained in a sequence of chart sets of themes resulting from satellite images (Landsat and Spot) from three years: 1975-1987-1989. With a simplified nomenclature "*forest - non forest*", the model of evolution takes into account the contemporary history of the face by analyzing the changes the of the existing forest areas for each image. These last, two methods - fuzzy logic and cellular automata make it possible to manage the inherent uncertainties and inaccuracies, which surround the modelling of the evolution of this unstable and dynamic forest environment.

A detailed statistical estimate is carried out specifying the compared contributions of the two implemented methods. We can also relate the statistical estimates of the Department of the Environment of Venezuela to this study, specifying that "in 1980, 39% of the forest surface of Ticoporo was destroyed". Since 1987, a comparable area to the east is provided by the space image processing for comparison. The evaluation of the 1994 projection (this being the most recent date possible due to the increased rate of nebulosity in this intertropical area since then, which has inhibited the capture of a new image), provides an encouraging estimate for the use of these tools and these space-time methods, which have been described in this article. The temporal validation of these two methods of modelling has yet to be confirmed. The acquisition of satellite images without cloud cover is, however, essential to carry out in assessment and validate the temporal modelling methods for this validation.

However, one can expect that this space-time modelling, in the future, will be enriched by new rules for explicit behaviours, thus integrating more of the ground data available, including all the factors impacting environmental, economic and social processes of evolution. The results of extrapolation would be without doubt refined by it.

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5 Prospective modelling of environmental dynamics: A methodological comparison applied to mountain land cover changes

Paegelow M, Camacho Olmedo MT, Ferraty F, Ferré L, Sarda P and Villa N

Abstract

During the last 10 years, scientists have made significant advances in modelling environmental dynamics. A wide range of new methodological approaches in geomatics –such as neural networks, multi-agent systems or fuzzy logics– have been developed. Despite this progress, the modelling softwares available have to be considered as experimental tools rather than improved procedures that are able to work for environmental management or decision support. In particular, the authors think that a large number of publications suffer from discrepancies, when trying to validate their model's results.

This contribution describes three different modelling approaches applied to prospective land cover prediction. The first one, a combined geomatic method, uses Markov chains for temporal transition prediction, while their spatial assignment is supervised manually by the construction of suitability maps. Compared to this *directed* method, the two others may be considered as *semi-automatic* because both the polychotomous regression and the multilayer perceptron only need to be optimized during a training step – the algorithms themselves detect the spatial-temporal changes in land cover.

The authors describe the three methodological approaches and their practical applications to two mountainous studied areas: one in the French Pyrenees, the second including a large part of Sierra Nevada, Spain. The article focuses on the comparison of results. The major result is that prediction scores are higher than the actual land cover is persistent. They also underline that the geomatic model is complementary to the statistical ones which perform higher overall prediction rates but produce weaker simulations when there are numerous land cover changes.

Keywords: combined geomatic model, land cover dynamics, modelling, multilayer perceptron, polychotomous regression, validation.

5.1 Introduction

This paper focuses on the comparison of results from three modelling approaches for land cover prediction in the Mediterranean mountains. The studied areas are located in the French Eastern Pyrenees (Garrotxes) and the south side of Sierra Nevada in Spain (Alta Alpujarra Granadina). The methodological approaches used for modelling the land cover are a combined geomatic model, based on Markov chain analysis, fuzzy logic and a cellular automaton, a linear parametric model (polychotomous regression modelling) and a neural network (multilayer perceptron).

Using former publications (Paegelow et al. 2002, 2003, Paegelow 2003, Paegelow and Camacho 2003), in which the results were derived from only one model or were applied to only one data set, we intend to study all of the obtained results in order to make an in-depth comparison. In the author's mind, this validation step is important for two reasons. First, it permits the evaluation of the quality of a model's performance. Only a meticulous validation can help to better understand the analyzed dynamic process and to lay out the limits and the capabilities of the modelling approach. Often, this aspect is neglected in scientific articles. A discussion of the combined results and validation indices is useful for understanding the advantages and disadvantages of each model in order to aggregate them into a better model.

We undertake prospective land cover modelling with a thin spatial resolution (grid cells have a length of about 20 m) and temporal intervals (about one to two decades), extrapolating over space and time in the context of complex social and environmental systems. In this framework, the main problems have a nonlinear behavior, with a high number of relevant criteria but a low number of available dates. Moreover, we note that land cover is evolving with inertia. This inertia is related to human activities but also to natural factors. Consequently, today's land cover results from earlier processes.

Basically, land cover modelling interpolates or extrapolates time when the model exceeds the known timeline. Prospective modelling is the prediction of a future state. Tools for time modelling only appeared in GIS during the last few years and should be considered as interesting and experimental algorithms rather than operational tools for decision support. At the same time, the social demand for decision support and modelling tools is increasing quickly helping in different management tasks such as risk prevention, land planning and environmental management.

Among methodological approaches for prospective modelling of high resolution land cover data, we distinguish between automatic and supervised models. We call a model *automatic* that analyzes the relationships among the training data (i.e. land cover training maps and land cover relevant criteria also deriving from the training period) in order to carry out a spatio-temporal simulated map at a close date. In the case of a *supervised* model, a specialist has to give some information about the suitability of spatial location and time transition. The results of this thematic analysis assist the modelling process, which leads to an approach similar to decision support. In practice, many models, like our geomatic approach, mix automatic and directed aspects. The presented model uses an automatic (markovian) procedure to compute time transition probabilities but a geographic directed analysis to establish the land cover suitability used for spatial assignment of predicted time transitions. In this context, we can cite various methods based on fuzzy logic (Zadeh 1988) often used in the context of GIS (Mezzadri-Centeno 1998) or on remote sensing data (Selleron and Mezzadri-Centeno 2002). Other models are almost totally automatic only a supervision of the optimisation of some parameters must be supervised. This is the case for statistical approaches by neural networks (Bishop 1995, Parlitz and Merkwirth 2000), particularly perceptron with one or more hidden layers. During the training phase of the model, the weights of the perceptron are chosen to minimize the quadratic error on the training data set. These neural multilayer networks are able to approach with a chosen precision any smooth function (universal approximation) (Hornik 1993). Generalized linear models are another interesting approach based on a special type of logistic regression, the polychotomous regression, where the qualitative predicted variable may have more than two values (Koopersberg et al. 1997). The polychotomous regression also needs a training phase to be optimized: the Newton-Raphson algorithm is generally used to perform this optimization.

5.2 Test areas and data sets

5.2.1 Test areas

To minimize the influence of a specific data set, we analyzed two test areas: Garrotxes (French Eastern Pyrenees) and Alta Alpujarra Granadina (Spain, Andalusia, Sierra Nevada) (Paegelow and Camacho 2003).

European mountain areas are affected by a deep social and economic reorganization, which leads to major changes in the landscape. In the French Pyrenees, the beginning of the 19th century was the maximum of human activity and population density. In the French studied area, changes began around 1850, with the decline of the traditional agro-pastoral economy and an important rural exodus. Cropland was transformed into pastures and later, often became colonized by forests again. The Andalusian site experienced the same decrease, but also a more substantial economic reorganization.

Garrotxes (Fig. 5.1) is a 8,750 ha catchment area located in the western part of the department of Eastern Pyrenees (France). The difference of height between the main summit at the north extremity (Madrès, 2,469 m) and the confluence of the Cabrils on the southeast border of the map (650 m) is important. On the right side, characterized by a ponderous geomorphologic relief based on granite, the space has a fast dynamic vegetation: almost all earlier terrace cultivations and coniferous forests (Pinus uncinata) are situated here. The left bank forms a large, steep and south-facing side of schist used as pasture. At the demographic maximum (1820/30), all natural resources were used intensively. In 1826, 25% of the whole area was developed as crop terraces (Napoleon cadastre of 1826). The population has decreased from 1,832 inhabitants in 1826 to about 90 inhabitants today. Crop terraces were transformed to pastures and later became bushes or forests. Actually, the crops are completely marginal and the near future depends on the intensity of pastoral activities and on the land management which controls the extent of spontaneous forest spreading (Métailié and Paegelow 2004).

Alta Alpujarra Granadina (34,500 ha) forms the western part of the south side of Sierra Nevada (Spain); a region with a characteristic landscape (Camacho et al. 2002a, 2002b, 2002c, Camacho 2003) for which historical development is documented since the 15th century (García 1999). The latitudinal shift to the Pyrenees is partially compensated by the important difference of height (the Spanish test area reaches 1,000 m higher than the French). The southern limit (600 m) is close to Guadelfeo, a river separating the studied area from Contraviesa. The northern limit is made by the highest summits of the Iberian Peninsula: Mulhacen (3,479 m) and Veleta (3,396 m). During the past 40 years, the population decreased from 4,200 to just 1,200 today. The proximity to urban centres (Granada, Almería or Malaga) explains the great development of rural tourism.

The maximal use of natural resources occurred at the end of the 19th century followed by a progressive decrease of agriculture. It only stopped during the 1940s (period of economic autarky). Since the beginning of the 1960s, the rural exodus became general in Spanish mountains with a successive desertion of non-irrigated land and irrigated land located at high altitudes. This process is followed by a (semi) desertion of irrigated lands which are located at a lower elevation. The transformation of croplands into fallow lands leads to a landscape homogenization. In the regional context, Alta Alpujarra Granadina is a significant example of this intensive process of desertion.

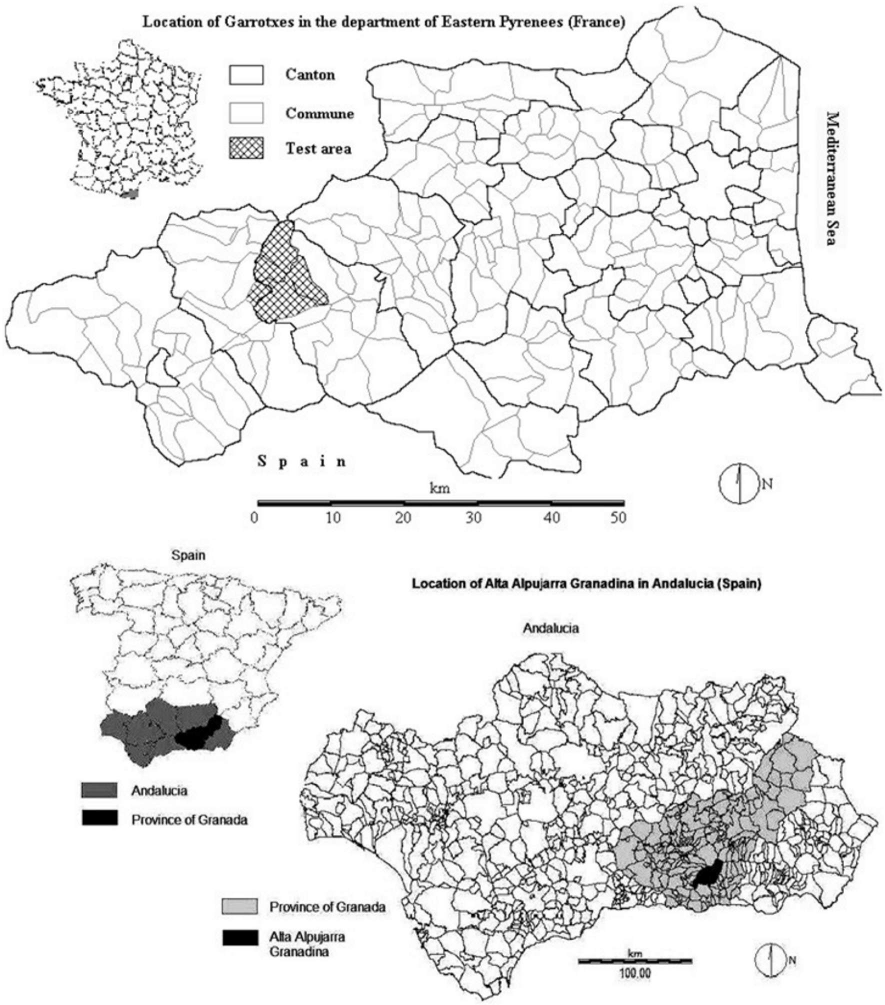

Fig. 5.1 Location of the studied areas: Garrotxes (top) and Alta Alpujarra Granadina (bottom)

5.2.2 Data sets

The GIS data base includes several maps with available land cover layers and relevant environmental and social factors (elevation, slope, orientation, accessibility cost maps, hydrographs, geomorphology, administrative limits and information about management status of particular areas such as public forests or pasture management).

Land cover layers come from many sources (Napoleon cadastre, aerial photographs and manual maps on the French site; aerial photographs, thematic maps and manual maps in Spain) and illustrate the historical evolution as early as possible: 6 land cover maps in Garrotxes (1826, 1942, 1962, 1980, 1989, 2000), and 4 in Alta Alpujarra (1957, 1974, 1987, 2001). The land cover maps of Garrotxes come from various sources and have various land cover layers: the first land cover map (1826), which has been built from the Napoleon cadastre, distinguishes forest, pasture, grassland, agriculture and urban use. The first aerial photographs (1942) permit the insertion of a category between pasture and forest: scrubs. The land cover map of 1962 has the same layers, while the scale and quality of later aerial photographs distinguishes deciduous from coniferous forests and broom lands from grass-based pastures (1980, 1989, and 2000). For modelling, we use only the latest three dates; earlier land cover reflects social and economic conditions to far removed from today's reality.

The Spanish land cover maps contain various levels of details. For this work, we used a simplified version with the same caption for all dates.

As shown in Fig. 5.2 and 5.3, land cover changes during the studied period are dramatic. In Garrotxes, we see that crops (terrace cultivating) that used to take up 25% of the area in 1826, have almost disappeared by the early 1980s. They first became pastures and then scrubs and forests. In Alta Alpujarra Granadina, the cultivated lands decreased from 21.9% of the area in 1957 to just 7.1% today. The irrigated land decreased from 14.6% to 5.8% of the area, but proportionally increased from 66.7% to 81.7% of the overall agricultural activity. Because the vegetal growth is very slow, the fallows became one of the major land covers of the area. Another important development is that coniferous forests increased twofold at higher elevations.

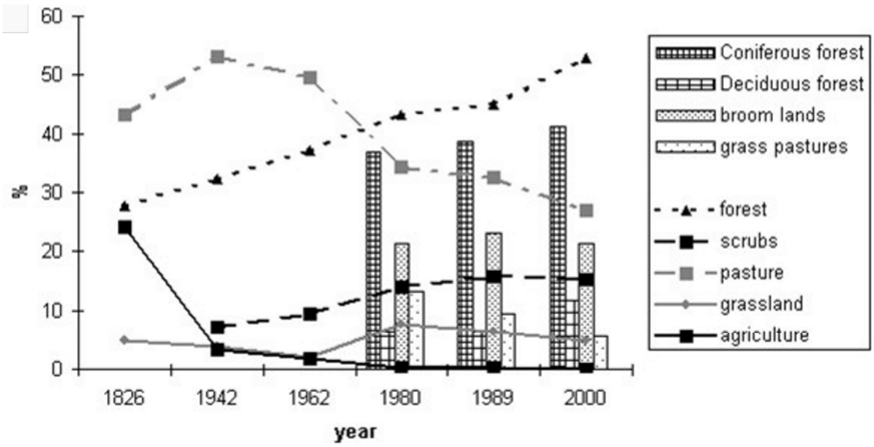

Fig. 5.2 Net quantity changes for land cover in Garrotxes (France): 1826 – 2000

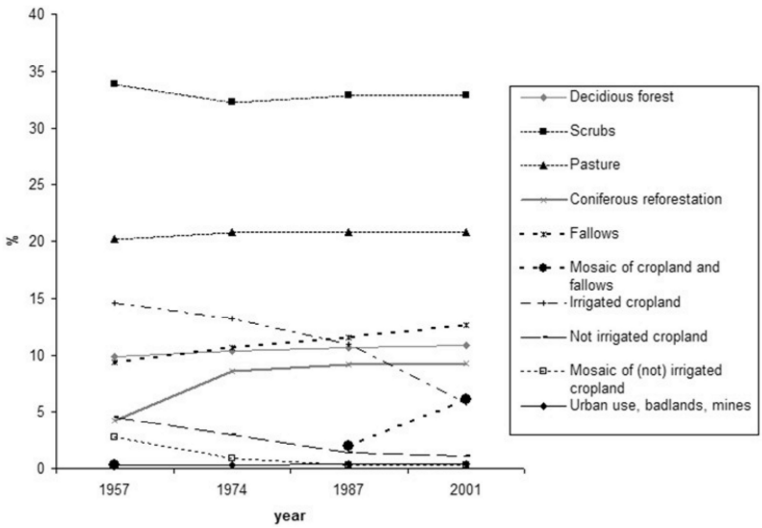

Fig. 5.3 Net quantity changes for land cover in Alta Alpujarra Granadina (Spain): 1957 – 2001 (data for Mosaic of cropland and fallows are not available in 1974)

5.3 Methodology and practical application to the data sets

5.3.1 Models

Three different models were applied to the two data sets. They have common features: maps have been set at almost equal time intervals and the list of all possible transitions is finite and related to the land cover captions. Each tested model uses exactly the same data (two earlier land cover maps and several relevant criteria) to train the model (calibration). The prospective simulation is made for the latest known land cover state, which is unknown by the models and only used for validation.

The first method, called combined geomatic model, is based on available GIS software modules. Time transition probabilities result from Markov chain analysis but the spatial assignment of the simulated land cover is assisted by a set of suitability maps, one for each land cover which expresses geographic knowledge and is performed manually by an expert.

In order to propose automatic alternatives to the GIS, two approaches have been adapted to estimate the evolution of the land cover: the first one, the polychotomous regression modelling, is a generalized linear model with estimation based on the maximum log-likelihood method. The second one, the multilayer perceptron, is a popular method, which has recently proved its great efficiency to solve various types of problems.

The idea is to confront a parametric linear model with a nonparametric one to provide a collection of automatic statistical methods for geographers. They both have their own advantages that have to be taken into account when choosing one of them: the polychotomous regression modelling is faster to calibrate than multilayer perceptrons, especially in high dimensional spaces and is not limited by the existence of local minima. On the contrary, multilayer perceptrons can provide nonparametric solutions that are more flexible. Both methods are easy to implement, even for non-statisticians, through pre-made software (for example, “Neural Network” Toolbox for neural networks with Matlab).

5.3.1.1 Combined geomatic model

- Construction of a knowledge base – multi criteria evaluation (MCE)

Knowledge about earlier dynamics is essential for attempting to predict future development or to create prospective scenarios. Therefore each model has to be supplied with the values of the initial conditions (calibration). For this step, we used the two training land cover maps used to perform time transition probabilities and criteria, which are correlated to land cover. Statistical procedures (logistic regression, PCA) helped us to choose the relevant criteria. We only used easily available data in order to provide a model that can be easily generalized.

The criteria were split up into Boolean constraints (a specific land cover is allowed or not) and factors which express the level of suitability for each land cover; this level depends on the localization of the pixel. The constraints simply masked some areas of the map, while the factors were weighted in order to permit a tradeoff between one another. The result of this multi-criteria evaluation is a set of suitability maps showing terrain suitability for each land cover. These maps assist in the spatial assignment of time transition probabilities performed by Markov chain analysis.

- Computing time transition probabilities – Markov chain analysis (MCA)

To perform land cover extrapolation, we used a Markov chain analysis (MCA), a discrete process for which values at instance t_1 depend on values at instance t_0 (Markov chain of order 1). The prediction was given as an estimation of the transition probabilities.

MCA produced a transition matrix, which contains the probability that each land cover will change into another land cover: we can then deduce the number of pixels expected to change. The algorithm also generated conditional probability maps for each land cover after a specified number of time units.

- Spatial assignment of predicted land cover probabilities – multi objective evaluation (MOE) and cellular automaton (CA)

The integrating step, combining knowledge about likely spatial distribution (MCE), time transition probabilities (MCA) as well as multi-objective land allocation, was performed by multi objective evaluation (MOE) using the amount of expected changes and MCE results. The land cover prediction procedure finally added spatial contiguity constraints. The cellular automaton (CA) is based on a standard contiguity filter (5 x 5) to recognize the suitability of the pixels that are far from existing instances of the land cover type under consideration. The algorithm is iterative so as to match with time distances between t_{-1} - t_0 and between t_0 - t_{-1}.

5.3.1.2 Polychotomous regression modelling

When we want to predict a categorical response given a random vector, a useful model is the multiple logistic regression (or polychotomous regression) (Lai and Wong 2001). A smooth version of this kind of method can be found in Kooperberg et al. (1997). Applications of these statistical techniques to several situations such as medicine or phoneme recognition can be found in these two papers. Their good behaviour, both on theoretical and practical grounds, has been emphasized. In our case, the predictors are both categorical and scalar and thus we have the derived model below:

Let us note, for k =1, …, K,

$$?\left(C_k \mid X_{i,j}(t)\right) = \log \frac{P\left(c_{i,j}(t) = C_k \mid X_{i,j}(t)\right)}{P\left(c_{i,j}(t) = C_K \mid X_{i,j}(t)\right)} \tag{5.1}$$

where $C_1,\ldots,C_k$ are the different values of the land cover, cii(t) is the value of land cover for pixel (I,j) at time t and $X_{i,j}(t)$ is the vector of social factors as well as values of land cover in the neighbourhood of pixel (i,j) at time t-1. Then, we get the following expression:

$$P(c_{i,j}(t)=C_k|X_{i,j}(t))=\frac{\exp\theta(C_k|X_{i,j}(t))}{\sum_{j=1}^{K}\exp\theta(C_j|X_{i,j}(t))} \tag{5.2}$$

Now, to estimate these conditional probabilities, we use the parametric approach to the polychotomous regression problem that is the linear model:

$$\theta(C_k|X_{i,j}(t))=\alpha_k+\sum_{c\in V_{i,j}(t-1)}\sum_{l=1}^{K}\beta_{kl}I_{[c=C_l]}+\sum_{r=1}^{p}\gamma_{kr}Y^r_{i,j} \tag{5.3}$$

where $V_{ij}(t-1)$ are the values of the land cover in the neighbourhood of the pixel (*i, j*) on the previous date $t-1$ and ($Y^r_{i,j}$), are the values of the environment variables. Let us call $\delta =$ ($\alpha_1, \ldots, \alpha_{k-1}, \beta_{1,1}, \ldots, \beta_{1,k}, \beta_{2,1}, \ldots, \beta_{2,k}, \ldots, \beta_{k-1,k}, \gamma_{1,1}, \ldots, \gamma_{1,k}, \ldots, \gamma_{k-1,1}, \ldots, \gamma_{k-1,p}$), the parameters of the model to be estimated. We note that we have $\alpha_k = 0$, $\beta_{k,l} = 0$ for all l = 1, …, K, and

$\gamma_{k,r} = 0$ for all r = 1, …, p. We now have to estimate the vector of parameters δ. For this, we use a penalized likelihood estimator, which is performed on the training sample. Let us write the penalized log-likelihood function for model. It is given by

$$l_?(?) = l(?) - ?\sum\sum u_{nk}^2 \tag{5.4}$$

where the log-likelihood function is:

$$l(?) = \log\left(\prod P_?\left(c^{(n)} \mid X^{(n)}\right)\right) \tag{5.5}$$

In this expression, $P_\delta(c^{(n)} \mid X^{(n)})$ is the value of the probability given by Eq. 5.2 and Eq. 5.3 for the observations $(X^{(n)}, c^{(n)})$ and the value δ of the parameter. In Eq. 5.4, ε is a penalization parameter and, for k =1, …, K,

$$u_{n,k} = \theta_\delta(C_k | X^{(n)}) - \frac{1}{K}\sum_{j=1}^{K} \theta_\delta(C_j | X^{(n)}). \tag{5.6}$$

Our penalized likelihood estimator δ satisfies:

$$\hat{\delta}_\epsilon = argmax_{\delta \in R^M} l_\epsilon(\delta). \tag{5.7}$$

where $M = K^2 + (K - 1) * p - 1$ denotes the number of parameters to be estimated.

As pointed out by Kooperberg et al. (1997), in the context of smooth polychotomous regression without the penalty term, the maximization of the log-likelihood function $l(\delta)$ can lead to infinite coefficients β_{kl}. In our model, it may be the case, for example, when, for fixed k, the value of the predictor is equal to zero for all *(i,j)*. Actually, this “pathological” case can not really occur in practice; but for classes *k* with a small number of members, the value of the predictor is low, creating a numerical instability when maximizing the log-likelihood. Then the form of the penalty, based on the difference between the value $\theta_\varphi(\xi_k \mid X^{(n)})$ for class *k* and the mean over all the classes, has the aim of preventing this instability by forcing $\theta_\varphi(\xi_k \mid X^{(n)})$ to be nearer to the mean. However for reasonable values of ε, we can expect that the penalty term does not greatly affect the estimation of parameters, because it guarantees numerical stability. Finally, numerical maximization of the penalized log-likelihood function is achieved by a Newton–Raphson algorithm.

5.3.1.3. Multilayer perceptron

Neural networks have a great adaptability to any statistical problems and especially in overcoming the difficulties of nonlinear problems even if the predictors are highly correlated; thus it is not surprising to find them used in the chronological series prediction (Bishop 1995, Parlitz and Merkwirth 2000, Lai and Wong 2001). The main advantage of neural networks is their ability to approximate almost any function with the desired precision (universal approximation) (see, for instance, Hornik 1991).

Here, we propose to estimate the function $P(c_{ij}(t|=C_k|X_{ij}(t))$ in the form of a multilayer perceptron ψ with one hidden layer (Fig. 5.4). This multilayer perceptron is a function from R^q to R that can be written, for all x in R^q, as:

$$\Psi_w(x)=\sum_{i=1}^{q_2} w_i^{(2)} g\left(\langle x, w_i^{(1)}\rangle + w_{i,0}^{(1)}\right), \tag{5.8}$$

where q_2 in N is the number of neurons on the hidden layer, $(w_i^{(1)})_{i=1,\ldots,q2}$ (respectively, $(w_i^{(2)})_{i=1,\ldots,q2}$; $(w_{i,0}^{(1)})_{i=1,\ldots q2}$) are in R^q (resp.R) and are called weights and bias, and where g, the activation function, is a sigmoïd; for example, $g(x) = 1/(1+e^{-x})$.

Then the output of the multilayer perceptron is a smooth function (here it is indefinitely continuous and derivable) of its input. This property ensures that the neural network took into account the spatial aspect of the data set, since two neighbouring pixels have "close" values for their predictor variables.

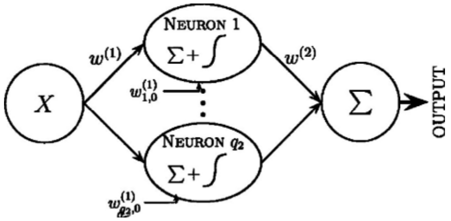

Fig. 5.4 Multilayer perceptron with one hidden layer

To determine the optimal value for weights $w = ((w_i^{(1)})_i, (w_i^{(2)})_i, (w_{i,0}^{(1)})_i)$, we minimized the quadratic error on the training sample, as it is usual for all $k = 1,\ldots, K$, we chose:

$$w_{opt}^k = argmin_{w \in R^{q_2(q+2)}} \sum \left[c_k^{(n)} - ?_w^k\left(X^{(n)}\right)\right]^{2,} \tag{5.9}$$

where $c^{(n)}$and the categorical data in $X^{(n)}$ are written in a disjunctive form. This can be performed by classical numerical methods of the first or second order (such as gradient descent, conjugate gradients, etc.) but faces local minima problems. We explain in Sect. 5.3.2.2 how we overcame this difficulty. Finally, White (1989) shows many results that ensure the convergence of the optimal empirical parameters with the optimal theoretical parameters.

5.3.2. Practical application to the data sets

The three models use exactly the same data.

Calibration and training period
The models were calibrated by two or three earlier land cover maps (1980 and 1989 for French Pyrenees; 1957, 1974 and 1987 for Spanish Sierra Nevada) and related maps of relevant criteria. The last known land cover map is unknown to the models and has been used for the comparison of the models.

5.3.2.1. Combined geomatic model

This model was implemented with GIS functions available in Idrisi Kilimanjaro software.

- MCE step

In order to assist spatial assignment of transition probabilities, we performed a list of constraints: some of them are common to any land cover (e.g., stability of built-up areas); others are specific to only some land covers (e.g., elevation limits the forests, distance to roads the crops, accessibility level, the grassland and public woods forbidden for pasture). These constraints are expressed in a binary form which allows, or not, that a given land cover can be predicted. Another sort of criteria is factors which express the local degree of suitability for each land cover. Table 5.1 gives the six original factors selected for the French area and the technique to convert them into suitability levels. The list is short for two reasons: first, we want to perform a simple model that can be implemented easily. Plus, acquiring high resolution data can be difficult.

Elevation, slope and aspect are important physical factors. The accessibility to roads and villages is a cost factor expressing the time needed to access any place. In the studied areas, the transport is exclusively road based and people live in grouped residential areas. The accessibility map results from a cost distance analysis, where the usual distance is weighted by the quality of roads. The proximity to existing land cover features is the distance (average and standard variation) of each land cover to borders of land cover of the same type during the training period. It takes into account border dynamics and spontaneous appearances (which are not induced by borders). This factor is important in rural and mountain areas where forest spreading is a widespread process. The probability for each change was worked out by cross tabulation of observed land cover dynamics into the training period.

Table 5.1 Factors used and involved techniques to process suitability

Factor	Technique to process suitability
Elevation	Manual recoding based on significant (99% and 99.9% level) differences between real and theoretic distribution
Slope	
Aspect	
Accessibility to roads and villages (cost distance)	
Probability for land cover change	Stretching of observed transitions during $t_{-1} - t_0$
Proximity to existing land cover features (distance)	Fuzzy function based on observed distance parameters for border and spontaneous appearances

Because each factor was expressed in its own unit, they had to be standardized: the original values (degrees, meters, per cent) were re-scaled into suitability values on a common scale reaching from 0 (lowest suitability) to 255 (best suitability). This standardization was processed in different ways: for each land cover, the suitability of elevation, slope, aspect and accessibility was carried out by analyzing the statistical significance of the spatial dependency versus a null hypothesis. Non-significant differences (less than a level of 99%) mean an average suitability (128). For smaller significant levels, the suitability is also smaller and vice versa.

Once standardized, the factors were weighted using Saaty matrix (Saaty 1977). This matrix contains the correlation of each pair of factors and a weight was deduced from it by eigenvalue decomposition.

Finally, Ordered Weighted Averaging (OWA) (Yager 1988) allowed the choice of a risk and of tradeoff levels. “Tradeoff” means the possibility to compensate a low suitability score of one factor by a high suitability score of another factor. A tradeoff level is related to a risk level (see Fig. 5.5), which ranges from And (risk adverse) to Or (maximum risk). The fuzzy axis of risk levels is called *andness*. Finally, the number of order weights is equal to the number of factors and the weights sum to 1. Order weights are calculated for each pixel and the first order weight is assigned to the factor with the lowest weighted suitability. The last order weight is assigned to the highest suitability among the weighted factors for the given pixel.

As illustrated in Fig. 5.5 the authors chose a strategy which may be considered as having a low risk and allowing for some tradeoff. The results of multi-criteria evaluation with ordered weighted averaging (MCE-OWA) are expressed as a land cover suitability map (one for each caption).

Fig. 5.5 Space of decision strategy and chosen approach into MCE-OWA. Order weights used: 0.45, 0.20, 0.15, 0.10, 0.07, 0.03

- Time transition probabilities

The prediction was performed by a Markov function from the two calibration dates.

- Spatial allocation of predicted land cover probabilities

MOE and a cellular automaton are included in the CA_Markov module. For more details about practical application of the geomatic model, see Paegelow and Camacho (2005).

5.3.2.2 Polychotomous regression modelling and multilayer perceptron

In order to compare the two automatic approaches, we applied the same methodology: first we determined the optimal parameters for each approach (training step, see below) and then, we used the land cover maps to predict the last one and finally we compared this simulated map to the real one (validation step, see Sect. 5.5).

As usual in statistical methods, there are two steps in the training stage: the estimation step and the calibration step.

- *The estimation step* consists in estimating the parameters of the models (either for the polychotomous regression or the neural network).
- The *calibration step* allows us to choose, for both methodologies, the best neighbourhood, for polychotomous regression, the penalization parameter and, for neural network, the number of neurons on the hidden layer. We only considered a square-shaped neighbourhood so here, choosing a neighbourhood is equivalent to determining its size.

For the Sierra Nevada, we saw that large areas are stable, thus we only used the pixels for which at least one neighbour has a different land cover. These pixels are called “frontier pixels”; the others were considered stable

(Fig. 5.6). For the generalized linear model, we used the whole frontier pixels of the 1957/1974 maps for the estimation set and the whole 1974/1987 maps for the calibration set. We then constructed the estimated 2001 map from the 1987 map. For the multilayer perceptron, we reduced the training set size in order to not have huge computational times when minimizing the loss function. Then estimation and validation data sets were chosen randomly in the frontier pixels of the 1957/1974 and 1974/1987 maps.

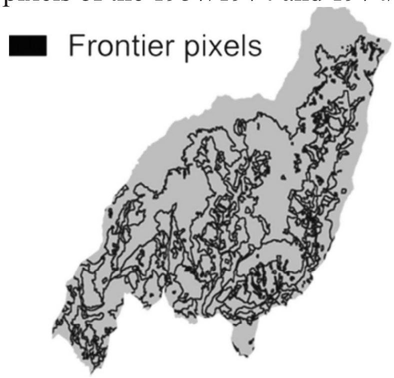

Fig. 5.6 Frontier pixels (order 4) for the 1957 map (Alta Alpujarra Granadina)

For the Garrotxes data set, due to the fact that we only had 3 maps and far fewer pixels, we had to use the 1980/1989 maps for the estimation step (only their frontier pixels for the MLP) and the whole 1989/2000 ones for the calibration step. This led to a biased estimate when constructing the 2000 map from the 1989 map but, as our purpose is to compare two models and not to control the error rate, we do not consider this bias as important.

1. Polychotomous regression modelling

• The *estimation step* produces the estimated parameter vector $\hat{\xi}$ if the parameters ξ of model (Eq 5.3) for a given neighbourhood and a penalization parameter ε. This step was repeated for various values concerning both the neighbourhood and penalization parameter.

• Validation step: Once given an estimated parameter vector $\hat{\delta}_\epsilon=(\hat{\alpha}_{1},\dots,\hat{\alpha}_{K-1},\hat{\beta}_{1,1},\dots,\hat{\beta}_{1,K},\hat{\beta}_{2,1},\dots,\hat{\beta}_{2,K},\dots,\hat{\beta}_{K-1,1},\dots,\hat{\beta}_{K-1,K},\hat{\gamma}_{1,1},\dots,\hat{\gamma}_{K-1,p})$, the quantities:

$$\hat{P}(c_{i,j}(t)=C_k|X_{i,j}(t))=\frac{\exp\hat{\theta}(C_k|X_{i,j}(t))}{\sum_{j=1}^{K}\exp\hat{\theta}(C_j|X_{i,j}(t))}. \tag{5.10}$$

were calculated, for all $k=1,\dots,K$, with:

$$\hat{\theta}(C_k|X_{i,j}(t))=\hat{\alpha}_k+\sum_{c\in V_{i,j}(t)}\sum_{l=1}^{K}\hat{\beta}_{kl}I_{[c=C_l]}+\sum_{r=1}^{p}\hat{\gamma}_{kr}Y_{i,j}^{r} \tag{5.11}$$

At each pixel (i ,j) for the predicted map on date t, we affected the most probable land cover type, namely the ξ_k, which maximizes

$$\left\{\hat{P}\left(c_{i,j}(t)=C_k \mid X_{i,j}(t)\right)\right\}_{k=1,\dots,K} \tag{5.12}$$

Programs were made using R program (R Development Core Team 2005) and are available on http://nathalie.vialaneix.free.fr/maths/article-normal.php3?id_article=49.

2. Multilayer perceptron

We used a neural network with one hidden layer having q_2 neurons (where q_2 is a parameter to be calibrated). The inputs of the multilayer perceptron were:

- For the *time series*, the disjunctive form of the value of the pixel;
- For the *spatial aspect*, the weighted frequency of each type of land cover in the neighbourhood of the pixel;
- The environmental variables.

The output was the estimation of the probabilities $P(c_{ij}(t|=C_k|X_{ij}(t))$. The estimation was also made in two stages:

- The *estimation step* produces the estimated weights as described in Eq. 5.9 for a given number of neurons (q_2) and a given neighbourhood. For this step, the neural network was trained with an early stopping procedure, which allows stopping the optimization algorithm when the validation error (calculated on a part of the data set) is starting to increase (Bishop 1995). This step was repeated for various values of both neighbourhood and q_2.
- *Validation step:* once an estimation of the optimal weights was given, we chose q_2 and the size of neighbourhood as for the previous model. Moreover, in order to escape the local minima during the training step, we trained the perceptrons many times for each value of neighbourhood and of q_2 with various training sets; the “best” perceptron was then chosen according to the minimization of the validation error among both the values of the parameters (size of the neighbourhood and q_2) and the optimization procedure results.

Programs were made using Matlab (Neural Networks Toolbox, see Beale and Demuth 1998) and are also available on request.

5.4 Results

We applied the three models previously described and obtained a simulated land cover mapsat 2000 for the Garrotxes. We found similar maps for the three methodologies and these maps are also close to reality (Fig. 5.7). The overall good prediction rates are about 73 – 74% (Table 5.2).

For the Spanish test area, the results (Fig. 5.8) are closer to reality, but are also more difficult to interpret. The comparison with real land cover in 2001 shows an overall prediction rate of 78.9% for the combined geomatic model and about 90% for the two semi-automatic models (91% for the polychotomous regression model; 88.7% for the multilayer perceptron model) (Table 5.3).

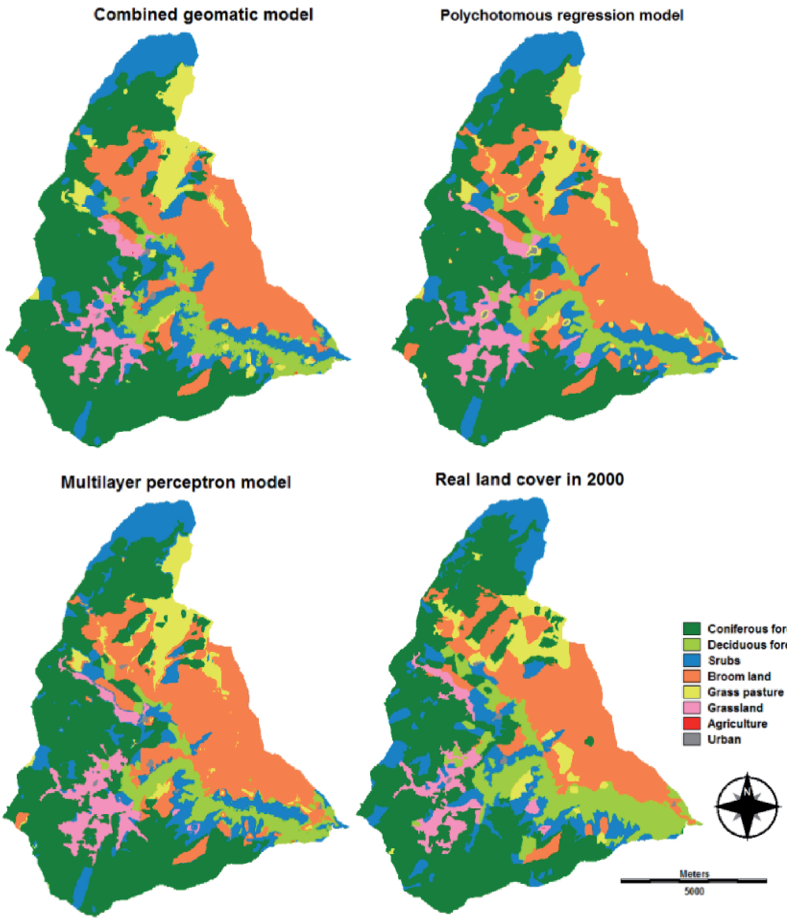

Fig. 5.7 Predicted land cover by combined geomatic model, polychotomous regression model and multilayer perceptron model for Garrotxes in 2000 and real land cover

Table 5.2 Misclassification rates for the Garrotxes

Land cover	Frequency	Combined geomatic model	Polychotomous regression model	Multilayer perceptron model
Types	in the area	error rate	error rate	error rate
Coniferous forest	40.9%	11.4%	11.9%	10.6%
Deciduous forest	11.7%	55.3%	51.7%	45.8%
Scrubs	15.1%	51.9%	57.1%	54.5%
Broom lands	21.6%	17.1%	14.4%	16.2%
Grass pasture	5.7%	54.4%	59.2%	59.4%
Grassland	4.8%	30.4%	25.6%	19.3%
Overall		27.2%	27.2%	25.7%

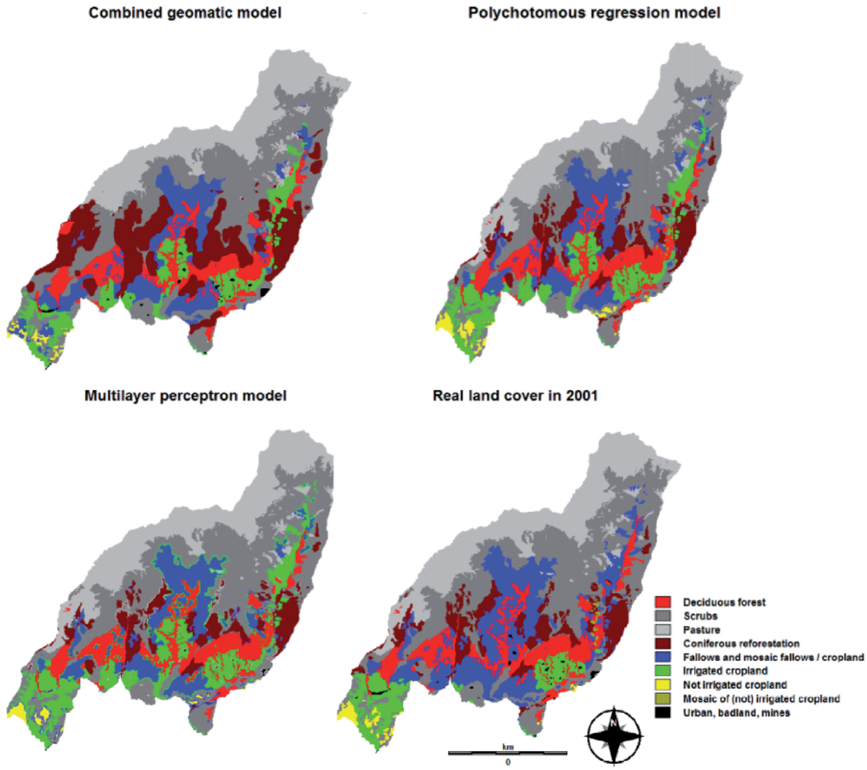

Fig. 5.8 Predicted land cover by combined geomatic model, polychotomous regression model and multilayer perceptron model for Alta Alpujarra Granadina in 2001 and real land cover

The simulation results are always closer to reality for the Alta Alpujarra Granadina as for the Garrotxes. Land cover of the Spanish test area is also more persistent through time. In Garrotxes, 75.5% of the area remained unchanged during the training period (1980 – 1989), 72% between 1989 and 2000. The Spanish area stability is about 90.4% during the training period (1957 – 1987) and concerns 83.9% of the area between the last date and the previous one (1987 – 2001).

Table 5.3 Misclassification rates for the Alta Alpujarra Granadina

Land cover	Frequency	Combined geomatic model	Polychotomous regression model	Multilayer perceptron model
Types	in the area	error rate	error rate	error rate
Deciduous forests	10.9 %	14.3%	3.5 %	2.6 %
Scrubs	33.0 %	15.2%	3.1 %	1.4 %
Pasture	20.8 %	12.5%	0.6 %	0.0 %
Coniferous refor.	9.2 %	1.9%	3.5 %	16.3%
Fallows	18.8 %	46.8%	32.5 %	41.4 %
Irrigated cropland	5.8 %	38.9%	8.9 %	6.8 %
Overall		21.1%	9.0 %	11.3 %

The results also show similar misclassification rates of the three models in the French test area, but misclassification rates of the combined geomatic model are higher as those performed by the polychotomous regression model and the multilayer perceptron model in the Spanish test area. We think that this difference of prediction performances is related to higher persistence rate for the Alta Alpujarra Granadina (Ferraty et al. 2005, Villa et al. 2007). This will be discussed in Sect. 5.5

Another interesting result is that the amount of predicted land cover (sum of pixels predicted without location) matches well with the reality and this for all land cover values and all models. Therefore, Table 5.4 shows the worst cases (the highest overall misclassification rates obtained by the combined geomatic model compared to reality for the Garrotxes).

Table 5.4 also shows that the model fits better to reality for the land cover values covering large areas like coniferous forests and broom lands. The prediction rate is lower for land cover values covering little areas and nears zero for crops that cover only 0.007% of the area (16 pixels). On the contrary, developed areas (urban) corresponds, by definition (constrained area), to reality. The confusion matrix for the Alta Alpujarra Granadina confirms the observed trends based upon the French study area.

5.5 Validation and discussion of results

The performed results are not intended to predict future reality, but they can help us to better understand complex environmental and social changes in time and space. Therefore the interpretation must be done carefully; the land cover modelling simulates what could be reality. The results are a possible scenario within the defined framework to support decision-making. Nevertheless, an accurate interpretation may be useful to improve the prediction rate. In both areas, good predictions are about ¾ of the whole area. In the following discussion, we will focus on the misclassified areas in order to understand the failures in modeling and to improve future simulations. At this point, it is important to say that each model is affected by random noise. Random phenomena, like forest fires and wind falls in Garrotxes, seem impossible to model correctly, even if they are not significant (less than 2% of the whole area). In the Spanish area, the same is caused by coniferous reforestation: an artificial reforestation leads to an important change of macro-conditions, which can not be predicted by earlier data.

Table 5.4 Matrix comparing real land cover in 2000 (rows) to land cover predicted by the combined geomatic model in 2000 (columns) in Garrotxes. Data are expressed in percent of the total area

		Coniferous forest	Deciduous forest	Scrubs	Broom lands	Grass pastures	Grassland	Agri-culture	Urban	Sum of real land cover
Real land cover 2000 %	Coniferous forest	35.81	0.12	3.47	0.63	0.43	0.47	0.00	0.00	40.93
	Deciduous forest	1.19	6.45	2.92	0.58	0.32	0.23	0.00	0.00	11.69
	Scrubs	2.28	1.26	6.87	1.70	1.82	1.13	0.01	0.00	15.08
	Broom lands	0.32	0.40	1.68	18.00	1.12	0.09	0.00	0.00	21.61
	Grass pastures	0.21	0.08	0.44	2.64	2.29	0.00	0.00	0.00	5.66
	Grassland	0.55	0.02	0.75	0.01	0.27	3.19	0.01	0.00	4.80
	Agriculture	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01
	Urban	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.23	0.23
Sum of predicted land cover		40.37	8.33	16.13	23.56	6.24	5.12	0.03	0.23	100.00

In order to analyze the residues of simulated land cover, we introduced a kind of "distance" between the simulated and the real land covers (prediction failures). The Garrotxes land cover is described as qualitative data, but may be put on a landscape rank scale, which goes from dense areas (1: forests) to open landscape corresponding to more intensive use (6: agriculture). Therefore, we grouped deciduous and coniferous forests. In this way, we defined a difference between two land cover values. A negative distance means a predicted landscape, "opening", while positive values express a predicted landscape, "closing" (that did not happen). The prediction failures occur outside stable areas, which are concentrated along the western and southern limits of the studied area (public forests) and on the left bank (large pastures).

The data of Table 5.5 show a contingency table of the model and the importance of the misclassification. Almost half of false predicted area corresponds to a prediction failure of only one land cover category. In other words, half of the residues are very close to reality from a thematic point of view. The most important misclassified areas (three or more ranks) are due to random phenomena.

In Alta Alpujarra, the vegetation dynamics is slower and consequently the land cover values are more static and can not be ranked in the same way.

Then let us describe the accuracy of the localization of each land cover: this can be expressed by a fuzzy logic based on a comparison between real and simulated land cover. Unlike a pixel by pixel comparison, fuzzy logic comparison allows a small error in localization. Fuzzy validation only improves the overall good prediction rates by about 2% for all models and the two data sets. This small gain may be explained by the qualitative nature of land cover. By carefully observing Fig. 5.7 and Fig. 5.8, we can observe that one important factor for misclassifying is the layered representation of land cover. Inside each land cover type, any variability can exist, but this fact is not included into the data base. This may be illustrated by an example from Garrotxes: the southeastern part of Fig. 5.7 shows a large oblong area predicted as scrubs (same land cover as in 1980 and 1989). In reality, this area changed into a deciduous forest by a natural dynamic; this emphasizes a general problem when dealing with qualitative data: the intra-class variability. In this case, scrubs grew higher and higher and, at the same time, the floristic composition changed and Quercus ilex got the upper hand.

Table 5.5 Prediction residues (%) according to the distances between real and simulated land cover, Garrotxes (Data for correct prediction differ from those mentioned earlier because the two forest categories were grouped)

	Combined geomatic model	Polychotomous regression model	Multilayer perceptron model
Correct prediction	74.16	74.27	75.62
1 difference	17.36	17.23	16.47
2 differences	4.29	4.67	4.23
3 differences	2.92	2.43	2.51
4 differences	1.28	1.40	1.17

Another way to analyze model behaviour and results consists in crossing simulated land cover maps. This was done for the Garrotxes: as shown in Table 5.6, the correct predicted area obtained by intersection of the three simulated maps is about 66.5%. This means there is a strong consistency between the three models; individual prediction rates of each model are about 73 to 75%. It is not surprising that these good predictions are higher on persistent and large areas like coniferous forests. The following columns show the good prediction rates obtained by the intersection of two model results (for pixels that are incorrectly predicted by the last model) or the good prediction rate of a single model (for pixels that are incorrectly predicted by the two other models).

Table 5.6 shows that the intersection of the two semi-automatic models improves more than (3.75%) the overall prediction rate than any of the two other combinations. The intersection of each one with the combined geomatic model is less efficient. This means higher consistency between the polychotomous regression model and the multilayer perceptron model. On the other hand, Table 5.6 also proves that the most important good prediction rate for a single model is made by the combined geomatic model (3.23%). This means that the combined geomatic model and the two semi-automatic models are complementary to each other.

Table 5.6 Prediction rates (%) of simulated land cover by crossing simulated results, Garrotxes. CGM = combined geomatic model; MPM = multilayer perceptron model; PRM = polychotomous regression model. Cropland that is less than 0.01% of area is not represented

Correct prediction performed by	Every model	2 models			1 model			None
		MPM + PRM	CGM + PRM	CGM + MPM	CGM	MPM	PRM	
Coniferous forest	85.35	1.65	0.40	0.68	0.96	1.75	0.76	8.53
Deciduous forest	46.26	0.90	0.57	3.11	4.98	3.93	0.50	39.75
Scrubs	32.38	5.92	2.64	2.50	7.75	3.89	1.03	43.89
Broom lands	76.98	4.99	2.45	0.74	2.82	0.70	0.93	10.39
Grass pasture	26.30	7.63	3.27	2.24	7.71	2.91	2.32	47.62
Grassland	59.14	11.64	1.66	4.70	1.06	5.26	1.99	14.55
TOTAL	66.49	3.75	1.42	1.54	3.23	2.33	0.92	20.32

In order to better understand the differences between the two semi-automatic models in comparison to the combined geomatic model, it is useful to analyze prediction rates according to land cover changes. As mentioned above the prediction rate is better for the Spanish area, particularly when land cover is simulated by a semi-automatic model. This may appear insufficient compared to the Null model (land cover persistence), but it is interesting to notice that the annual land cover change rate during the training period is different from the change rate between the two last dates. This average annual rate decreased moderately in Garrotxes (from 2.7% to 2.5%), but increased in Alta Alpujarra Granadina (from 0.3% to 0.95%).

The previous remarks seem to prove that the good prediction rates are related to the number and the velocity of land cover changes. Therefore we calculated LUCC budgets between the last two maps.

The LUCC-budget for Garrotxes (Table 5.7) shows an important total change (about 28%) and the swap part (20%) is much more significant as its net change (8%). In comparison to this real LUCC-budget, those per-formed by real land cover in 1989 but by simulated land cover in 2000, are systematically lower; particularly, polychotomous regression and multi-layer perceptron simulated land cover decrease land cover dynamics. Only the combined geomatic model leads to a proportion of "swap/net" changes close to the real ones. However the total amount of change is only half of the real one.

Table 5.7 Garrotxes real LUCC-budget 1989-2000 and 1989-2000 LUCC-budgets for simulated land cover in 2000

	Real land cover changes					Combined geomatic model				
	Gain	Loss	Total change	Swap	Abs value of net change	Gain	Loss	Total change	Swap	Abs value of net change
Coniferous forest	5.92	3.60	9.53	7.21	2.32	2.43	0.68	3.11	1.35	1.76
Deciduous forest	6.20	0.51	6.71	1.01	5.70	2.40	0.08	2.47	0.15	2.32
Scrubs	8.25	8.92	17.18	16.51	0.67	3.87	3.49	7.36	6.98	0.38
Broom land	4.34	6.17	10.51	8.68	1.83	3.35	3.21	6.56	6.43	0.13
Grass pasture	2.39	6.18	8.57	4.79	3.79	0.62	3.81	4.43	1.23	3.20
Grassland	0.83	2.44	3.27	1.66	1.61	0.27	1.56	1.82	0.53	1.29
Agriculture	0.01	0.13	0.14	0.01	0.12	0.00	0.11	0.11	0.00	0.11
Total	27.95	27.95	27.95	19.93	8.02	12.93	12.93	12.93	8.34	4.59

	Polychotomous regression model					Multilayer perceptron model				
	Gain	Loss	Total change	Swap	Abs value of net change	Gain	Loss	Total change	Swap	Abs value of net change
Coniferous forest	2.76	0.21	2.96	0.41	2.55	2.84	0.09	2.93	0.18	2.75
Deciduous forest	0.48	0.19	0.66	0.37	0.29	1.30	0.07	1.37	0.14	1.23
Scrubs	0.53	1.70	2.23	1.06	1.17	1.50	3.12	4.62	3.01	1.61
Broom land	2.97	0.53	3.50	1.06	2.44	2.87	1.25	4.13	2.51	1.62
Grass pasture	0.37	3.62	4.00	0.75	3.25	0.23	3.65	3.88	0.47	3.41
Grassland	0.17	0.91	1.08	0.34	0.74	0.21	0.66	0.88	0.43	0.45
Agriculture	0.01	0.13	0.14	0.01	0.12	0.00	0.13	0.13	0.00	0.13
Total	7.28	7.28	7.28	2.00	5.28	8.97	8.97	8.97	3.36	5.60

So all of the models, but particularly the two semi-automatic models, simulate persistence and underestimate land cover changes. The following tables underline this observation. Table 5.8 shows the correct prediction rate of each model depending on the number of land cover changes over three dates (1974, 1987 and 2001) for the Spanish test area.

Table 5.8 proves that land cover is simulated almost perfectly by each of the two semi-automatic models for areas with land cover persistence. The combined geomatic model is clearly less efficient when land cover does not change. It is areas for which land cover becomes different. The more land cover changes are numerous, the better the combined geomatic model predictions are. On the other hand, changes are so rare that predicting them is very difficult.

Table 5.8 Correct prediction scores obtained by the three models in Alta Alpujarra Granadina depending on the number of land cover changes between 1974 – 1987 – 2001: persistence (86.89%), one land cover change (12.83%), two land cover changes (0.28%)

Land cover changes\Model	Number of land cover changes		
	Persistence 86.89%	1 change 12.83%	2 changes 0.28%
Combined geomatic model	83.9%	61.5%	22.2%
Polychotomous regression model	98.0%	45.6%	1.5%
Multilayer perceptron model	96.0%	41.6%	2.0%

Table 5.9 shows the correct prediction rates of the models applied to Garrotxes depending on the number of land cover changes. It confirms the trends observed on the Spanish test area. First, we can see that the persistence over only two decades is significantly smaller (less than 60%) than in Spain (about 87% over 27 years). We observe that less than 1% of the whole area has two changes in Andalusia, whereas about 11% of the French Pyrenees is concerned with a double change of land cover. Data in Table 5.9 show that persistence is easy to predict. 93.5% of the studied area is correctly predicted by every model (Boolean intersection of the three simulation maps). The better prediction rate for coupled models is obtained by the two semi-automatic models (2.89% - in bold).These common correct prediction scores decrease for areas with land cover dynamics. Nevertheless, the combined geomatic model is the most efficient for areas with land cover changes.

5.6 Conclusion and outlook

The authors underline that the three applied models perform very similarly. The total prediction scores are better when the land cover is persistent. By intersecting model outputs, performing LUCC-budgets and comparing simulated land cover depending on land cover changes, we highlighted the similarities between the two semi-automatic models compared to the combined geomatic model. This combined model may be seen as a manual or directed model. It clearly appears that chaining semi-automatic and manual supervised modelling steps can improve the simulations. Polychotomous regression and multilayer perceptron models work better if land cover is persistent. On the contrary, the combined geomatic model is closer to reality when there are land cover changes.

Table 5.9 Prediction rates (%) of simulated land cover by crossing simulated results, Garrotxes, depending on the number of land cover changes between 1980 – 1989 – 2000: persistence (58.87 %), one land cover change (30.16 %), two land cover changes (10.97 %). CGM = combined geomatic model; MPM = multilayer perceptron model; PRM = polychotomous regression model

Correct prediction performed by	Every model	2 models			1 model			None
		MPM + PRM	CGM + PRM	CGM + MPM	CGM	MPM	PRM	
Persistence – 58.87	93.50	**2.89**	0.96	0.79	0.47	0.50	0.32	0.57
1 change – 30.16	35.28	5.89	2.16	1.97	**6.12**	4.36	1.31	42.92
2 changes – 10.97	9.51	2.47	1.85	4.29	**9.79**	6.44	3.05	62.61

The authors emphasize the fact that the models are based on a minimal amount of data that are easily available so that the application of the methodologies described in this paper to other areas should be easy to perform. To improve prospective land cover modelling, the authors apply the models to other areas characterized by high speed land cover changes (tropical deforestation) based on remote sensing data. Using various data sources and land cover dynamics may contribute to a better understanding about the ability of our modeling approaches to be generalized. It would also be helpful to consider intra-class variance by using semi-quantitative land cover data (covering rates) and to compare the models to other methodological approaches and available software.

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Decision support and participatory modelling

6 GIS-supported modelling and diagnosis of fire risk at the wildland urban interface. A methodological approach for operational management

Galtié JF

Abstract
The recent evolution of the rural and urban areas has led to the progressive emergence of a complex and multiform wildland urban interface. Today this interface has turned into a fire threat which is omnipresent The evolution in progress raises in particular the question of the safety of the people and goods and, more generally, that of the management and durability of development of these territories. Taking into account these problems in installation and planning tasks requires a risk analysis, which is often too complex to be implemented by traditional techniques. The recourse to GIS-supported modelling is tested here as an integrated, dynamic and operational tool for spatial diagnosis, display and recommendation as regards to risk management. This chapter describes the original approach that was implemented, the constitution of the data base, and the resulting diagnosis and display of risk created by the model.

Keywords: Wildland urban interface, risk, fire diagnosis, modelling, GIS, urban planning.

6.1 Introduction

The evolution of rural and urban areas during the last thirty years has led to the progressive emergence of built-up spaces/natural spaces interfaces that is complex, multiform and mono-functional (Ewert 1993, Hardy 2005, Theobald et Romme 2007). It results from a double continuous process of creation: urban scattering of natural space by induced constructions (diffuse or grouped) and networks, progression of natural spaces due to plant regrowth/renewal and progressive incorporation of the anthropogenic elements. Today this interface is simultaneously an omnipresent, total and growing (see above) fire risk (Xanthopoulos 2004). Fire, confined for a long time in the heart of natural spaces, finds in this interface a new ground, favourable to its ignition and its propagation. It comes into contact and/or penetrates extremely prized spaces (hence the pressure in favour of development and extension of these zones of contact). It has specific stakes (notably human and economic) with very serious vulnerability issues (human presence, technical difficulties in controlling fires and keeping populations safe, combustible material expansion, surface-wise and biovolume-wise). Recent cases of fires, which received great media attention, demonstrate the negative ecological, economic and human impact. Initial stakes (protection of forest viewed as social and ecological legacy, financial impact of fires, etc.) have been caught up by new stakes related to keen and demanding social desires regarding living space, people and goods protection. This protection - dependent on durable and concerted development of these territories - requires a voluntary policy to secure existing interfaces and to control their future development (Haight RG et al. 2004). With this intention, tools that developers use for diagnosis must be powerful, reliable and adapted to the specificities of suburban fire. There is today no unifying and generalizing approach and such tools are cruelly lacking.

Specificities of wildland urban interface (WUI) make specific assessments and take into account risk. From this point of view, the needs expressed by those who are responsible for "informing about risk" and dealing efficiently with risk may be synthesized into four points (Galtié 2007): (1) to characterize existing constructions (and induced networks of infrastructures) risk-wise, in order to direct qualitatively and quantitatively the preservation of such installations; (2) to characterize - in the current context of pressure in favour of development of interface territories - potential support- spaces of constructions (and induced networks of infrastructures) risk wise, in order to prohibit, authorize or condition any realization to come; (3) to treat on a hierarchical basis installations to be realized considering the stakes (current and future) and the politico-administrative organization of the territory (local to regional scales); and (4) to have an interactive tool for management and simulation, allowing to evaluate, direct and optimize growth and development of interface territories.

Recent developments in spatially explicit GIS models [principally in knowledge-based index models (Dagorne 1990, Chou 1992, Chuvieco et al. 1997, Petrakis et al. 2005), spatially weighted index models (Clark et al. 1994, Setiawan et al. 2004), fire probability density function models (Chou et al. 1993, Preisler et al. 2003) and direct simulation models (Green et al. 1995, Finney 1998)] have contributed highly to fire risk diagnoses across large scales. These models allowed managers to map, combine and analyze different variables that contribute to fire occurrence and propagation, as well as to produce operational maps of differential sensibility to fire (Salas and Chuvieco 1994, Caprio et al. 1997). Comparative analysis of the models' methodology and accuracy is only very rarely (and with much difficulty) evaluated and discussed in a satisfactory way (Viegas et al. 1999, Farris et al. 2001). The quality of the latest results seems more related to the mode of abstraction of the phenomena (number and nature of variables taken into account, formalization of the risk, etc.) and more related to the constraints of treatment than to the level of complexity of the model (Keane et Long 1998); therefore, the choice of a model for diagnosis depends above all on the modelling purpose and, if need be, a hybrid approach can prove to be efficient (Keanes et al. 1996). The operational appropriation of the models by the developers is correlated to their apparent precision, to the conditions of implementations (required parameter settings, computing time, etc.) and to the institutional and social constraints surrounding the process (statutory environment for risk apprehension, required scales for observation of the phenomena, social representation of risk, etc.).

The purpose of this contribution is to set out an exploratory methodology of GIS-supported modelling and diagnosis of forest fire risk in the wildland-urban interface. This work falls under the recent context of restoration of the French statutory framework for taking into account the fire risk, translated in particular by the institution of a plan for prevention of the forest fire risks (Garry et al. 2002). It was initiated by a multidisciplinary group (researchers, foresters, authorities, etc.) with the prospect of satisfying the obligation of current and prospective managing of WUI territories. In this paper, Sect. 6.2 describes test areas and data sets (required data and initial data processing). Sect. 6.3 describes how to make diagnoses by developed observation scaling, how to post up risk and how to derive prevention orientations. Validation and discussion of results and processes are raised in Sect. 6.4 and 6.5, conclusions and outlooks in Sect. 6.6.

6.2 Test areas and data sets

6.2.1 Wildland urban interface support

Interface spaces are now widely represented in most parts of the world subject to fire risk. Despite local specificities in regards to how they are created and how they work, vocabulary used for risk diagnosis (and not solutions to be brought) is relatively similar, and therefore fairly easy to apply overall. Developments described in this text are based on extensive field exploration carried out at the scale of southwestern Europe (Spain, France, Italy and Portugal). They are applied to two test areas located in France. These test areas were chosen according to their differentiated sensitivity to fire and according to the opportunity of associating the method major institutional partners involved in fire risk management (foresters, fire-fighters, politicians, etc.). In the political and administrative French context, delimiting test zones was accomplished with the help of spatial levels of references, the department and the municipality.

The first test area is located in the eastern Pyrenees and covers the Pyrénées-Orientales department (Fig. 6.1). This department, the furthest south in France, stretches over more than 400,000 hectares, and encloses almost as many inhabitants. It has a triangular shape: its smallest side measures 65 km and runs along the sea and its height increases from east to west over 160 km culminating at 2,000 meters. This configuration provides a great variety of topography and landscape (seven major natural regions) as well as modes of enhancing the area (activities and populations). The climate tends to be Mediterranean and to be modified in altitude due to more or less strong mountain influences. Winds come from the west to the north or the south and are very frequent with critical speeds, respectively every other day and 1 day on 8. Woods (very diverse, from green oaks to black pine trees), moors and brown fields cover nearly two-thirds of the space with just one quarter for agricultural activities (vines, livestock, etc.), which is regressing everywhere. Continuity and fuel load increase steadily in the context of agricultural decline and of quite ineffective structural measures of prevention. Population is very unevenly scattered over the territory and largely concentrated in the lowlands, highly attractive for local populations and even more for those outside the department (a few thousands per year). It is mainly in this area that building/forest interfaces have developed over the last thirty years (particularly in the form of housing estates) and are problematic; however, current saturation in housing is leading to the extension of the phenomena to greater elevations. In this test area, sensitivity to fire is relatively important (about 3,700 fires for nearly 50,000 ha since 1973) even with its very strong gradient. For natural regions, sensitivity to risk is expressed in the number of days per year of severe to very severe weather conditions and it ranges from less than one day per year to more than 30 days per year.

The second test area (agglomeration of twenty municipalities) is located in the Lot department, a hundred kilometres north of Toulouse, in an area traditionally considered out of the area at risk (Fig. 6.1). It covers nearly 33,000 ha lie between 100 and 380 meters above sea level and has a little more than 32,000 inhabitants. This area presents a “bowl or funnel” topographic type, combining downs landscapes and great crossing valley. A double climatic influence, Mediterranean and Atlantic, sets up a fairly mild climate (750 to 900 mm of rainfall per year, 12° C for annual average): hot and dry in the summer, under the influence of weak west and southeast winds. Woods (pubescent oak dominates, mingled with a few conifer stands), moors and brown fields occupy almost 70% of the territory. Nearly two-thirds of the population is concentrated in 10% of the territory, corresponding to the physically saturated and isolated agglomeration of Cahors. The economic attraction produced by the latter increases the regular arrival of new populations and the development of interface areas. Except for a handful of striking events, fire risk is potentially quite great but so far fairly well-contained (397 fires for about 800 ha since 1984).

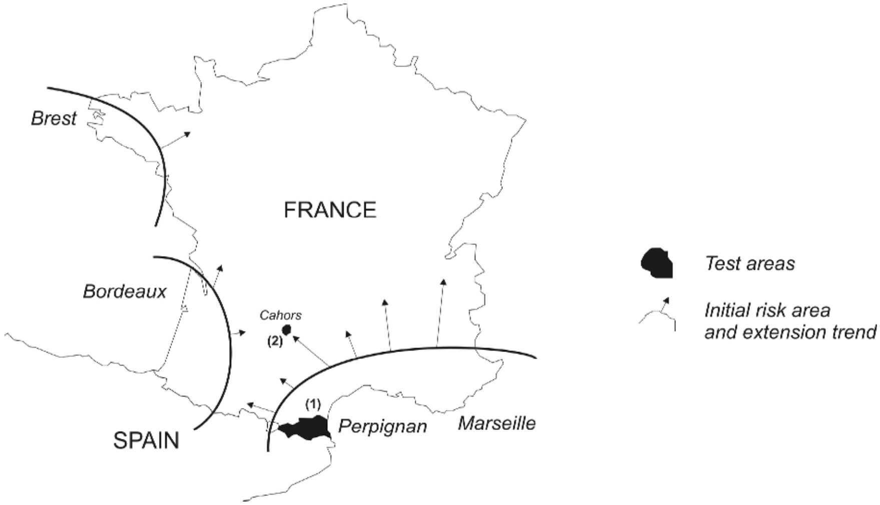


Fig. 6.1 Location of test-areas supporting

6.2.2 Statistical and geographic data

Fire diagnosis integrates the principal factors for fire risk (wind, topography, vegetable cover, human installations, etc.) following the logic of the principal practices and recommendations in that matter (Gouma et al. 1998, Garry et al. 2002). Statistical and cartographical basic data are elementary data (not yet valorised) mobilized by practicing the methodology described in Sect. 6.3. Table 6.1 specifies the type, items and origin of these data. They are mainly generic data, initially spatialized or derived from spatial extrapolation models. Generic data is used in order to make the methodology transferable, geographically comparable, as well as its results. Data integration and management (and treatments) are carried out under ESRI/ArcGIS 9.0, in both georeferenced raster and vector modes.

Table 6.1 Type, format and origin of main geographic data

TYPES	ITEMS	SOURCES		
		Macro-scale	Meso-scale	Micro-scale
Vegetation	Types, Structure, Dominant species and Biovolum	Generic maps (>1/50000) Remotely data (decametric data) Field (ponctual measurments)	Remotely data (metric data) Field (systematic measurem.)	Field obs.
Relief	Slope / Orientation	Altimetric data (decametric data)	Altimetric data (metric data)	Field obs.
Planimetry	Runway network / Building areas	Generic maps (>1/50000) Remotely data (decametric data)	Generic maps (>1/25000) Remotely data (decametric data) Field observations	Field obs.
Climate	Mean temperature and rain / Wind distribution	Regional climatic synthesis Regional wind models	Local climatic synthesis Field expertise	Field obs.
Fire	Fire history	Fire database (kilometric data)	Fire database (hectometric data)	Field obs.

6.3 Methodology and practical application to the data sets

6.3.1 Fire risk diagnosis

Diagnosing fire risk points at the same time towards evaluating (qualification and quantification), posting up (graphical and statistical transcription, hierarchization and zoning) and directing actions for risk prevention (Fig. 6.2). It meets the needs of the developers and respects their constraints, and it has three scales of observation, which are precise and have specific purposes, which fit into each other hierarchically in space and chronologically in the process (Fig. 6.2): (1) macro-scale observation (low level of precision / department scale or equivalent) hierarchically identify “basins at risk” (grouping of municipalities); (2) micro-scale of observation (intermediate level of precision / municipality scale or equivalent) aiming to hierarchically identify “basin of risk”; (3) medium-scale of observation (high level of precision / infra-municipality scale) aiming to specify “sensitive points”. The scale of observation determines the type of diagnosis and the level of geometrical and informational precision: ex situ diagnosis with macro and medium-scales, based on generic cartographic data enhanced by a good field knowledge (macro-scale) or by a precise and systematic field sampling (medium-scale); in situ diagnosis with micro-scale based on very precise field observations and directed grading of risk (evaluation grid).

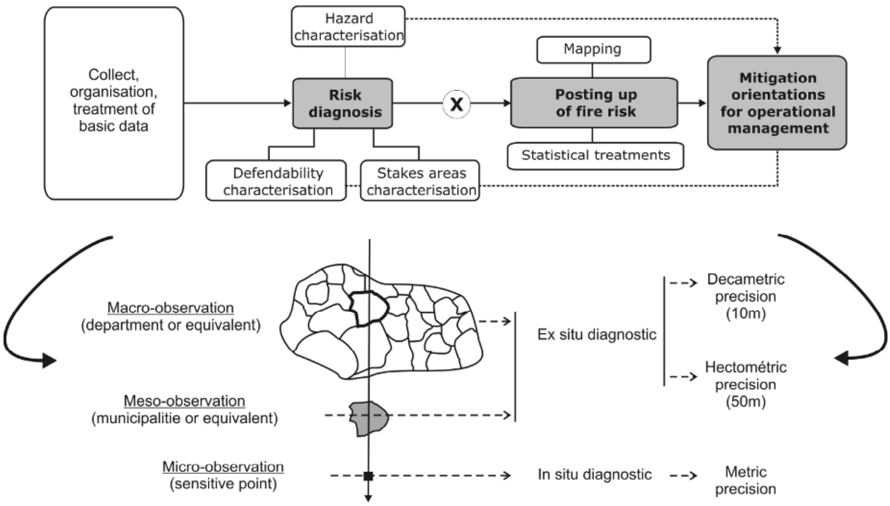


Fig. 6.2 Fire diagnosis approach

6.3.2 Fire risk modelling

6.3.2.1 Fire risk concept

The concept of fire risk is now fairly well understood even though it covers different realities that tend to be complex and generalizing. The definition used in this work refers to the superposition of three components. First, a risk related to the level of vulnerability for a given point of getting the occurrence and the uncontrolled development of a fire in a certain scope, intensity and duration, outside the context of any active or passive protection; this vulnerability is said to be "incurred" when it refers to the probability for that point to be affected by a fire because of its neighbourhood, or" induced "when it refers to the probability for that point to be the cause of a fire spreading to its neighbourhood. Secondly, a risk of fire for areas subject to fire risk related to the level of vulnerability of a given point to get potential damage caused by a fire with a determined intensity. This predisposition is proportional to the stakes, to the predictable effects of fire on these stakes and to the level of defensibility of these spaces, which reflects the responsiveness of society (deployment and utilization of emergency means). At a given point, level of risk is expressed in such a way (Eq. 6.1):

$$\text{RISK} = f\,(\text{susceptibility, defensibility, stakes}) \tag{6.1}$$

6.3.2.2 Hazard and defensibility modelling

- General modelling terms and calibration processes

Risk modelling, which means developing models only covers hazard and defensibility components; the stakes component mainly refers to an inventory work. Risk modelling was developed to study hazards and defensibility components.

Fire is regarded as a process of contagion and the level of hazard in a given point as the resultant from a local situation and an influence of the more or less immediate environment. The analysis of the hazard relies on empirical modelling of the phenomenon based on scientific knowledge and on field observations concerning fires starts and behaviours, field realities, human behaviours and hazard management practices. The suggested model fits in combinatorial types and it is a spatially-weighted index model. Hazard and defensibility are determined through a combination of synthetic indicators for hazards derived from intermediate indicators coupled in pairs. Each intermediate indicator is itself derived from statistical and cartographic basic data and incorporates one or more components identified as crucial in the level of hazard or defensibility.

The modelling implemented favours a pragmatic, complex and hierarchical approach of susceptibility, based on specific models and expert statements. The specific models are mainly physical ones (influence of the slope on the spread of the fire front, etc.) and statistical ones (spatial distribution of outbreaks, etc.) and they come from literature or they are developed on the occasion (for tests and/or statistics). Expert statements are developed or validated (for literature) within the framework of a multidisciplinary working group composed of researchers and field practitioners (foresters, firefighters, developer contractors). Preparation of an expert statement is prepared through collective discussions or individual anonymous questionnaires utilized in a statistical way. Experts say intervention both upstream (setting parameters) and downstream (validation) of modelling is necessary.

- Space and time considerations

Taking account of the neighbourhood favours the potential of the buffered neighbourhood (a ring with adjustable thickness) to initiate and spread a fire, in its direction and from its core. The determination of ring thickness responds to time-based technical argument (average propagation speed of an ordinary fire) and operational argument (presumed maximum reaction time of fighting services). In the case incurred hazard, it is estimated that for every fire triggered beyond the limit of the neighbourhood ring, fire-fighter teams will be able to secure the neighbourhood of concern, before the fire comes to close. Conversely, below this limit, and especially since the outbreak will be close to the considered point, the arrival of fire may precede the implementation of emergency means. In the case of induced hazard, it is estimated that the hazard of free spread (without intervention of fighting teams) is maximum in the close vicinity of the point and that it decreases gradually (at least for a time) with distance until becoming very low beyond the limits of 500-1,000 meters. In local contexts, average propagation speed of an ordinary fire and presumed maximum reaction time of fighting services are two variables that are differentially vary in time. The first variable is considered varying the time step ten according trends in land cover and land use changes. The second one may vary at a time step smallest in connection with the setting up of facilities and defence against fire (implantation of roads or fire stations, etc). For considered test areas, ring thickness has been determined at 500 (Lot area) and 1,000 meters (eastern Pyrenees area).

Because intervening in a differential way in the determinism of the hazard associated with the item considered, the portion of space covered by the 500 to 1,000 meter ring is the object of a double space weighting, according to the distance and dominant winds. The weighting according to the distance is based on a decametric and concentric discretization of neighbourhood. It is linear and decreases from the considered point towards the outer limit of the 500-1,000 meters (weighting factor from 1 to 10). The choice of the discretization step is mainly based on technical considerations (dynamic of the fire, opportunities of confinement and / or self-protection, minimum area of regulatory clearing of brushwood).

Azimuth weighting by wind sectors defined according to their vulnerability to blossom and to spread (Fig. 6.3a). These sectors, varying in number, in extension and in position according to the area in question and the nature of the hazard in question (induced or incurred), delimit isocritic portions of space for which any fire starting off in their centre will tend to spread towards the considered point (simplified model of elliptic propagation, using a 45 degree angular matrix (Fig. 6.3b).

Modelling is based on a short time scale including actual and recent multiannuel (last decade) data. Actual data reflect the state of the main components of risk (land cover, land use…) and the last reference state. The aim is to derive an instantaneous and quasi real-time updated level of risk; the update depends on the availability of data and the ability of users to perform and take into account this update. Modelling terms (components combination and calibration) relies on a decade training period, the last ten years preceding the risk assessment.

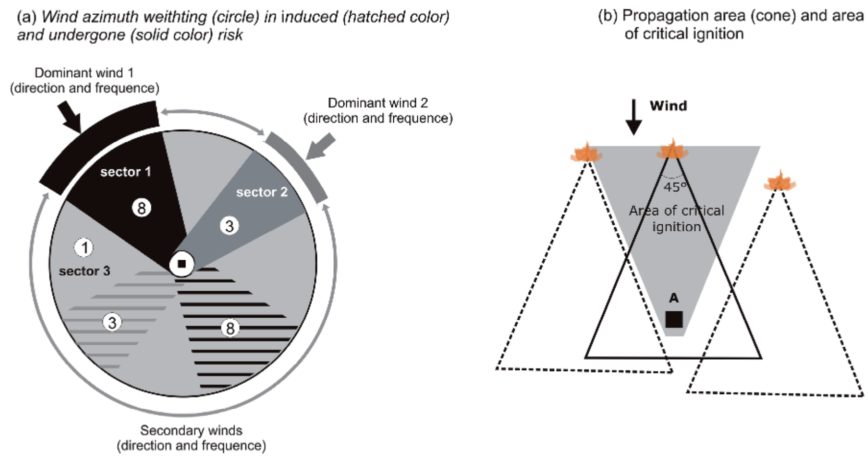


Fig. 6.3 Neighbourhood weighting related to distance and wind influences

6.3.2.3 Stakes mapping goals

The characterization of stakes aims to take inventory, identify and locate any component of the space carrying an existing stake, that is a challenge being currently present (urbanized areas, infrastructure…), or a future stake, that is resulting from a city planning action still to come (implanting a housing estate, closing a lane…). It is based on a typology of spaces and an inventory of specific stakes associated with them. The proposed typology (Table 6.2) observes three types of spaces and five subtypes to which are attached one or more of the four stakes identified (human, economic, natural and patrimonial).

Table 6.2 Type and subtypes of spaces and stakes

	Nature of considered stake and indicators		
Types and subtypes of spaces	*Macro-scale*	*Meso-scale*	*Micro-scale*
Urbanized areas			
Built-up areas	Human, Economic	Human, Economic, Patrimonial	Human, Economic
Areas of concentration of people	Human	Human	
Non-urbanized areas			
Natural or cultivated areas	(Economic)	Human, Economic	-
Natural areas of production	Economic	Economic	-
Sensitive and/or protected areas	Natural	Natural, Patrimonial	-
Infrastructures & aerial networks			
Travel lines	Human, Economic	Human, Economic	-
Energy transportation	Economic	Economic	-

6.3.3 Data processing

The development of intermediate indicators requires for input some statistical and cartographic basic data described in Sect. 6.2.2. These data are processed and valorised (intermediate data) so specific for each indicator intermediary. Each implements one or more intermediaries' spatial data and combined them in image mode and/or object. The changes in value of an indicator reflect its greater or lesser sensitivity test (x) (s) concerned (s). In the interest of getting in touch and comparability indicators among them, the values described by each indicator are normalized by coding in a range from 0 to 100, a 0 value is attributed to local sensitivities and the lowest value 100 to locally situations worst. The indicators are standardized and so-called "gross indicators." These "gross indicators" are then processed (matrix 50 m resolution) so as to apply the weighting associated with the incorporation of the neighbourhood; output data processing are the "intermediate indicators final." They describe in turn values in the range 0-100, but more often with reduced amplitude because of the "averaging" effect induced by taking into account the neighbourhood. Synthetic indicators are obtained by crossing two by two final intermediate indicators and by encoding into 5 levels of intensity (Table 6.3). Each intermediate indicator is discretized into five classes, according to a reclassifying method common to all indicators. The discretizating technique used here consists of splitting into five classes of variable amplitude (exponential growth of classes' size) at the lower limit of 99 percent (floating range). This method favours the magnification of local contrast to the detriment of a comparability of situations observed between separate areas of study (static range).

6.4 Results

6.4.1 Fire risk modelling

6.4.1.1 At macro and medium-scales of observation

- Characterization of forest fire hazard

The fire hazard reflects the level of susceptibility of a given point to the occurrence and uncontrolled development of a fire. It includes both a dimension of spatial occurrence and a dimension of probable intensity, out of the context of any active or passive protection. Determining the hazard is based on four synthetic indicators of hazard derived from eight intermediate indicators (Fig. 6.4).

Table 6.3 Determination cross values synthetic indicators

SYNTHETHIC INDICATOR		*Intermediate indicator 1*				
		Class 1	***Class 2***	***Class 3***	***Class 4***	***Class 5***
Intermediate indicator 2	***Class 1***	1	1	1	2	2
	Class 2	1	2	2	3	3
	Class 3	1	2	3	4	4
	Class 4	2	3	4	4	5
	Class 5	2	3	4	5	5

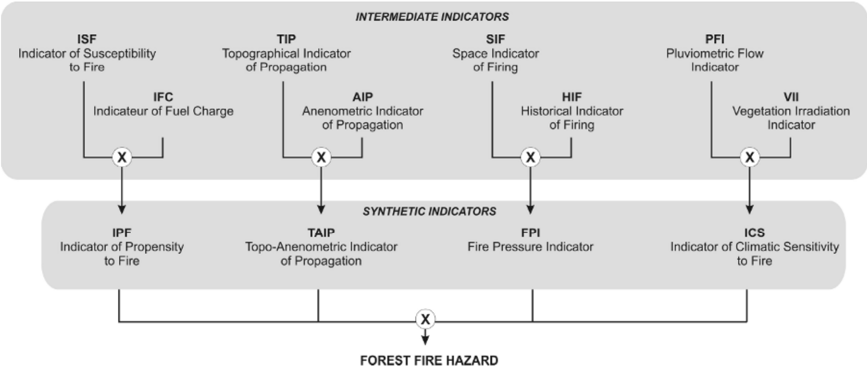


Fig. 6.4 Structure of the forest fire hazard model

IPF, indicator of propensity to fire, translates the propensity of the combustible layer to ignite under the action of a heat source and to stimulate blaze-to-fire transition. It combines two intermediate indicators:

– **ISF**, an ***indicator of susceptibility to fire***, mixing (1) a structural susceptibility defined by types of combustible layer (vegetable stratification combinations) and describing depth and behaviour of the layer regarding combustion deployment and (2), a specific susceptibility derived from the vegetable composition of the combustible layer.

  The value of structural susceptibility (ISFst) represents a mark of sensitivity and vulnerability of the average vegetation (Table 6.4). The mark of sensitivity describes the ease with which the vegetation will be ignited by a heating source and ensure the initial spread of fire. It privileges complex open plants, both rich in fine combustible elements (initial combustibles for fire), and intermediate combustibles enabling fire to gain power and spread to high tree and wood strata (transition). Conversely, it penalizes vegetations with more limited potential for development to fire (herbaceous or low wood plants) or ones that are more closed and / or discontinuous in the vertical plane. The mark of vulnerability describes the behaviour of each type of vegetation in relation to the behaviour of the established fire. It gives importance to plants loaded with combustibles, constant in both dimensions and supplying high power of fire. Conversely, it penalizes plants with low load of combustibles forming a heating source less important and more ephemeral.

Table 6.4 Types of plant fuel structure and related susceptibility to fire

	Recovery of			*Susceptibility to fire*		
Types	High woody (>2 meters)	Low woody (<2 meters)	Herbaceous	Sensibility value	Vulnerability value	ISF_{sp} value
LHd	75-100%	0-100%	0-100%	3	10	6
Lhac	50-75%	0-100%	0-100%	8	8	8
LHc	25-50%	0-25%	0-25%	2	3	2
LHH	25-50%	0-25%	25-100%	7	5	5
LBH	0-25%	25-100%	25-100%	5	7	6
LHBH	25-50%	25-100%	25-100%	10	9	10
ZC	0%	0%	<25%	0	0	0

The specific susceptibility of vegetation (ISF_{sp}) is described from the dominant species composing high and low woody strata and herbaceous strata. Among the species forming the various vegetations, are taken into account the three most representative species in terms of abundance/dominance, regardless of connection stratum. In the case of multi-strata vegetations (covering of each stratum is at least more than 25%), the description considers at least one dominant species per stratum; and where for one of these strata, two or three species show a comparable abundance, the mark of sensitivity and vulnerability taken into account is constituted by the average of the respective marks. The different species are characterized by a mark of flammability and combustibility (IC) coded from 1 to 5 (Table 6.5). The mark of flammability (I) describes the ability of the species for ignition under a heating source; this mark is determined by the average time of ignition. The mark of combustibility (C) describes species' propensity to burn and to spread fire; this mark is based on the criterion of flame persistence and / or superior calorific power.

Table 6.5 Specific values of sensitivity, vulnerability and susceptibility to fire (extract)

High woody				**Low woody**				**Herbaceous**			
Species	**I**	**C**	**IC**	**Species**	**I**	**C**	**IC**	**Species**	**I**	**C**	**IC**
Quercus pubescens	3	5	4	*Erica arborea*	5	5	5	*Brachypodium ramosum*	5	2	4
Quercus ilex	4	5	4	*Cistus monsapeliensis*	4	2	3	*Dactylis glomerata*	4	1	3
Pinus nigra	3	5	4	*Ulex parviflorus*	5	4	4	*Polypodium vulgaris*	1	1	1
…				…				…			

ISF is determined as such in Eq. 6.2:

$$\text{ISF} = \sum 2(\text{ISF}_{st}),\ 2(j_{IC}),\ k_{IC},\ l_{IC} \tag{6.2}$$

with ISF_{st}, the structural susceptibility and j_{IC}, k_{IC}, and l_{IC} the specific susceptibility described through flammability and combustibility values of the three mains species.

– ***IFC***, an ***indicator of fuel charge***, specifying the phytomasse that is available for combustion. The amount of combustible available for combustion is estimated at the scale of each plant by adding up observable availabilities for each stratum (high woods, low woods and herbaceous species). Combustible biomass is determined at the scale of each stratum produced by multiplying the covering rate of the stratum (by ten) and its thickness (meters). The considered thickness is limited to the thickness of the stratum of fine elements forming the main fuel for fire. CLM is determined such as in Eq. 6.3:

$$\text{IFC} = \Sigma(\text{t x R})_{\text{H}},\ (\text{t x R})_{\text{LW}},\ (\text{t x R})_{\text{HW}} \tag{6.3}$$

with t is t, layer thickness, R, layer recovery LB and LH, layer types [herbaceous (H), low woody (LW, < 2 meters) and high woody (HW, > 2 meters)]

TAIP, ***topo-anemometric indicator of propagation***, translates the propensity of the topo-anemometric environment to propagate a fire towards and from a given point. It combines two intermediate indicators:

– ***TIP***, a ***topographical indicator of propagation***, describing, in a given point, the heterogeneity of the surrounding relief and the conditions of propagation that result from it. The slope, upward or downward, exercises a direct influence on fire behaviour including propagation spread. This differential effect is described by a relative factor of propagation exponentially related to the percentage of slope (Van Wagner 1977): over the relative propagation factor, the greater the spread of the fire front is fast, and inversely.

Fig. 6.5 illustrates situations leading to different values of propagation factor on average divergent heterogeneity of the area of propagation (alternately, in the axis of propagation of the fire, upward and downward slopes) characterized by an average of the factors integrated in the linear propagation. It is determined from the weighted average (wind and distance) of the relative factors of propagation, established by topographical facet (50x50 meters). Each facet is described from points of view of its exposure ("to the wind" or "under the wind" in relation to an axis of propagation "facets in question/reference point") and of its slope ("upward" or "downward", slope value), then characterized by a relative factor of propagation.

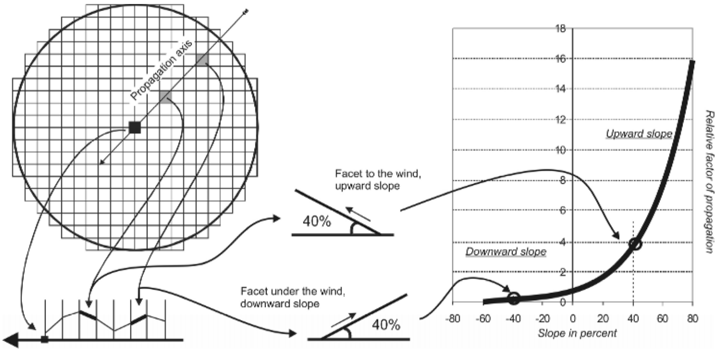


Fig. 6.5 Relative factor of propagation determination according to topographical factor

– ***AIP***, an ***anemometric indicator of propagation***, describing the differential influence of wind speed on the propagation of a fire. The wind has an all the more favourable action on the propagation of the fire because its speed grows and this up to a threshold from which the propagation loses some efficiency (partial combustion, blow-off of flames…). A statistical report carried out on a representative forest fire dataset analysis makes it possible to suggest a grading of the differential influence of the wind (Fig. 6.6). It is this grading that, spatialized on the basis of numerical wind simulation(s) at critical speed(s), determines the AIP.

FPI, ***firing pressure indicator***, translates the sensitivity of the neighbourhood of a given point to fire starts. It combines two intermediate indicators:

– ***SIF***, a ***space indicator of firing***, describing the starting risk at the level of the point in question and at the level of its neighbourhood, via the relative importance of critical spaces for fire starts. The latter are determined according to two criteria commonly judged as deciding: proximity of transportation routes and proximity of dwellings (Table 6.6). Critical spaces are materialized with the means of buffer zones marked out around dwelling and transportation routes. The close proximity of flammable vegetation is a selection criterion for buildings or portions of roads to be considered. The selection of channels of communication is limited to tracks easily and freely accessible to the public and used by it. The communication channels meeting the criteria are ranked according to their potential frequenting into three categories: low (Type 3), medium (Type 2) and high utilization (Type 1). On the basis of entities thus selected, near areas of concentric proximity (buffer zones) are delineated around each building and each portion of road. The distances listed are respectively 15, 50 and 100 m for buildings and 50 and 100 m for communication channels.

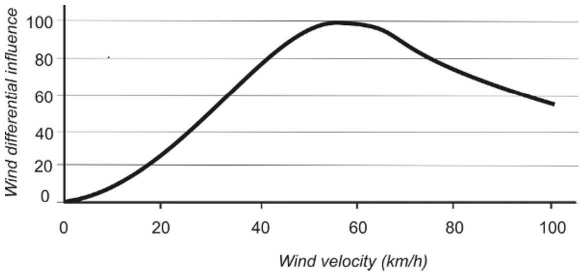


Fig. 6.6 Differential influence of wind on fire propagation

Table 6.6 Fire hazard related to roads proximity versus buildings proximity

		Proximity to road								
		0-50m			50-100m			>100m		
		Type 1	Type 2	Type 3	Type 1	Type 2	Type 3	Type 1	Type 2	Type 3
Proximity to buildings	0-15m	20	16	10	10	8	5	5	4	2
	15-50m	60	48	30	30	24	15	20	10	10
	50-100m	100	80	50	40	32	20	20	16	10
	>100m	70	56	35	30	24	15	5	4	2

– ***HIF***, a ***historical indicator of firing***, describing, by geographical reference unit, the cumulated number of significant fires occurring during the last decade.

ICS, ***indicator of climatic sensitivity to fire***, translates the specific sensitivity of a given place to start and development of a fire, according to its climatic characteristics. It combines two intermediate indicators:

– ***PFI***, a ***pluviometric flow indicator***, describing local climatic characteristics as regard air and soil dryness parameters (amplitude and duration). It is based on the link between air and soil dryness and biological status of the combustible (hydric state, flammability and combustibility).

– ***VII***, a ***vegetation irradiation indicator***, integrating duration of sunshine and amount of solar energy received and cumulated in a given location at the critical point of the diurnal cycle of burning. The illumination received in this place is subject to a number of parameters (including astronomical and topographical parameters), and affects environmental and biological burning conditions (relative humidity, air temperature, air phenomena, heating of combustible…). Conditions of reference for calculating VII are determined from the characteristics of the critical burning period (diurnal seasons and windows). Calculating VII is based on simulations of illumination calendar with astronomical conditions of the burning season's median date, from sunrise till the worst time of the day. These simulations are integrated over time in order to determine, at each point of the space, a period of sunshine and received cumulated solar flux. The intersection of these two variables determines the irradiation indicator of vegetation.

The indicial formulation of the hazard relies on the weighted linear combination of the four synthetic indicators of risk: IPI, ITAP, IPMF and ISC. Various combinations of possible situations for indicators values between 1 and 5 were submitted to a group of experts; for each one of them, the group of experts came to a conclusion about a level of hazard itself spread out between 1 and 5. The statistical processing of the result-data (multiple regressions) allowed the formulation hereafter (Eq. 6.4):

$$\text{Hazard} = 0.45\ \text{IPF} + 0{,}13\ \text{ICS} + 0{,}13\ \text{FPI} + 0{,}29\ \text{TAIP} \tag{6.4}$$

- Characterization of defensibility to fire

The self-defence ability of areas subject to forest fire risk describes their level of predisposition for deployment and action of emergency means. The scope of action of emergency teams - especially in the initial phase of fire development- largely determines the more or less favourable outcome of a disaster and the impact of the fire phenomenon at a particular point.

The self-defence ability model implemented is a structural model for areas subject to fire risk. Regardless of the more or less favourable conditions at the time (exceptional dryness, abnormal unavailability of fighting means related to simultaneity of several fires…), each point of the area presents, because of its geographical location and its equipment, an intrinsic ability to be defended. Thus, an area badly served by lines of communication, about ten kilometers away from emergency facilities and with no defence equipment against fire, is comparatively more difficult to defend than a identical area located along a national highway, in the immediate vicinity of an emergency structure and having unlimited water supplies.

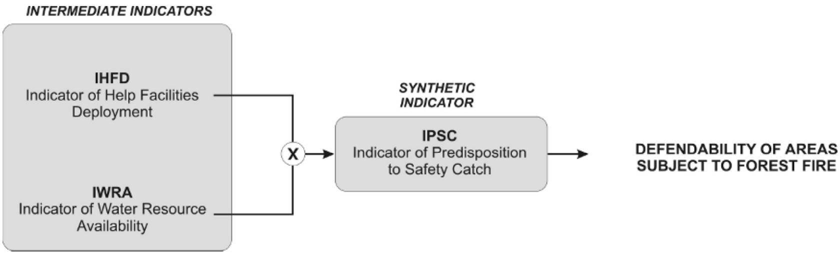


Fig. 6.7 Structure of the forest fire risk model

Determining vulnerability is based on a synthetic indicator (IPSC) derived from combination of two intermediate indicators (Fig. 6.7). ***IPSC***, ***indicator of predisposition to safety catch***, describes the potentiality of the neighbourhood of a given point to ease the action of terrestrial helps in order to limit the risk of seeing a fire being propagated until reaching the aforementioned point. It integrates:

– ***IHFD***, an ***indicator of help facilities deployment***, describing the risk covering level via the relative importance of rescuable spaces described in terms of times for intervention and possibilities for action. The ability of fighting means to move across space and to act quickly on a disaster structurally depends on two factors: on one hand, the presence of a network of channels of communication enabling crews to travel from their parking spot to the fire area; on the other hand, the distance between these two points, which affects the intervention spell. A rapid deployment of the emergency crew most often enables attacking fire in the early stages of its development. This initial attack is crucial and critical since it corresponds to a stage where the fire, easily challengeable, is going to turn into a fire more difficult to contain, consuming more fighting means and much more damaging.

  Times for intervention are determined from transit isochrones (10, 20, 30, more than 30 minutes), established from parking places for help facilities, on the basis of standard vehicle of intervention. Calculation considers three types of lanes to which are associated specific speeds, indexed on the percentage of slope (Table 6.7). It also integrates, for a given time of intervention, the possible starting points of help facilities: from one parking place or at least two parking places (Table 6.8). Given that the possibilities of action of the terrestrial help facilities decrease according to the distance from the transportation routes on which they move, space is cut out in four geographical sectors with optimal (0 to 100 m), reduced (100 to 200 m), minimal (200 to 300 m) and inexistent (beyond 300 m) possibilities of action.

Table 6.7 Relationship between road types, slope and speed (km/h).

	Slope values			
Types of roads	Zero slope (0-10%)	Low slope (0-30%)	Moderate slope (30-60%)	High slope (>60%)
Main roads [highways]	60 [70]	50 [70]	40 [60]	25
Secondary and minors roads	30	25	15	10
Access paths				

Table 6.8 Relationships between, road proximity, help nature and transit times

		Proximity of road		
Transit times		0/100 m	100/200 m	>200 m
d<5’	*Help from one parking place*	80	60	20
	Help from several parking place	100	80	30
5<d<10’	*Help from one parking place*	50	30	10
	Help from several parking place	70	50	20
10<d<15’	*Help from one parking place*	20	10	5
	Help from several parking place	40	20	10
15<d<20’	*Help from one parking place*	10	7	2
	Help from several parking place	15	10	5
d>20’	-	5	2	1

– ***IWRA***, an ***indicator of water resource availability***, describing the level of water cover via the relative importance of spaces where the availability of the resource is real and continuous. In a given point, this availability is determined from geographical position that it occupies and theoretical time of rotation. Theoretical time of rotation (TTR) is defined like the time taken by a fighting vehicle to reach a water point, fill its tanks, reach back its starting point and get back to its duty. This theoretical time of rotation is calculated according to four variables: medium flow of watering per machine, water capacity of the machines, flow of aspiration or feeding and time of manoeuvring. Around each usable water point, one defines limits of zones for which theoretical time of rotation is equal to once, two and three times the watering time of a machine (WTM) (Table 6.9). For each zone, one also considers the number of usable water points (one or two at least).

Table 6.9 Time-based water availability

		Proximity of road network		
TTR / TAE		0/100 m	100/200 m	>200 m
TTR=WTM	*Access to one water point*	80	60	15
	Access to more than one water point	80 →100	60 → 80	
TTR=2WTM	*Access to one water point*	40	30	10
	Access to more than one water point	40 → 60	'30 → 40	
TTR=3WTM	*Access to one water point*	15	10	5
	Access to more than one water point	15 → 30	10 →15	

6.4.1.2 At micro-scale of observation

Risk is appreciated thanks to a field expertise directed and synthesized in a grid of pre-formatted evaluation (Table 6.10). For each “sensitive point”, the expert comes to a conclusion about the levels of hazard and vulnerability in relation to the criterion identified by the grid. The selected criteria describe either one or the other of the hazard /vulnerability components of the hazard, or both. With each criterion several methods are associated, which describe the local configuration, and with each method, a mark of danger is associated. The level of risk is obtained by the average of the various marks of danger.

6.4.2 Fire risk display

Displaying constitutes the bring-to-knowledge of the risk. It pursues three major goals: graphical and statistical transcription of the risk, its hierarchization and the establishment of a regulatory zoning of the territory for development. Fig. 6.9 synthesizes the risk displaying procedure. The four maps which support the display are presented thanks to a variable scale that differs according to the observation scale (macro, medium or micro-scale). Hazard, defensibility and hazard-defensibility synthesis ones share the same colour code (from yellow (weak risk) to red (very high risk)) that materializes the five levels of risk. These maps are analyzed as such and are coupled with a multi-scale cartography of the current or future stakes. Stakes are associated to types of space, to a nature (human, economic and patrimonial) and to an indicator of stakes.

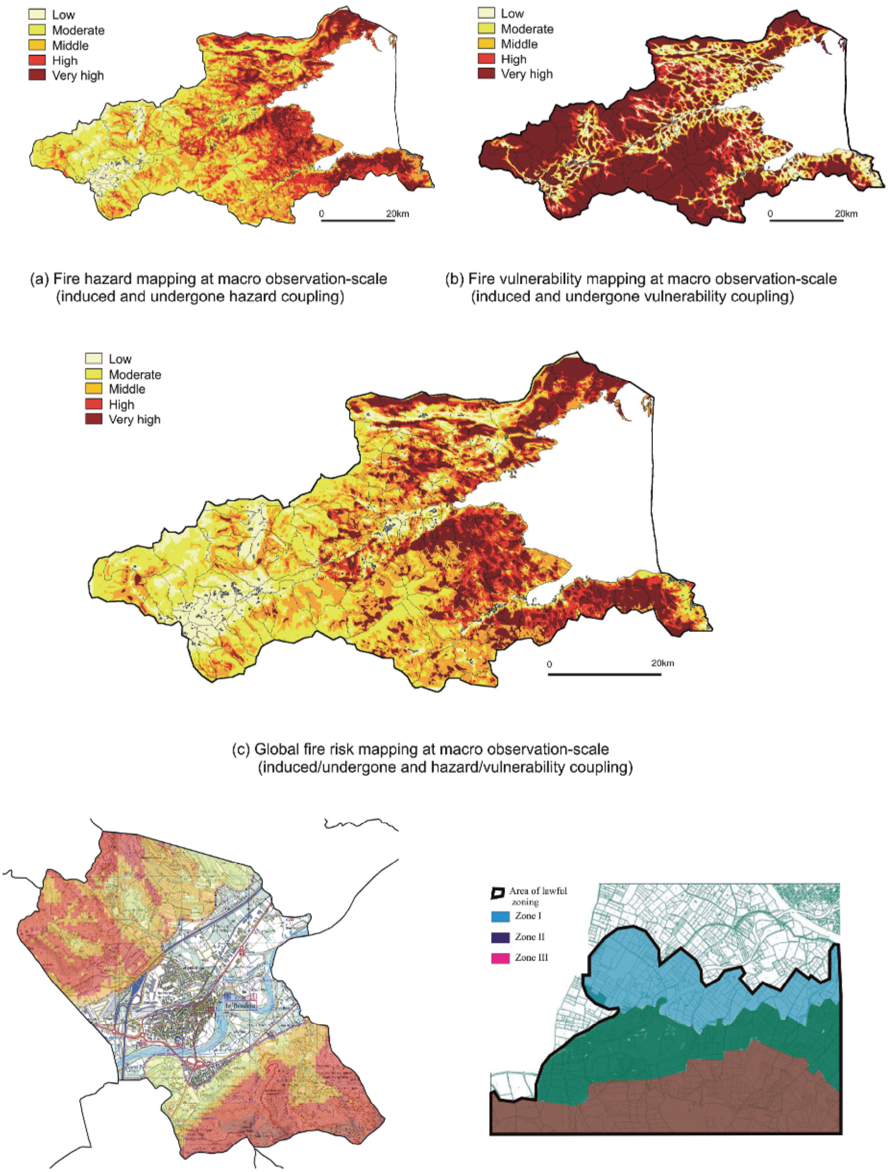
At macro-observation scale (department or equivalent), risk display is based on a 1/100,000 cartography (risk and stakes). The basic risk display unit is the municipality (or equivalent). For each municipality, one automatically determines the ventilation of the municipal territory by types of induced, undergone and global risk. One then evaluates the proportion of spaces with current and future stakes (by type and nature) by municipality. This method makes it possible to organize municipalities into a hierarchy, by levels of sensitivity to the risk, and to delimit “basins of risk” grouping municipalities of equal sensitivity. Three profiles of groupings are identified: municipalities having priority for a more detailed approach of the risk (medium and micro approach); municipalities for which a more detailed approach of the risk is advised (medium approach); municipalities that do not require a more detailed analysis of the risk.

At medium-observation scale, the risk display is based on a 1/10,000 municipal cartography (risk and stakes). According to a procedure comparable with the preceding one, one identifies “basin of risk”, which are classified in five levels of increasing sensitivity. Each soil of level III, IV and V is analyzed more finely (micro-observation) and is the object of a 1/1,000 cartography characterizing sensitive points that are more or less strongly subjected to the risk (classification in five levels of risk).

Table 6.10 Presentation of the pre-formatted grid evaluation (micro-observation)

Expert identification: **Date :**
Municipality identication: **Sensitive point identification :**
Observations :

Criterious	Identification keys	Modalities and notation of risk					Note
		1	2	3	4	5	
I. VEGETATION							
1. Charge combustible	Relative vegetation recovery (aerial and ground fuels)	<10%	10-30%	30-50%	50-70%	>70%	
	Biovolume combustible total	<20	20-40	40-60	60-80	>80	
	Vertical continuity	Low	Moderate	Middle	High	Very high	
	Fractionnement du combustible (fine fuels versus total biovolum)	<20%	20-40%	40-60%	60-80%	80%	
2. Vegetation/bulding interface	Relative independance of houses (distance between house and vegetation)	>40m	30-40m	20-30m	<20m	Contact	
	Mean vulnerability to fire of vegetation	1	2	3	4	5	
II. TOPOGRAPHIC CONTEXTE							
1. Position	Bulding location	Down side		Middle side		Top side	
2. Slope	Mean slope	<10%	10-25% uniform	10-25% gullied	>25% uniform	>25% gullied	
III. ACCESSIBILITY SERVICES							
1. Characteristics of access	Number of access	>3	3	2 two-lane road	2 one-lane road	1 dean end road	
	Principal access type	Tared road (high size)	Tared road (médium size)	Tared road (low size)	Access path suitable for vehicle	Access path no suitable for vehicle	
	Predisposition to facilities deployment (safety parking / about-turn areas / crossing areas / tactical evolutions)	All criteria with satisfactory level	At least 3 criteria with satisfactory level	At least 2 criteria with satisfactory level	At least 2 criteria with satisfactory level	No criteria with satisfactory level	
	Accessibility to aerial facilities (helicopter)	Drop zone <300m	Landing possibilities <300m	Drop zone <500m	Landing possibilities <300m	No landing possibilities <500m	
2. Access	Laying out of runway	Very high quality	High quality	Moderate quality	Low quality	No laying out	
	Human pressure on safety access	Very high	High	Moderate	Low	No pressure	
IV. BULDINGS AND RESIDENTS VULNERABILITY							
1. Vulnerability to fire of buldings	Fire resistance of construction materials to termal punctual exposition (structure / shutter / roof)	High		Moderate		Low	
	Efficiency and regularity of clearing	Clearing efficient and regular	Clearing efficient and irregular	Clearing partial and regular	Clearing partial and irregular	No clearing	
	Presence/absence of sensibles equipments (gas tanker, barbecue…)	No sensible equipments		Safety implantation		Non-safety implantation	
2. Residents safety	Awarness programme to people safety and human behaviour in critical situations	Regular actions with written instructions	Regular actions with oral instructions	Ponctual actions with written instructions	Ponctual actions with oral instructions	No action	
	Presence/absence of self-defence equipments	Appropriate and autonomous equipments	Appropriate and low autonomous equipments		No appropriate equipments	No equipments	



(a) Fire hazard mapping at macro observation-scale (induced and undergone hazard coupling)

(b) Fire vulnerability mapping at macro observation-scale (induced and undergone vulnerability coupling)

(c) Global fire risk mapping at macro observation-scale (induced/undergone and hazard/vulnerability coupling)

(d) Fire risk mapping at meso observation-scale

(e) Exemple of landscape lawful zoning for urban control and management

Fig. 6.8 Examples of based-methodology fire mapping issues

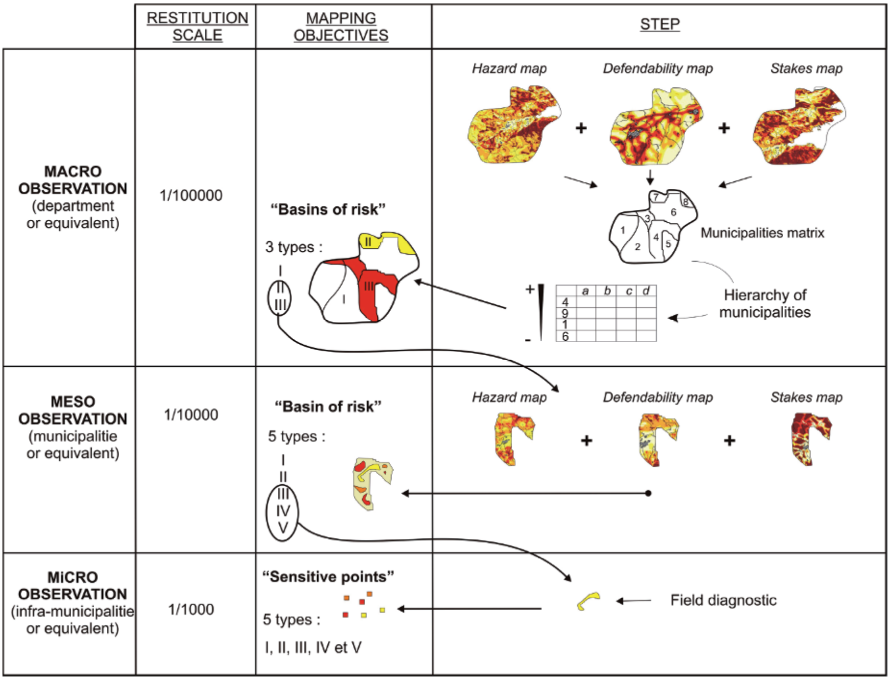


Fig. 6.9 Posting up of fire risk

6.4.3 Fire mitigation orientations

In a given point, actions of mitigation proceed from the diagnosis phase. For a same risk level, the importance of one or the other of the indicators of risk can vary significantly. Therefore, actions must be defined by taking account of the specific determinants of the risk through observed values of indicators. Considering the current and future situation, it has been defined, for each indicator, thresholds of risk acceptability with respect to these values; thresholds are not determined once for all and can vary locally according to field realities and general ambitions in terms of prevention (Table 6.11). For each indicator, orientations are offered, for risk treatment in favour of regional development.

6.5 Validation and discussion of results

Processes and results obtained lead to discussing three main points. The first relates to the validity of modelling approach. Model validation is of primary importance since the diagnosis of the risk resulting from it, meant correspond to reality and to appear in the regulation, conditions the nature and the importance of the development of the territories concerned. It is very difficult to establish, both from qualitative and quantitative point of view. Three techniques were undertaken. Validation by crossing risk values and historical and current fire occurrences doesn't give a very satisfactory indication. This method of validation imposes a significant number of events that can be achieved, as a rule, only after several years. And this, with the risk that the components of the fire risk evolves at the same time (encroachment, new construction…). With regard to the two areas considered tests, the observation period post-diagnostic is too short to implement this type of validation (less than one year to Cahors test area, one to four years depending the scales of observation considered for the Pyrénées-Orientales test areas). Yet with the exception of a few firings atypical (less than 3% of all fires), there is a close spatial correlation between the areas identified as critical (severe risks to very severe) and the distribution of fires once the diagnosis risk established ($r^2 = 0.92$ and $r^2 = 0.88$ respectively to macro and micro scales observation in the Pyrénées-Orientales test areas). For the same test area, it notes that the fires whose area burned is more than 5 hectares are hatched in areas with severe hazards or very severe ($r^2 = 0.91$) and then spread (at least in the initial phase of propagation) sectors with low levels of défendability ($r^2 = 0.99$).Validation by comparison of the results issued from various methods (knowledge-based, spatially weighted and fire probability density function methods) is the second track validation explored. Areas tests that support this study have not been to date comparable spatial analysis. Several simulations risk levels were performed with the methods of Dagorne (1990), Chou (1993), Gouma and Chronopoulou-Sereli (1998), Preisler et al. (2003), NFB (2003) and Petrakis et al. (2005). Because of the cumbersome implementation of the various methods, these simulations were generated on experimental plots square 4 km aside selected in the test area of Eastern Pyrenees. Results comparison is quite as difficult and results comprise differences that are sometimes important. Submitted according to experts, different zoning obtained appear broadly consistent but with wide disparities in detail. The correlative analysis simulations (two in relation to two of all the simulations) show coefficients coefficient of determination (r^2) staggered between 0.31 and 0.79. Among the explanatory factors, spoke to the special characteristics of the plots and, most importantly, predominantly, the nature and number of variables involved. Validation by expert statements –baring its limits in mind– is the third mode of validation tested and the one that has been selected. The validity of this approach holds for the most in the objectivity of the expertise and its definition. Each expert has tried (and often in an objective manner) to guide its position based on his experience, his training and his own beliefs at the time. Objectivity is a sought objectivity college at the expense of a detached objectivity and categorical: then considered objectively as the sum of multiple viewpoints. To do this, several independent and external experts (at least two scientists, two foresters and two firemen, always in equal proportions) are brought to disclose the risk associated to several referential sites. The number of sites is based on the heterogeneity of the study area, by all five sites maximum. At the end of their evaluation, results are compared and the group of experts carries out a critical analysis of the result at the model output. In practice, a moderator is responsible for guiding the critical analysis by promoting consensus. The technique is renewed several times on other five sites, after adjustments of the model, until evaluations conformity.

The second point relates to the question of hazard display, its contents and the contribution of the GIS. One of the major contributions of GIS technology resides in the incomparable capacity to mobilize, combine, and enhance dense and variable space informations. Thus the variables in question tend to becoming more and more complex and often more precise (propagation speed of fire, time of help facilities transit…). The relation between variables as well as the respective contribution of each one of them becomes difficult to establish. Arises then the fundamental question of the optimal level of complexity and precision to be sought. Since hazard display has for vocation to serve as “official support” (and often statutory support as well) to hazard management, the elements it encloses become the reference. Excess of complexity and/or precision (one is not always the consequence nor the condition of the other), when not justified, can lead to an erroneous representation of the hazard level (often heading towards an over-estimate of the hazard) and to an exacerbation of the institutional responsibilities. In terms of operational management, an erroneous representation of hazard tends to go against a durable and sedentary development of the interface territories: on one hand, development or reinforcement of areas sensitive to fire; on the other hand, abusive restriction of the potential of development that any territory must have. Integration of variables such as effectiveness of a planning for fire fighting or such as time of intervention by help facilities is important but sets up a reference to put at fault qualified institutions. During our work, we have been able to measure the importance managing and institutional entities attached to the avoidance of these ways. Such ways do not question at all fundamental contributions of GIS technology. They only ask modalisators for rigour and pragmatism.

Table 6.11 Acceptability thresholds of fire risk in management strategies

	Indicators	*Acceptability Thresholds / Prenscription Management Orientations* Current		Future
MACRO AND MESO - OBSERVATION	Indicator of propensity to fire (IPF)			
	Low	●		●
	Moderate	●	Fuel reduction	●
	Moderate	●	Forestry management	○
	High	●		○
	Very high	○		○
	Firing presure indicator (FPI)			
	Low	●		●
	Moderate	●	Awarness actions	●
	Moderate	●	Use codification	○
	High	○	Fuel reduction	○
	Very high	○		○
	Indicator of predisposition of safety catch (IPSC)			
	Low	●	Preventive means of fire attack	●
	Moderate	●	Realisation/improvment of access	○
	Moderate	○	path and water tank	○
	High	○		○
	Very high	○		○
MICRO - OBSERVATION	VEGETATION			
	Low	●		●
	Moderate	●	Fuel redución	○
	Moderate	○	Fuel treatment	○
	High	○	Forestry management	○
	Very high	○		○
	ACCESIBILITY / SERVICING			
	Low	●	Realization/improvment of access	●
	Moderate	●	path	●
	Moderate	○	Accessibility codification	●
	High	○	Laying out of runway	●
	Very high	○		○
	HOUSES / RESIDENTS VULNERABILITY			
	Low	●	Building prescriptions	●
	Moderate	●	Improvment of equipmens safety	●
	Moderate	●	Awarness actions	○
	High	○		○
	Very high	○		○

The third point relates to operational implementation and method transposability. The methodology demonstrated in this paper is today implemented in the experimentation department (macro and medium- scales of observation) and is used as reference for departmental policy as regards fire hazard management. Several plans for prevention of forest fire hazards in the course of instruction are based on this methodology of hazard diagnosis. It was also successfully applied in other departments of the south of France. The multi-scale and relative aspects of this diagnosis partake of generalization of that methodology to all types of territories. Experiment has confirmed that the conditions favourable to operational transposition depend: on the context of the process (initial expression of the needs by end-users, collegial structure researchers/developers/institutions…); on the nature and the availability of data requested at the input of the model (generic geographical data, easily accessible, not very expensive and regularly reactualized); on the man-machine interfacing and in particular on the characteristics of processes (computing time, interactivity of procedures…) and of hardware and software environment; on the institutional environment and on its aptitude to adjust its vision of the hazard.

6.6 Conclusion and outlook

The objective of this research was to provide operational support tool and methodology allowing managers to diagnose, display and manage fire risk for wildland urban interface. Articulating the process around GIS and development of a spatially weighted index model makes it possible to answer to main expectations expressed by risk managers. It allows to take into account and to compare a significant number of factors conditioning risk, following the logic of methodological concepts that are at present the authoritative work (concepts of risk and vulnerability, induced risk and undergone risk…). Information provided by synthetic output maps represents a strong added value in the global and localised perception of risk. The multi-scale approach at the root of the process allows a gradual, comparative and downward hierarchical approach of the risk; it thus supports establishing and justification of priorities and choices of management in a context of growing risk and strong social pressure. The interactive dimension of tools and methodology also argues in this direction, with the possibility given to the developer: to give a dynamic point of view to the risk reality and to the regional management, via direct integration of the modifications for the ground occupation (new constructions, parcels reforestation, stakes evolution…) and via automatic update of the fire risk diagnosis and of its graphical and statistical transcription; to simulate impact of a new installation (construction, preventive installation…) on the level of risk; to make plans of installation (proposal for an orientation in terms of mitigation) and of development (town planning documents) from various scenarios.

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7 Participatory modelling of social and ecological dynamics in mountain landscapes subjected to spontaneous ash reforestation

Monteil C, Simon C, Ladet S, Sheeren D, Etienne M and Gibon A

Abstract

The future of the agriculture in mountain areas constitutes an important stake for sustainable development in relation to landscape functions and their role in local economies. This future depends highly on its ability to develop innovative and multifunctional agricultural systems and to preserve its attractiveness for future generations. Encroachment and reforestation of landscapes, which comes from land abandonment and extensification of land use, raise important topical issues. In Pyrenean valleys, where the land is colonised by the ash tree (*Fraxinus excelsior*), local land managers and policy-makers want to understand better the relationships between the ecological and social processes in order to assist in the design of policies supporting constructive change. Here we present the "companion modelling" approach in which we are all together constructing a simulation model for carrying out a prospective study of land use and landscape changes in the region. According to the principles of this participatory approach, we started developing a spatialised multi-agent model, whose main conceptual aspects are presented here below. The model simulates the evolution of land cover of the agricultural landscape in relation to both the natural and anthropogenic dynamics. Ecological field studies having stressed the role of mowing and grazing practices at the parcel level on colonisation of the local landscape by the ash tree, we focus on the account of prospective change in farmers' land management practices (viewed as a set of decision rules) and their impact. This ongoing study underlines the interest of spatially explicit modelling of the inter-relationships between social and ecological dynamics at the agricultural landscape scale based on an interdisciplinary approach for dealing with rural development topical issues. Both the advantages gained and the difficulties raised are discussed.

Keywords: modelling, participation, multi-agent system, geographic information system, landscape dynamics, ecological processes, management practices, farm, Pyrenees mountains.

7.1 Introduction

7.1.1 Controlling rural landscapes dynamics

Rural landscapes and their changes are topical issues of major importance both in science and policy. There is an important international effort for the scientific assessment of global environmental change on the one hand and a growing awareness of the variety of environmental, economic and social services landscapes provide on the other hand. Indeed, a variety of landscape functions is increasingly regarded as an important basis for sustainable development (Brandt and Vejre 2003, Wiggering et al. 2003). Landscape management in a multi-functional scope is henceforth an explicit item in the agenda of public policies for agricultural and rural development, especially in Europe (e.g., Council of Europe 2000).

Both rationales result in an international research effort towards the spatially explicit modelling of the interrelationships between land use and landscape change and the simulation of their dynamics. On the one hand, landscape ecologists became aware of the importance of the implications of past, present and future patterns of human land use for biodiversity and ecosystem function, and are therefore developing progressive landscape models accounting for their socio-economic drivers, i.e. land use (Turner et al. 2003). On the other hand, land use scientists are increasingly building models on a spatially explicit basis to assess the variety of environmental, economical and social impacts of land use change for rural development (Verburg et al. 2006). A variety of approaches are being developed for building spatially explicit models integrating both land use and landscape dynamics in order to assess their historical changes and to make projections or prospects for their future. They range from the use of spatial statistics, such as models of Markov transition probabilities (Brown et al. 2000) to cellular automata and agent-based simulation models (Parker et al. 2003). The expansion of this later type of approach is very recent. It develops from an evolution in future studies (scenario methods) for supporting environmental policy-making, and also from experience gained in natural resource management (NRM) research and development (Bousquet and Le Page 2004). Methodology of future studies applied to environmental issues evolved continuously with a growing awareness of the importance of uncertainty, of individual human behaviour and of feed-back processes attached to adaptive capacities of ecosystems and social systems (e.g., Greeuw et al. 2000). NRM research developed participatory approaches in which spatially explicit Multi-Agent System (MAS) models constitute a basic media for consultation between land managers (e.g., Etienne et al. 2003).

In this chapter, we present the approach we are developing for modelling social and ecological dynamics in mountain landscapes subjected to spontaneous reforestation. Our approach makes use of recent advances in both future studies and NRM in order to contribute support to local stakeholders in their search for directions for sustainable rural development. The quality of the various landscape functions is all the more important in mountain areas because they are often of a high natural and cultural value and local economies mainly rely on primary production, tourism and leisure activities. The process of spontaneous landscape encroachment by shrubs and trees, concurrent with the decline and modernisation of mountain agriculture, has strong impacts on landscape structure, biodiversity and ecosystem function, the visual and cultural characteristics of the landscape, and on resource availability for agropastoral activities (Bignal and McCracken 1996, Chassany 1999, Caraveli 2000, MacDonald et al. 2000, Olsson et al. 2000). The future of landscape reforestation is all the more uncertain and a matter of social debate, because prospects for silviculture of spontaneous forests are not well established (Curt and Terrasson 1999). The research work we present here is aimed both at supporting local mountain development stakeholders and policy-makers, and at improving scientific understanding of social-ecological dynamics in mountain regions (Curt et al. 1999, Terrasson 1999).

7.1.2 Historical and geographical context

A participatory research project on the spontaneous reforestation of the mountain valleys of Bigorre (French Pyrenees) began in 2003 by the initiative of the Pyrenees National Park (PNP). The project had two objectives: creating knowledge about the ash tree (*Fraxinus excelsior*) overspreading phenomenon and developing references and tools to contribute to the sustainable development of the concerned territories.

The mountains of Bigorre are in the western part of the French Central Pyrenees. Local landscapes are shaped by an old agro-silvo-pastoral tradition (Gibon and Balent 2005). The economy of the region is mainly based on agriculture and tourism, and landscape amenity is very important. The agricultural land, located between 500 m and 1,500 m a.s.l., is mainly occupied by grasslands. It is experiencing a significant encroachment by the ash tree. This species, which is pledged to traditional agro-pastoral systems, is ever-present in the landscape as loose hedges or isolated trees. Since the 1950s, while the number of farms has been reduced by a three factor, more than one-eighth of the used agricultural area has been colonised by ash (Mottet 2005). Local land planners and those involved in development are concerned about the impact of reforestation on the sustainability of agricultural activities, biodiversity, landscape amenity, and on the prospects for economic valorisation of the spontaneous forest settlements. This raises the question for the future of mountain agriculture, which is specialised in breeding and its ability to develop innovative systems in response to the expectations of society and to maintain its attractiveness for future generations.

7.1.3 Integrative modelling of social and ecological dynamics

Our participatory research project brings together researchers from ecology, agricultural and forestry sciences, and geo-informatics (members of the DYNAFOR research unit) and a set of institutional stakeholders of the rural development from the study area (DDAF65, CDA65, CRPGE: see acknowledgements). It began with the building of a visualisation toolkit of future landscape scenarios (Gibon et al. 2006). Now our approach is focusing on building a MAS simulation model for prospecting a set of landscape-change scenarios based on the principles of the "companion modelling" (ComMod 2006).

The rationale for using this participatory method is to involve the local resource managers and policy-makers of the peripheral area of the National Park of the Pyrenees into the various stages of the model development, in order to facilitate sharing knowledge about political measures able to support sustainable development of the mountain area under consideration. Recent works showed that the individual behaviour of the farmers and land owners, as regards maintenance or abandonment of the agricultural use of their land, is an important factor for the spatial patterns of landscape reforestation (Gellrich et al. 2007, Mottet et al. 2006). The objective of our participative research is the co-construction of a simplified and shared representation of the situation at the landscape/village scale that can make it possible to assess scenarios of land use change according to various assumptions about forthcoming changes in the local environment and public policies. It relies on the development of a common view of the interactions between the change of agro-pastoral land management and the processes of ash tree encroachment.

From the research point of view, our first question has been to perform an interdisciplinary assessment of the relationships between the social and ecological dynamics at the landscape scale. In a first step of the project (2003-2006), we characterised the main aspects of the processes involved from various field studies: the ecological processes of ash tree colonisation and their impact on biodiversity (Julien 2006, Julien et al. 2006); the variety in the structure, spatial layout and land use practice of the individual family-farms and their evolution since the 1950s (Mottet 2005, Mottet et al. 2006). A study of the growth potential of spontaneous ash tree forest and its interest for wood production according to two silvicultural management schemes has been started since 2005.

The participatory prospective study we report here benefits from the results of these various research studies, aiding in the development of a common integrated view (i.e., a conceptual model) of the interrelationships between land use and landscape change.

7.2 Study area and data sets

The studied area is the agricultural landscape of Villelongue village (42°57'N, 0°3'W), located about 180 km to the southwest of Toulouse, and 20 km to the south of Lourdes. It covers a small catchment of approximately 2000 ha in the peripheral area of the Pyrenees National Park (Fig. 7.1).

The average annual temperature is 12.5°C (6°C for January and 20°C for August) and the average annual precipitation is 1,000 mm (59 mm for July and 111 mm for April; data from Meteo France, years 1983–2001). Common lands and summer pastures represent about 1,700 ha. Private agricultural land, which covers about 300 ha, lies between 450 and 1,300 m a.s.l. Often steeply sloped (7% of the surface area has a slope over 30%), this land is currently worked by eight farmers.

Most of the farmland utilised area is dedicated to grassland for pasture and haymaking. The agricultural holdings are quite small (average of 18.2 ha) and have extensive livestock farming systems: goat, cattle or mixed cattle and sheep farming (mainly for meat).

The village conditions in 2003 are used as the baseline to simulate the interactions between land use options and ash encroachment for the long term (30 years). Spatial information is maintained in a geographical information system (GIS). Each cell of the landscape map is characterised with a land cover category (cropland, grassland, encroached grassland, young reforestation, woodland, building, and other), a land use category (crop, meadow, pasture, abandoned, wood, and urbanised), slope (less than 10%, 10 to 30%, 30 to 50%, and more than 50%), and identification numbers (farmer, cadastral parcel, and agricultural parcel). Agricultural parcels are used as the basic units for simulating the farmers' technical management of the farmland. Each farm is characterised with the farmer's age, a type of land management strategy, the size of its herd, the cadastral parcels it includes and its agricultural parcels, i.e., its land management units (Fig. 7.1). Types of land management strategy are characterised into the four categories established by Mottet (2005) at the farms in the region.

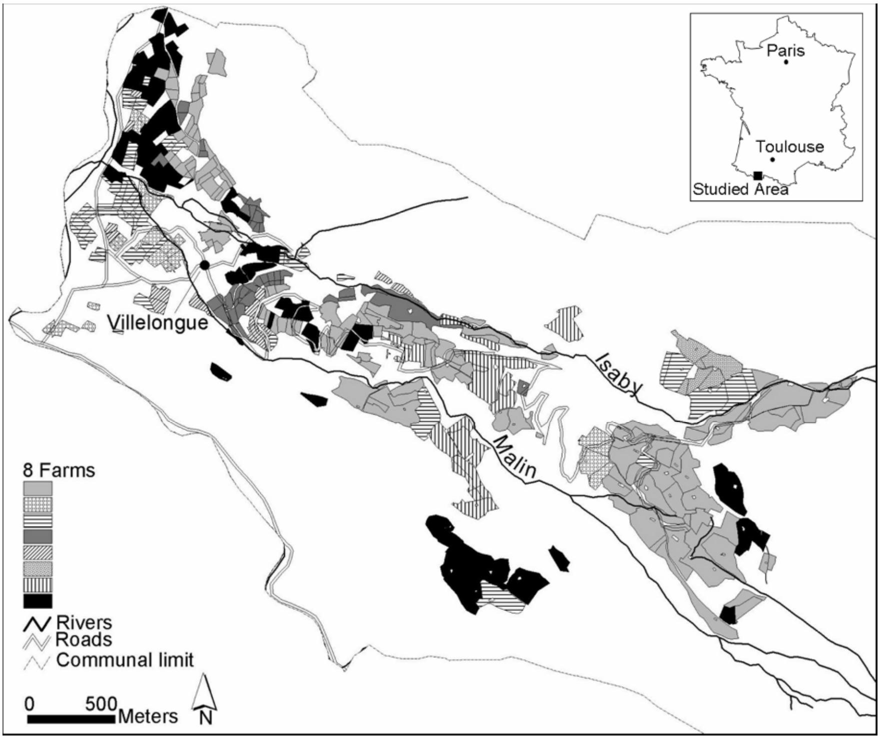

Fig. 7.1 Layout of territories of the farms in the Villelongue village (peripheral area of the Pyrenees National Park). Agricultural parcels of each of the farms are represented using a specific grey nuance. Unfilled areas correspond to village buildings, abandoned farmland and common grazing lands

7.3 Methodology and practical application to the data sets

The questions, of the local participants in charge of rural policy-making, concern anticipating the spatiotemporal dynamics of the landscape reforestation process and their impact on local economy (through change in landscape functions) on the one hand, and assessing the land management orientations that can help control the process on the other hand. The common understanding we built for the interactions between the ecological processes and the agricultural land use lead us to assume change of land management at the individual farms as the main proximate factor driving the landscape reforestation patterns. Therefore we considered it necessary to simulate and evaluate on a spatially explicit basis, assuming changes in individual farmer behaviour in regard to land management and their impact on land covers, according to various scenarios of change of public policies. We selected the multi-agent system (MAS) method for computer modelling, because of its capacity to represent behaviours of actors in their environment (Pahl-Wostl 2005, Parker et al. 2003), and the platform CORMAS (Bousquet et al. 1998) as model development tool, which is well adapted to NRM simulation (e.g., Etienne et al. 2003).

7.3.1 The companion modelling framework

There are several ways of integrating participation of local actors in the development of a model. Parker et al. (2003) identify three main levels of interaction between actors and the model: the actors participate in the design process itself, the actors use the model in the form of role playing games, the actors use the model as a fully functioning scenario-analysis tool. These three levels of interaction between actors and the model can also be combined into a given participatory modelling approach. But the above-mentioned authors note however that the third level of interaction is the most widespread in the literature.

The "companion modelling" approach we adopted (see upper section) relies indeed on a co-construction of the models used with the actors of concern (D'Aquino et al. 2002). The scientific posture adopted in this approach, designed by a research group of the CIRAD Montpellier (Bousquet et al. 1996, Barreteau et al. 2003) and applied for several years for supporting NRM in various contexts (Etienne et al. 2003, Castella et al. 2005), is based on an ethics of transparency concerning the mobilised knowledge and the formulated assumptions (ComMod 2005). The participatory building and use of simulation models and/or role playing games help common learning about the dynamics of socio-ecological systems, and the exploration of scenarios supports reflexion and collective decision-making (Bousquet et al. 1996, Barreteau et al. 2003, Becu et al. 2006).

The development of our model follows an iterative methodological process including conceptualisation, implementation and validation phases in several loops. Conceptualisation and validation phases are carried out through workshops between researchers and local partners, and meetings with researchers only. During these workshops, the results of research studies and expert views of local partners are discussed and combined for modelling the current condition of the land use/landscape system under study, and a set of plausible evolutions for the next 30 years are created.

The implementation of the computer model is carried out in parallel to facilitate feedbacks with the conceptualisation phases. This procedure makes it easier to detect inconsistencies or gaps in the conceptual model and thus helps to improve it. The validation phases consist of a comparison of the implemented and the conceptual models by researchers and local partners, according to the method of social validation of simulation models (Bareteau et al. 2003, Castella et al. 2005). This method is in agreement with the view that the concept of validity is dependent on the purpose of the models under examination (Küppers and Lenhard 2005).

Simultaneous to the conceptualisation of the model, we have commonly agreed which fields should be explored in the scenarios for the future: the demography of the farm population, the municipal policy of urbanisation, and the agricultural and environmental national policies. Indeed scenarios that will be analysed are "external" scenarios (Börjeson et al. 2006, Simon et al. 2006), i.e., scenarios that focus on factors of change beyond the control of the future-study's participants – here the local partners. The ex-ante definition of scenario topics enables us to direct the construction of the simulator and make sure it will integrate the required elements to address them and assess their impact.

7.3.2 A tool: the multi-agent system modelling

In the companion modelling approach, the model plays the role of an intermediary object that allows for the sharing of knowledge and representation, and assessment of scenarios for change (Etienne 2006). Multi-Agent Systems (MAS) are Artificial Intelligence tools particularly adapted to the simulation of dynamics of natural resource management systems, and the exploration of hypotheses about their future (ComMod 2005). A MAS is able to represent a common resource space in which several categories of computer entities "agents" are able to get information from their environment, operate on it and interact with other agents (Ferber 1995, Franc and Sanders 1998, Parker et al. 2003). These agents can be computer implementations of various actors that operate on the resources or that are dependent on them, and make their decisions according to their own decision criteria with regard to the spatial and temporal characteristics of the common space (Bousquet et al. 2002).

We adopted this formalism for representing simultaneously (1) the farmers' land management rules according to their individual strategies and the conditions of their immediate and overall environment, (2) the ecological processes of colonisation and encroachment of the grasslands and (3) the interactions between land use and ecological dynamics.

7.3.3 A method: the ARDI (Actors, Resources, Dynamic, Interactions) approach

The first phase of our companion modelling approach consisted in collectively identifying the relevant actors to be represented, their management entities, and the ecological dynamics to be considered. For this purpose, we used the ARDI method that suggests answering the four following questions (Etienne 2006):

- Who are the main actors (A), who have or can have a decisive role in land management on the landscape considered? While identifying them, one has to differentiate between the "direct" actors, whose practices have a direct impact on land cover dynamics, and the "indirect" actors, whose actions influence the direct actors and induce change in their management practice.
- Which are the main resources (R) to be taken into account?
- What are the main ecological dynamics (D), and how are these dynamics affected by the actors selected?
- How does each actor use the resources and interact (I) with the other actors?

The answers to these questions were first formalised in the form of structured diagrams developed during workshops between researchers and partners. These diagrams were used to facilitate both a common understanding between the workshop participants, and the computer implementation of the answers.

We wrote detailed minutes of every workshop in order to monitor the choices agreed upon and their rationale, and to facilitate common decision in case of potential revision later. Additionally, we updated a structured review detailing the state of development of the model after each workshop and business meeting.

We consider these documents important for several reasons: (i) they facilitate the integration of new partners into the project; (ii) they will support the ex-post evaluation of our project, and (iii) they will facilitate the refutability of the model developed.

7.3.4 A requirement: a simplified but relevant simulation model

The modelling choices rely on our objective to develop a simplified but relevant model of the interactions between the social and ecological processes. The objective of simplification comes from our desire to facilitate the understanding of the model operation and building assumptions and its use as a simulator of various scenarios for change. The objective of relevance refers to the capacity to simulate the spatiotemporal land cover changes on a sound basis as regards to the evolution of the landscape properties consecutive to land use change. The objectives of simplicity and relevance are often in opposition to one another. This led us to compromises in the selection of system entities to be represented in the model and the degree of accuracy adopted for it. In particular, the choices of spatial resolution (size of the pixel) and temporal resolution (time step of the simulation) of the MAS model have been very challenging within the participatory group. The knowledge gained in the research studies on the socio-technological dimensions of local land management practice and their rationale, the ecological processes of landscape colonisation by the ash tree and their interactions under local conditions played an important part in the common design of the simulation model and the levels of simplification which could be applied to its different parts.

7.4 Results

7.4.1 The SMASH model

The result of our participative work is the creation of the SMASH multi-agent model (Spatialised Multi-Agent System for ASH colonisation of landscape). SMASH is based on a set of sub-models accounting for social dynamics (land use according to farmers' farm-management strategies) and ecological dynamics (process of grassland encroachment by the ash tree in relation to land use practice). The various sub-models are built with common representations agreed upon within the participatory research group from both scientific knowledge from our research team and expert knowledge from our partners. The SMASH model is currently under development. We present here the most important aspects in reference to the steps of the ARDI method.

7.4.2 Social actors and natural resources management

The static structure of the model is synthesised in a class diagram (Fig. 7.2) using UML conventions (Unified Modeling Language) (Muller 1997). This diagram specifies the key classes and their relations.

The main direct social actor is the farmer. He is considered to manage a farm made up of spatial entities (its farmland) and non-spatial entities (its herd). His behaviour has a direct impact on ash colonisation of grassland through his agricultural land use practices at the parcel level (mainly mowing and grazing), which itself depends on his farm management and development strategy. We plan thereafter to model other social actors playing a part in agricultural land management and the land use dynamics, e.g., people which purchase agricultural barns to turn them into holiday houses (agent "secondary resident"). These people are regarded in the model as indirect actors who impact on land management decisions of the farmers.

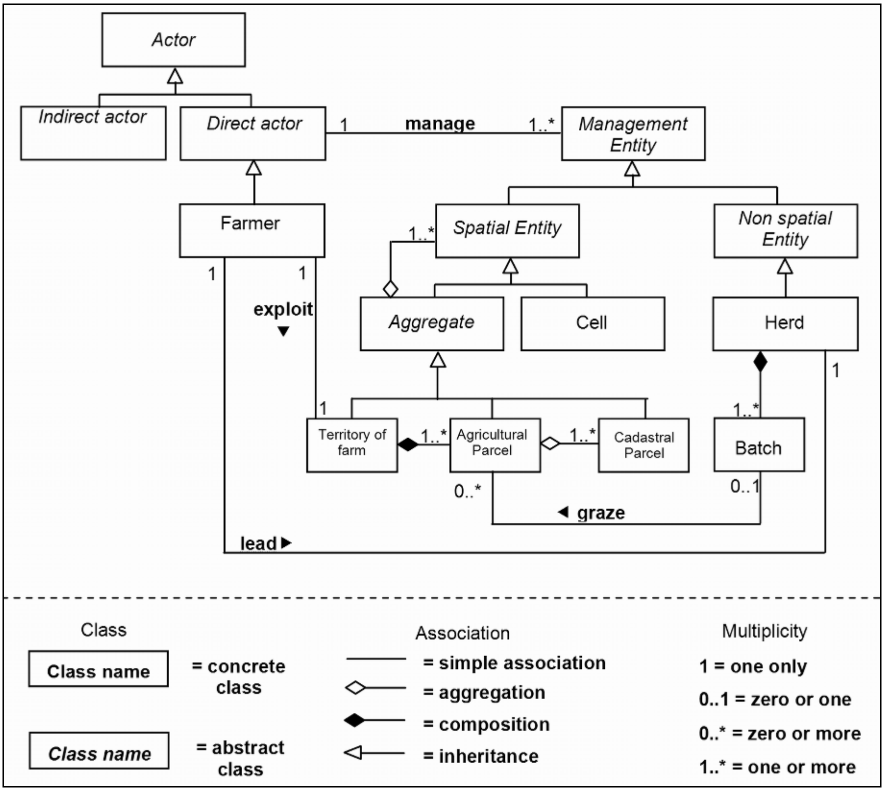

Fig. 7.2 Simplified UML class diagram (Muller 1997) illustrating the key entities of the SMASH model

Landscape space is represented by a grid of elementary space units, the cells. Each cell is characterised with a set of attributes, among them land cover, which allows for the characterisation of the dynamics of installation and expansion of the ash tree in the landscape: i.e., cropland, grassland, encroached grassland, young reforestation, woodland, building, and other.

Three essential spatial entities are superimposed on the spatial grid: the cadastral parcel, the agricultural parcel and the territory of the farm.

The cadastral parcel is the basic unit for land transactions in regards to ownership (transfer by inheritance; sales) and land use rights (land renting). These changes interact for a large part with the individual farm development strategies and individual farmland restructuring. They later impact in return farmers' land management and land use.

The agricultural parcel is the basic unit of the farmland technical management at the farm level. Every agricultural parcel is currently defined in the model as an aggregate of cadastral parcels, characterised by a land use category: crop, meadow, pasture, wood, abandoned land (i.e., in a transition state characterised by the lack of a regular agricultural use). The technical actions operated by the farmer on the agricultural parcels result from his year-round management strategy of the farmland he works. The whole set of agricultural parcels managed by a farmer constitutes the territory of his farm (his farmland).

In the local conditions, the farmer's land management strategy is driven by his herd feeding objectives. Herd feeding year-round includes a wintering period when the herd is fed hay (harvested on the farm meadows) and cereals and maize (harvested on the farm croplands), and a grazing season during which the herd gathers grass on the farm pastures and meadows by themselves, and additionally on the common grazing lands during summer time. The land management strategy consists in a year-round adaptive plan (set of rules) with regard to the spatio-temporal arrangement of mowing operations on the farm meadows, and the batching and allocation of herd animals to farm pastures and meadows, and to common lands. This plan and the climatic conditions of the year determine the harvest type and consumption yield of the grass produced at every grassland parcel. It impacts in return on the dynamics of ash installation in space and time.

7.4.3 Dynamics of the natural resources and ecological processes

Spontaneous reforestation can result not only from a complete abandonment, but also from an extensification of land use (Baudry 1991). Ecological studies carried out by members of our research unit showed that, under the conditions of the study area, (i) every agricultural parcel is subject to an ash seed-rain, because of the spatial distribution of old ash trees throughout the landscape (Julien 2006), and (ii) while mowing prevents efficiently ash colonisation in mown grasslands (i.e., meadows), grazing alone cannot prevent it, when the grazing intensity results in an annual consumption rate of the herbage biomass produced by the parcel below a certain threshold (Julien et al. 2006) (Fig. 7.3). The threshold corresponds to a quantity of grazed herbage amounting to 50% of the grass produced (Balent, comm. pers.).

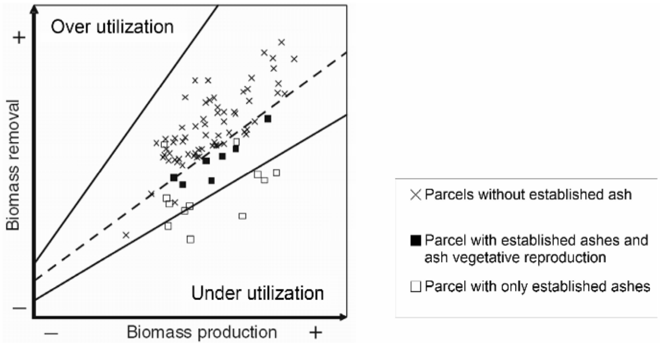

Fig. 7.3 Model of the interactions between the installation of ash trees and land use of the agricultural parcels in the PNP peripheral area (Julien et al. 2006). Parcels located in the area above the upper line suffer from an over utilisation and the ones located below the lower line an under utilisation. The dotted line represents a threshold of intensity of use (ratio biomass removal/biomass production) below which the ash can establish in grasslands which are regularly grazed but not mown

During the participatory workshops, we could build from these results and additional results about ash populations' growth a simplified model of the dynamics of land cover succession in the form of rules of transition. The resulting diagram (Fig. 7.4) indeed illustrates the close interactions between human interventions and those related to the natural processes at the agricultural parcel level: for example, a pasture becomes colonised by ash if it is not grazed for three consecutive years or if the grazing pressure is lower than the threshold for a five years period. A colonised pasture, if not sufficiently grazed, becomes encroached by ash after seven years when there is not any farmer action such as for instance roller chopping.

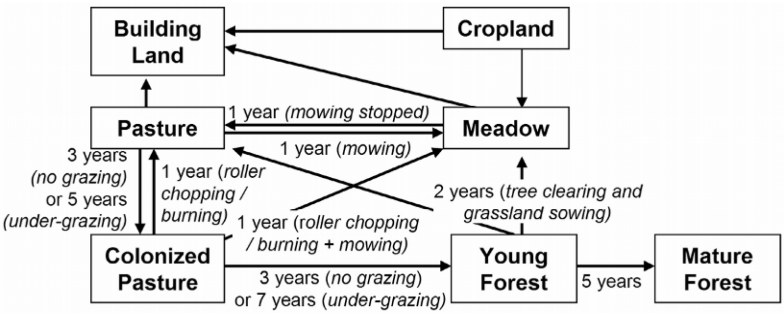

Fig. 7.4 Diagram of transition of natural resources in the case study area

Applying this model requires the assessment of the grass production yield and the herbage consumption for the pasture (grazed-only grasslands). Therefore we introduced in the MAS (1) a grassland model to estimate their grass production on a realistic basis and (2) a detailed model of technical management of the grassland parcels to estimate the herbage consumption by the herd.

The grassland production model used is derived from a dynamic model of herbage accumulation according to grassland category, growth cycle and climatic factors established from studies in other valleys in the Pyrenees (Duru et al. 1998). In this model, three types of grasslands based on annual productivity are considered: poor, medium and productive meadows; for their successive growth cycles, their respective grass growth is modelled from daily climatic data (temperature and rainfall). In SMASH, we use a simplified model according to grassland category and cycle consisting of a growth curve at a 15 day step calculated from the Duru et al.'s model and local meteorological data (see the first cycle of grass growth in Fig. 7.5). We use it to estimate annual grass production on the grassland parcels according to the technical operations carried out, to the date on which they took place, and their duration in the case of grazing operations. The impact of the variations in annual climatic conditions is not yet integrated into the calculation of the grass production.

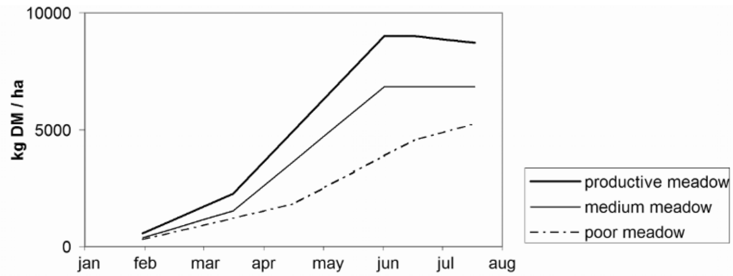

Fig. 7.5 Model of the cumulated grass production during the first cycle of grass growth under the study area conditions (in kg of dry matter per hectare)

The simulation of the operations made on the farm's meadows and pastures at the parcel level from the application of the farmer's land management strategy thus allows for the calculation of the annual herbage consumption on every parcel, by cumulating the days of pasture it provided the herd with over the grazing season.

7.4.4 Dynamics of the use of the agricultural parcels and management of the farms

In farming systems research, farm management year-round and farm development over many years are today generally regarded as general strategies driven by farm-family factors, aims and values (family size and composition, livelihood needs; labour force available, etc.), factors of the local environment (e.g., local market of the agricultural lands; interactions with other farmers, secondary residents, etc.) and overall environment (public policies and agricultural markets). Four strategies have currently been identified among the farmers of our study site: patrimonial strategy, selective strategy, retreat strategy, and niche strategy (Gibon et al. 2006). Within this framework, various research studies showed the livestock farmers' decision making with respect to the farm technical management results from an adaptive behaviour, especially in relation with climatic uncertainty and its impacts on grass production (Duru et al. 1988).

From former modelling of fodder systems (Gibon et al. 1989, Girard et al. 1996), we represented the organisation of the land management practices on the farm parcels to combine (i) a year-round action plan specifying the technical operations to realize on the various agricultural parcels and (ii) methods and rules of adjustment of the plan through the year according to the climatic hazards.

The year-round action plan in reference to production system and main climate characteristics includes periods and related rules for technical operations at the parcel level: for early grazing (e.g., pasture of the meadows before the growth of the hay), spring pasture, first and second mowing, summer, and autumn grazing. The plan includes the definition of the set of parcels at which each type of operation has to be done. It is also at this level that the farmer takes into account the operational constraints on the parcels induced by other land use stakeholders.

In SMASH, actions which apply to the agricultural parcels are carried out every 15 days. This time step was selected to allow a relevant representation of the interactions between the characteristics of the climate of the year, and the dynamics of grass production and consumption at the parcel level. A coarser time step (annual for example) would smooth and simplify the assessment of the annual consumption of grass on the grazed parcels in such a way that would not fit with a realistic enough modelling of the ecological process of colonisation of the pastures by the ash.

7.4.5 Implementation of the model and coupling with GIS

A first prototype version of the model SMASH is implemented using the CORMAS platform (Bousquet et al. 1998) in Smalltalk language. This version is intended to test the validity of the basis of the conceptual modelling and is currently limited to the most common farmer strategy on the study site: the "patrimonial" strategy (Dedieu et al. 2007).

The initialisation of the cell attributes is made with the vector data resulting from the geographical information system (GIS) developed on our study site under the ArcView 3 software. The changeover from their vectorial representation in the GIS to the matrix representation of the spatialised multi-agent model required a rasterisation of the vector layers. We used import-export procedures available in ArcView to rasterise a vector layer in a matrix of numerical values, which is saved with the text format, and we imported into CORMAS the resulting file to initialise attributes of the cells space.

The choice of the cells' size constitutes a generic topical issue when developing a spatialised multi-agent system. It must allow a visualisation of the principal indicators of interest for local actors, and provide a sufficiently precise mapping of the land management entities and ecological processes, while the size of the rasterised representation of the geographical area must remain compatible with the data-processing constraints, e.g., speed of treatment, initialisation of the attributes of the cells starting from the data layers available on GIS (Etienne 2006).

For supporting the choice of a suited cell size, we carried out a comparative analysis of the effects of the rasterisation of the vector layer of agricultural parcels according to various levels of granularity using two methods:

- by the centre of pixel (the only method implemented in ArcView 3): the pixel is affected to a parcel if its centre is included in it;
- by the relative majority surface (method which we implemented in the form of additional script): the pixel is affected to a parcel if the square intersects at least 1 parcel – in that case the pixel is affected to the parcel of which it contains the greatest surface; if the background has the greatest surface, the pixel is not affected with a parcel.

Thus, we compared the results of the two methods for several pixel sizes (100 m², 200 m², 400 m², 2,500 m²) using the following comparison criterion: calculation of the least square of the relative variations of surface of the farm, each one being balanced by its relative surface. A size of 200 m² (side of 14.14 m) was thus retained. The effect of a shift of a half-pixel on X or Y was also tested to select the one minimising the criterion among the 4 possibilities.

7.5 Validation and discussion of results

Our current results consist mainly of two methodological advances: (i) progress in the production of an integrated framework of the interrelationships between social and ecological systems for the modelling of landscape dynamics, from a combination of field studies, interdisciplinary analysis, and participative workshops, and (ii) its expression into modelling choices for simulation of scenarios. Complete simulation outputs are not yet available, unlike most of the other models presented in this book.

The main objective of this model study, which assesses possible future landscape development in our case study area, is not to predict or prospect future land cover change per se, but to develop an integrated understanding of how the underlying processes operate and interact, and to elicit their driving forces in order to be able to design and assess a set of scenarios to help facing uncertainty.

The intent of our scenario study is to develop "realistic" prospects of the impacts of a set of assumed changes in local and global environments from an account of socio-ecological systems features with significant impact on the quality of the scenario's results (e.g., Greeuw et al. 2000). In particular, uncertainty (climatic risk) and human behaviour (adaptive character and individual variety) are important examples of dynamic features. For predictive scenario purposes, models like cellular automata, Markov chains or neural networks usually compute a set of parameters (transition potentials, transition matrix, weights and biases of activation functions) from training sets of past data in order to minimise an error criterion or maximise a likelihood coefficient. The main limitation of these models is that they behave like a black box with good predictive abilities but poor explanatory power. Creating a glass box with a transparent surface, out of a so-called black box for such models, is difficult because of their fundamental nature, in which it is not always possible to meaningfully associate parameters or functions with real processes (Monteil et al. 2005). In our case, the purpose is clearly to account for ecological and social processes, especially for human behaviour variety and reflexivity, using models of decision-making processes in a mechanistic, formal, and spatially explicit way, at different levels from the parcel, the farm level, to the whole landscape.

Taking into account social interaction, adaptation, and individual decision-making will make the model difficult to validate using classical procedures, because basic rules cannot be directly related to the observation of a single output. However, various kinds of validation may be applied to such models. Rykiel (1996) distinguishes between operational validation (i.e., demonstrating that the model outputs meet some performance standards required for the model purpose) and conceptual validity (i.e., ensuring that assumptions underlying the conceptual model are correct or justifiable and that the representation of the system in the model is reasonable for the model's intended use). The validation of our MAS model falls into the latter category.

We included in our modelling process some facilities for computer model verification (correct implementation of the conceptual model) on the one hand, and validation of the conceptual model with local partners on the other hand. These facilities include several kinds of outputs to visualise and assess the behaviour of the model, either when a simulation is running, or after its completion:

- Spatialised points of view: a dynamic map of given attributes of selected classes can be displayed during the simulation (e.g., land cover, land use); each point of view can be displayed when the simulation is paused, at pre-selected time steps or at the end of the simulation. In addition, the CORMAS platform makes it possible to save JPEG images or AVI videos for preparing meaningful outputs before a workshop with local partners;
- Probes: they graphically plot the evolution of given attributes or indicators through time once the simulation is completed;
- Transcript window: this window displays textual messages as the simulation runs; this facility is useful to demonstrate what the model does when running it in a step by step mode;
- MS Excel data file: in the course of the simulation, a text file is saved with all the operations performed by farmers, and all the transitions that occurred in land use and land cover at the parcel level. After the simulation is completed, this file is imported into an Excel workbook (Fig. 7.6) with a script, which performs a formatting of the operations, hierarchically structuring the lines according to years and fortnights, colouring the background of cells according to the type of farmer operation, and activating the filtering mode of Excel. This makes it possible to analyse the succession of all the operations simulated, qualitatively and quantitatively, to filter the output according to a selected year or fortnight by clicking on small buttons in the margin, or again according to a selected farmer or agricultural parcel with drop-down list boxes. Transitions in land use and land cover are analysed within the same worksheet. Other worksheets containing pre-defined dynamic crosstabs allow for the provision of crossed data between columns (e.g., number of operations by parcels, quantity of dry matter annually cropped by parcel or type of operation, etc.). Additional crossings can be interactively performed thanks to Excel facilities.

Furthermore, the algorithmic procedures coding the dynamics of the system can also be visualised. This makes it possible to understand why a result is observed, and thus can validate or improve the corresponding rule. Meetings between researchers and partners showed that unexpected results are particularly profitable because they force us to analyse why they are computed by the model, and thus to validate the rule or modify it, or to add new outputs.

	A	B	C	D	E	F	G	H	I
1	YEAR	Fortni	Farmer	OPERATION	Agric. Parcel	Dry Matter	Unit	Batch	Remark
103	year 1	fn 12							
112	year 1	fn 13							
169	year 1	fn 14							
170	year 1	fn 14	Farmer 1	grazing	AgricP 1303	-1024	kg DM	Batch 1	Prioritary AgP
171	year 1	fn 14	Farmer 1	grazing	AgricP 1902	-15551	kg DM	Batch 1	sufficient
172	year 1	fn 14	Farmer 1	mowing	AgricP 101	10070	kg DM		
173	year 1	fn 14	Farmer 1	mowing	AgricP 1302	7265	kg DM		
174	year 1	fn 14	Farmer 1	mowing	AgricP 8	4635	kg DM		
175	year 1	fn 14	Farmer 2	providing fodder		585	kg DM	Batch 1	
176	year 1	fn 14	Farmer 3	providing fodder		6630	kg DM	Batch 1	
177	year 1	fn 14	Farmer 3	mowing	AgricP 16	5886	kg DM		
178	year 1	fn 14	Farmer 4	grazing	AgricP 15	-3770	kg DM	Batch 1	insufficient
179	year 1	fn 14	Farmer 4	grazing	AgricP 21	-396	kg DM	Batch 1	insufficient
180	year 1	fn 14	Farmer 4	grazing	AgricP 22	-72	kg DM	Batch 1	insufficient
181	year 1	fn 14	Farmer 4	providing fodder		1222	kg DM	Batch 1	

Fig. 7.6 Operations performed by farmers; each line represents an operation with its properties: the date (year and fortnight), the farmer, the type of operation (grazing, mowing grass, or providing supplementary fodder to meet herd requirements) with coded background colour, the agricultural parcel concerned, the quantity of dry matter, the batch of herd and any potential commentary

The implementation and the validation of the SMASH simulation model are currently under progress, so the model has not yet been used for simulation of scenarios of change. The next steps of our work plan address the conceptual validation of the farm's technical management model according to the patrimonial farmer strategy (i.e., the most frequently observed strategy under the current conditions), then the implementation and integration of the other farmer strategies to account for the variation in their individual behaviour, before starting the development of scenarios.

7.6 Conclusion and outlook

For supporting local policy decision makers in a Pyrenean mountain area, who are in the search for paths for sustainable landscape development, we developed a methodology for landscape change simulation based on the co-construction of a multi-agent model in a participatory research framework. The objective of our work is to run an integrated prospective analysis of both land use and landscape change that can account for the interactions between the two of them. Such a use of the MAS technology has yet to date little representation in the literature (Parker et al. 2003). The use of MAS simulation models for supporting policy decision makers until now has mainly been based on expert models developed by researchers, which are then proposed to the policy decision makers for validation and use, e.g., modifications of variables or parameters can then be applied for simulation and analysis of scenarios (Antona et al. 2002).

The participatory construction of the SMASH model allowed for a fruitful interaction between the participants of the project (researchers and local partners). The exchange of general ideas and concepts, and information about the individual perceptions used for addressed themes, facilitated the emergence of an integrated understanding of the socio-ecological system's operation under consideration, and the construction of a conceptual model of the dynamic relationships existing between land management and landscape. Thus, it facilitated an interdisciplinary integration of both scientific and local expertise and enabled a more robust knowledge of the interactions between ecological and social processes, which can help to better deal with topical issues of sustainable rural development in the study area.

The iterative character of the method used for conceptualisation, implementation, and validation helped the appropriation of the model developed by each of the participants of the project. It made it possible to maintain a balance between the two objectives of our project - production of scientific knowledge and support of policy decision making.

This co-construction process should also easily enable the creation of alternative scenarios, thanks to the knowledge acquired by the participants, as well as the analysis of their results, because the participants have seen how the driving pressures of change were integrated into the computer model.

The experience we gained in our case of study stresses that even within a co-construction process, the contribution of scientific knowledge and data analysis remains critical for the modelling of socio-ecological dynamics. If part of the conceptualisation relied on enquiring workshops bringing together researchers and local partners, a significant part of the time was nevertheless devoted to carrying out concrete integration of scientific knowledge into computable entities, rules and processes using the results of disciplinary and interdisciplinary fields studies and scientific conceptual frameworks. The respective degree of scientific and other stakeholder investment in the participatory modelling of interactions between social and ecological processes, and their respective contributions in terms of knowledge and expertise, remain a matter of debate, at the crossroads between research and development.

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8 Land use scenarios: a communication tool with local communities

Cuevas G and Mas J-F

Abstract

The municipality of La Huacana in the Mexican state of Michoacán, is currently undergoing a process of intense land use change, which has severe environmental repercussions. This dry tropical region has a high rate of population emigration leading to the abandonment of crop land, largely due to the low agricultural yields. At the same time small-estate holders are converting the forest cover to pasture. All of these topics have resulted in land degradation and increased water depletion, which are already some of the most severe problems in the region.

Landsat and ASTER images dated 2000, 2003 and 2006 were classified in order to generate land use/cover maps of the municipality. Then, we modeled land use/cover changes using DINAMICA, a spatially explicit model for land cover change modelling. The selection of the variables used to explain the land use/cover transitions was determined using the information obtained in a workshop carried out on the Rural Development Council Assembly along with a statistical analysis based upon the land use/cover changes maps for the period 2000-2003 derived from the remotely sensed data. The 2006 land use/cover map obtained through the model calibrated on 2000-2003 data was compared with the map derived from 2006 ASTER images analysis. This comparison showed a reasonable performance of the model. As the next step, the model was used to mimic three possible scenarios for 2015 that encompass a plausible range of future trajectories of deforestation. The first one assumes that 2000-2003 deforestation trends will continue, the “cattle” scenario assumes that deforestation rates will increase and finally the “sustainable” scenario assumes that the communities will implement protected areas and that deforestation due to cattle ranching will decrease.

The perspective of local inhabitants and authorities was useful to conceptualize the model. Showing the different scenarios to the community and local authorities could be a valuable tool for making future decisions and to become aware of the need to establish strategies to protect the community’s resources.

Keywords: land use change, model, scenarios, local communities

8.1 Introduction

Current research on land use change has matured in terms of theories, models and tools. In addition, interdisciplinary research is gaining relevance; the studies have a more holistic approach than in the past and interdisciplinary scientific collaboration is being promoted (Briassoulis 2000).

The modalities of land use change study differ depending on the goals pursued. In general terms, two main approach trends may be distinguished:

1) Studies focused on monitoring land use change, i.e., measuring conversion. Despite its descriptive nature, such studies are essential and often the results are used as data for more elaborate studies. At present, land use changes are detected mainly through satellite image data. Multiple techniques have been developed, however, no optimal application exists that may be applied to all cases. New techniques continue to be developed, allowing for the effective use of remote sensing data techniques, which are increasingly more diverse and complex (Lu et al. 2004).

2) Explanatory studies attempt to understand the mechanisms acting in land use change and, in particular, to establish the forces and factors that promote such changes. One framework to understand the causes of land use/cover change is that of proximate sources and driving forces. In this framework, proximate causes refer to activities that directly affect the environment, while driving forces indicate the underlying social processes that give rise to the proximate actions effecting landscape change (Chowdhury 2006).

Proximate causes may be grouped into three broad categories: i) expansion of crop land and pasture, ii) harvesting or extraction of wood, and iii) expansion of infrastructure. In terms of scale, these factors operate at the local level. On the other hand, driving forces may be grouped into five categories of factors: i) demographic, ii) economic, iii) technological, iv) political and institutional, and v) a complex of socio-political or cultural factors. Those factors operate at the local level, or indirectly from the national or even global level (Geist and Lambin 2001).

Within this trend of explanatory studies are the models for the simulation of land use change dynamics, making predictions of future changes under several hypothetical scenarios.

In this study, we investigate the magnitude (rate and location) of the land use/cover changes in the municipality of La Huacana in the Mexican state of Michoacán, as well as the driving factors and probable areas to undergo land use change in the near future. The information is provided by a model of land use/cover change, which was run under three scenarios that encompass a plausible range of future trajectories of deforestation.

8.2 Test areas and data sets

8.2.1 Test area

The municipality of La Huacana has an area of 1,950 km^2 and is located in the southern portion of the state of Michoacán, Mexico, between the coordinates 18º 13’ and 19º 04’ N; and 102º 13’ and 101º36’ W, as is shown in Fig. 8.1. The elevation varies from 160 m in the margin of the Tepalcatepec River up to 2,060 m in the north-eastern limit of the municipality.

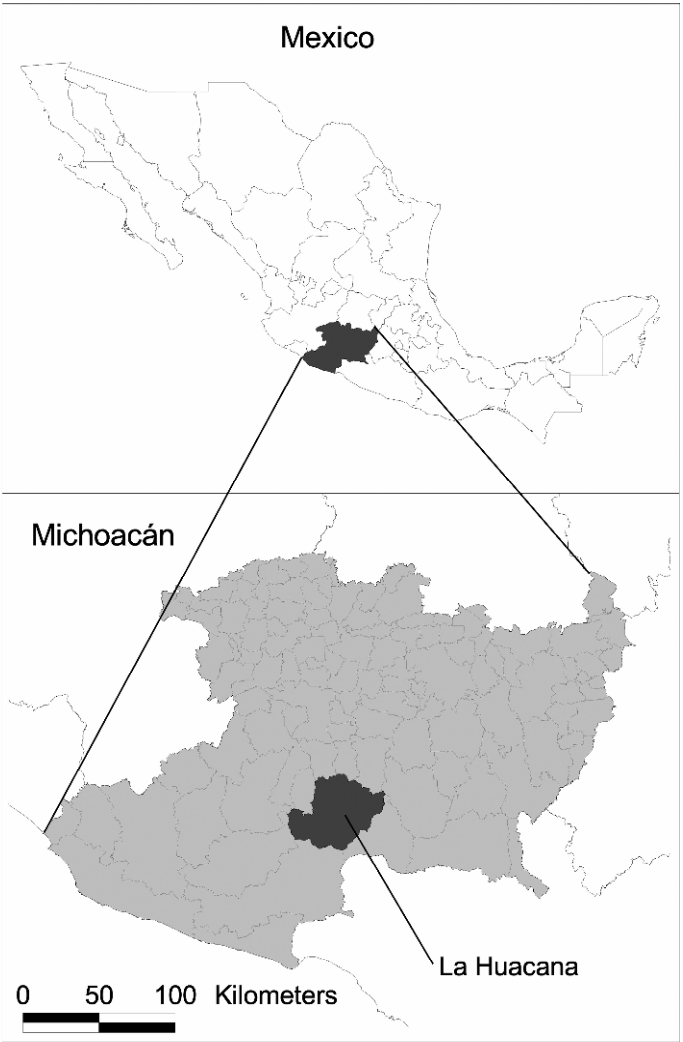

Fig. 8.1 The State of Michoacán and La Huacana Municipality

The municipality is part of the dry tropical environment in which the dominant land covers are the low and median (sub)deciduous tropical forests. These vegetation types are widely found in Mexico (Burgos and Maass 2004) but are undervalued and insufficiently studied and modelled due to the analytical and technical difficulties for their study; difficulties which are in part derived from the sharp seasonal changes displayed by these forests that have no foliage between 6 to 8 months (Rzedowski 1986). In addition, these forests are among the ecosystems with the highest biodiversity levels, and at the same time being among the most vulnerable to change (Trejo and Dirzo 2000). A Natural Protected Area (Infiernillo-Zicuirán) is being designed in order to protect this biodiversity. This reserve is expected to operate in 2008 and will include an important part of the municipality.

The temperature varies depending on the elevation, the lower part (less than 800 m) has higher temperatures with an annual average temperature of 26°C, this area is part of the so-called "Tierra caliente" (warm lowlands). The annual average temperature is 26°C at sea level and decreases 4°C for each 1000 m gain in elevation (Vidal 2005). In the region the annual precipitation is less than 600 mm, with some variations related to the elevation and temperature as mentioned above.

In 2000, the municipality of La Huacana had 33,986 inhabitants distributed in 118 settlements, of which only two are considered urban and the other 116 as rural (i.e. with less than 2,500 inhabitants) (INEGI 2000). There are two main types of land tenure: private property and community lands (ejidos). Each ejido has representatives who meet each month in a Rural Development Council Assembly, where subjects of common interest are discussed.

According to an official demographic survey, the degree of marginality is very high for 57 of these localities, high for 60 and only one is medium. This marginality index is based on factors, which indicate the availability of the main services; such as water, electricity, the number of inhabitants per household, and the proportion of illiteracy (CONAPO 2000).

In Mexico international migration, especially to the USA, has increased dramatically in the past decades and involves mostly small-rural-town farmers travelling frequently to the USA, motivated by the absence of employment and low salaries among other reasons. Abandonment of crop land, especially in marginal and less productive areas has become an important trend in land use change in areas like La Huacana. This process, which follows the migration trend, seems to facilitate ecosystem recovery (López et al. 2006).

The land use dynamic is dominated by different levels of degradation and not only by the complete clearing of the forest cover. People use the tropical dry forest for different activities like pasture, extraction of wood and firewood, and these activities impact the forest's openness differently.

8.2.2 Data sets

The datasets used were: two Landsat ETM images (path/row 28/47) taken in January 31, 2000 and February 8, 2003; three Aster images: two taken in April 5 and the other in April 30, 2006; INEGI's digital topographic cartography scale 1:50,000; very high-resolution (1 to 2 meters on the ground) digital aerial photography of 2000; INEGI´s orthophotographs scale 1:20,000, made from aerial photographs, taken in 1995 and 1996 (resolution 2 meters) and ejidos cartography from the National Agrarian Registry.

8.3 Methodology and practical application to the data sets

8.3.1 Data Processing

In order to prepare input layers for DINAMICA, and to asses land use change, the materials had to be processed, as described below:

- Geometric correction and interdependent visual interpretation (FAO 1996) of the Landsat ETM and Aster images. In a previous study, a digital supervised classification approach was used, but the results were poor due to spectral confusion between land cover classes in dry tropical forest environment (Cuevas 2007). Interdependent interpretation, which consists of interpreting first the oldest image and then using this first delineation as a reference when interpreting the second (recent) image, ensured the highest level of consistency between the classification of recent and historical sets of images.
- The original topographic data sets were processed in order to obtain some of the layers used as explanatory variables in the model.
- A digital elevation model (DEM) and a slope map were derived from the contour lines using the ILWIS program.
- To calculate distances to roads, streams and urban areas the coverage features were converted to raster and the Euclidian distance to the closest source was calculated for each cell using the Arc/Info GIS.

8.3.1.1 Classification

The classes employed to classify the images are shown in the Table 8.1:

Table 8.1 Land use/cover classes

Acronym	Land use/cover category
TF	Temperate forest
DTF-c	Dry tropical forest (closed)
DTF-so	Dry tropical forest (semi-open)
DTF-o	Dry tropical forest (open)
RV	Riparian vegetation
M	Malpaís
RFA	Rainfed agriculture
IA	Irrigated agriculture
HA	Humidity agriculture
HS	Human Settlement
Mi	Mines

The pasture land class was not included as a separate class because it was easily confused with Rainfed agriculture; therefore they were combined.

Once the areas of land use/cover types were obtained for each period, the rate of change, r, was calculated by using the following equation (FAO 1996):

$$r = 1 - \left(1 - \frac{A_1 - A_2}{A_1}\right)^{1/t} \tag{8.1}$$

where A1 is the area covered by a given land use/cover at time 1, A2 the area at time 2 and t is the number of years for the period of analysis.

8.3.2 Spatial transition probabilities

The spatial transition probabilities used to estimate the most favourable areas to experience land use change, were calculated using weights of evidence. The weights of evidence are derived from the Bayesian method of conditional probability, and its strong performance has been proven in combining evidence mainly in medicine and geology (Bonham-Carter 1994). This is a data-driven method, applied when sufficient data are available to estimate the relative importance of evidence by statistical means (Almeida et al. 2003). An advantage of this method is that it is not constrained by the classical assumptions of parametric methods, which are often violated by spatial data.

In general terms, the weights of evidence as previously stated, are derived from the posterior or conditional probability, this is, the probability that an event (D) occurs (for example a specific transition of land use change), given the presence of certain evidence (B) (explicative variable), and it can be expressed by:

$$P[D \mid B] = \frac{P[D \cap B]}{P[B]} \tag{8.2}$$

where P[D | B] is the conditional probability of an event D occurring, given the presence of the evidence B.

Algebraic manipulation allows us to represent the conditional probability in terms of its odds ratio and then to define positive and negative weights (W+ and W-) as follows:

$$W^{+} = \log_e \frac{P[B \mid D]}{P[B \mid \overline{D}]} \tag{8.3}$$

$$W^{-} = \log_e \frac{P[\overline{B} \mid D]}{P[\overline{B} \mid \overline{D}]} \tag{8.4}$$

where,

B = presence of an evidence (conditional factor),

$\overline{B}$ = absence of an evidence (conditional factor),

D = presence of an event,

$\overline{D}$ = absence of an event,

W^{+} indicates the importance of the presence of the factor for the occurrence of the event. If it is positive the presence of the factor is favourable for the occurrence of the event and if it is negative it is not favourable.

W^{-} is used to evaluate the importance of the absence of the factor for the occurrence of the event, when it is positive the absence of the factor is favourable for the occurrence of the event, and negative when it is not.

DINAMICA uses a fixed transition matrix within each phase. This matrix describes a system that changes over discrete time increments, in which the value of any variable in a given time period is the sum of fixed percentages of the value of the variables in the previous time period. The sum of fractions along the column of the transition matrix is equal to one. The diagonal line of the transition matrix needs not be filled in since it models the percentage of unchangeable cells.

The transition matrices were derived by means of the Markovian chain property (Eq. 8.5), in order to project the trends of change on an annual basis (Bell and Hinoja 1977, Soares-Filho et al. 2002).

$$P^t = HV^tH^{-1} \tag{8.5}$$

where P is the original transition matrix, H and V are its eigenvector and eigenvalue matrices, and t is the fraction or a multiple of its time span.

8.3.3 DINAMICA's Cellular Automata

As a cellular automata system, DINAMICA represents the landscape as a regular n-dimensional array of cells that interact within a certain vicinity, and the state of each cell in the array depends on the previous state of the cells within a cell neighbourhood according to a set of transition rules. All cells are being updated simultaneously at discrete time steps (Soares-Filho et al. 2002).

8.3.4 Field methods

8.3.4.1 Land use sampling

Field work in La Huacana was conducted during July 2006. An exploratory visit was made to gather information on land use/cover and areas of change in the region. Due to limitation of the accessibility and security on the study area, an opportunistic sampling following the main roads, emphasizing on areas that have experience changes on their land use/cover was used. The samples were described with help of municipality workers with a good knowledge of the area, although they do not have a formal education. Information on dominant vegetation type was recorded. Field work was done in order to visualize the dynamic of change in the region and to collect information to classify the satellite images, verify the land use/cover classification and asses the accuracy of the resulting land use/cover maps. A GPS receiver was used to record the position of the samples. Ancillary information used to support the routes were a topographic map scale 1:50,000 from INEGI and a false colour image at scale 1:100,000.

8.3.4.2 Interviews with key informants

A workshop was held in the La Huacana ejido's council assembly in which, based on maps and images of the region, the participants were able to recognize the converted areas and suggest the reasons why changes occurred. Additionally, the participants carried out a prospecting exercise for the areas that, in their opinion, are most susceptible to land use change in the near future. The people worked in three different groups, depending on the region they pertain to: La Huacana, Zicuirán and Infiernillo. These regions have different availability of water and therefore different opportunities of land uses.

Each group had to answer the three same questions. They were provided an anaglyph built encoding a three-dimensional image in a single picture using as input the orthophotographs and the DEM. This anaglyph was used to allow the groups for geographic visualization as they answered the questions. These were:

– Which areas have experienced recent land use changes?
– What kinds of changes have been experienced and what are the causes of those changes?
– In the near future, which are the areas which are most likely to change?

The conclusions of each group were presented and discussed in a plenary session.

Also some interviews with the municipal authorities were conducted in order to obtain a general view of the municipality.

8.3.5 Application of DINAMICA

The model was calibrated using the period 2000-2003 and run to generate a map for 2006 (for validation purpose) and to 2015 (scenarios). All data used in this application were represented at 30 m x 30 m raster cell. The cells form a 2,160 by 1,665 grid, there are a total of 3,596,400 cells defining the region for simulation.

The maps that were constructed identified 11 distinct land use/cover categories from which we are focusing on seven land use changes or transitions that are shown in the Fig. 8.2. From those transitions five are in the direction of the degradation and only two are of recovery.

The selection of the variables used to explain the seven land use transitions was determined by the statistical analysis of the data (weights of evidence computing) and using the information obtained in the workshop and the interviews with key informants. The six variables used in the statistical analysis of land use change were elevation, slope, distance to the main rivers, distance to roads, distance to human settlement and land tenure.

We used the Cramer's coefficient to test the variables independence and eventually exclude a variable due to dependence. Cramer's V is a statistic measuring the strength of association or dependency between two (nominal) categorical variables in a contingency table. The closer the index is to 0, the smaller the association between the categorical variables. On the other hand, a value being close to 1 is an indication of a strong association between the variables.

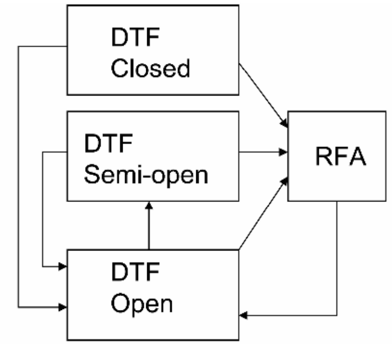

Fig. 8.2 Land use transition

8.3.6 Scenarios

The trend scenario maintains the same trend of 2000-2003 and therefore is based upon the same change matrix and behaviour of explanatory variables.

To run the “cattle” scenario one variable was added consisting in the categorization of the according to the possibility of maintaining their cohesion, or selling their lands to small-state holder who convert the dry tropical forest to pastures for the cattle. Also the rate of deforestation was increased proportionally to the incremental trend of the price of the cattle and to the governmental support.

The sustainable scenario is based upon an increase of the incentives for the conservation of the tropical dry forest and for the sustainable use of the resources, like the promotion of “sustainable cattle” and protected area implementation. To run this scenario the boundaries of the planned Natural Protected Area of Infiernillo-Zicuirán was added as a new variable. As the current municipal policy focused on conservation is expected to continue, the rate of deforestation was decreased and the ejidos obtain economical benefits for not changing the current land use of their lands.

8.3.7 Integration of local knowledge

The information gathered during the workshop and the interviews was used in different phases during model construction (Fig. 8.3). First it helped to select the explanatory variables used as conditional factors of the different land use transitions. Second, it was useful as expert knowledge in the modification of the weights of evidence, and finally it helped to conceptualize the different possible future trends.

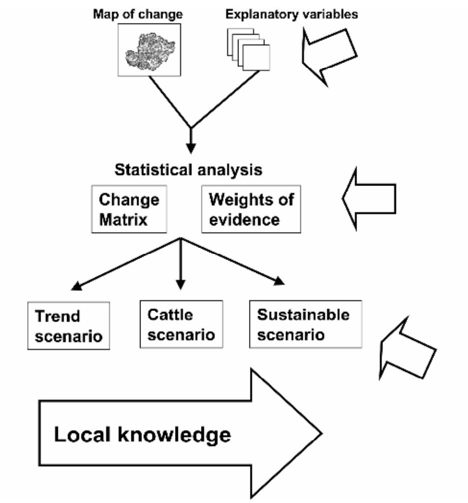

Fig. 8.3 Local knowledge in different stages of model construction

8.3.8 Validation

To validate the land cover prospective model, we applied it to the 2003 map in order to model known land use/cover (2006). The evaluation of the model was then based on the comparison between the simulated and the observed maps. As pointed out by Paegelow and Camacho Olmedo (2005), modelled land cover maps can be very close to reality but the correctness is due for a major part to persistence. The comparison was therefore focussed on change areas (both observed and simulated changes). Spatial models require a comparison within a neighbourhood context, as even maps that do not match exactly pixel-by-pixel could still present similar spatial patterns and likewise spatial agreement within a certain pixel vicinity. To address this issue several vicinity-based comparison methods have been developed. For example, Costanza (1989) introduced the multiple resolution fitting procedure that compares a map fit within increasing window sizes. Pontius (2002) presented a method similar to Costanza (1989), but that now differentiates errors due to location and quantity. Power et al. (2001) provided a comparison method based on hierarchical fuzzy pattern matching. Couturier et al. (2007) used a fuzzy approach based on the epsilon band approach. In turn, Hagen (2003) developed new metrics, including the Kfuzzy, considered to be equivalent to the Kappa statistic, and the fuzzy similarity which takes into account the fuzziness of location and category within a cell neighbourhood. The method implemented in DINAMICA is a modification of this latter approach.

The fuzzy similarity test is based on the concept of fuzziness of location, in which a representation of a cell is influenced by the cell itself and, to a lesser extent, by the cells in its neighbourhood (Hagen 2003). The overall similarity of a pair of maps can be calculated by averaging the two-way similarity values for all map cells. As random maps tend to score higher, it is recommended picking up the minimum fit value from the two-way comparison. This last approach was used in the present study.

8.4 Results

8.4.1 Data from fieldwork

8.4.1.1 Land use samples

A total of 77 field samples were collected, eight of them are out of the study area. Fig. 8.4 shows the distribution of the field samples into the study area and Table 8.2 gives a summary of the samples according to the legend.

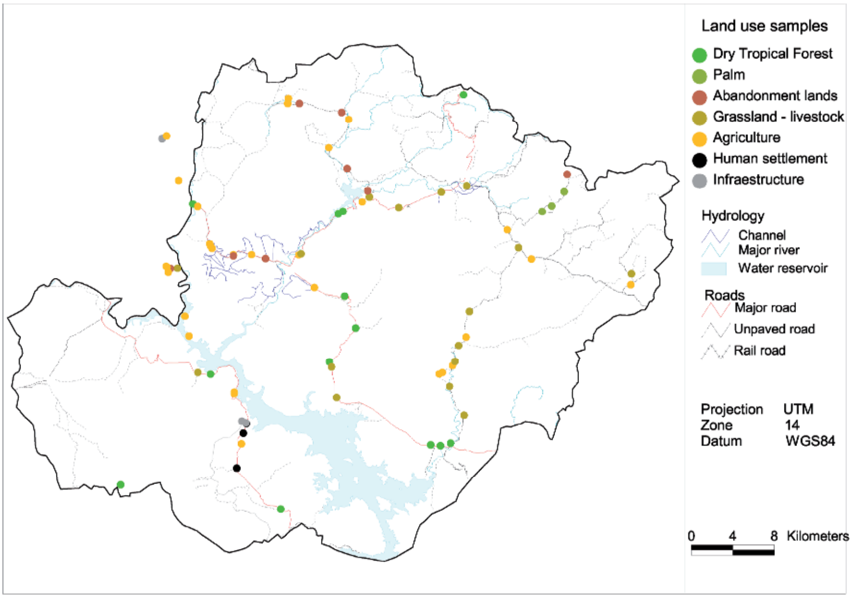

Fig. 8.4 Land use samples

The number of points in the categories grassland and agriculture are considerably larger than the other classes, because the field work was conducted along the main roads and paths, and so correspond mainly to the cultivated lands.

Table 8.2 Summary of field samples by land use/cover type

Land use/cover	Number of samples
Tropical forest	13
Palm	4
Abandonment lands	8
Grassland - livestock	16
Agriculture	30
Human settlement	3
Infrastructure	3

8.4.1.2 Interviews with key informants

A workshop was carried out in the Rural Development Council Assembly of July 20 2006; the attendants of the meeting are the representatives of the ejidos and of some groups of producers. There were 55 persons at this meeting. Most of them are peasants that have a good knowledge about the region but the most of them do not have a formal education.

- Areas that have experienced recent land use change

The information derived from the workshop, about the areas that have experienced recent land use changes, is shown in Table 8.3.

Table 8.3 The areas in La Huacana showing the most change according to the workshop participants

Region Subject	La Huacana and Surroundings	Zicuirán dam and surroundings	Infiernillo dam and surroundings
Most changing areas	Zapote Jorullo Pedregosa Fincas de Inguarán Naranjito El Estradito Cuimbio Manga de Cuimbio La Huacana Ichamio La Sauda Ojo de Agua San Ignacio El Valle Cerrito Colorado Agua Blanca Puerta La playa Mata de Plátano Los Copales	Zicuirán dam' border Najanjo de Tziritzícuaro Manga Chávez Zicuirán Caja de Zicuirán	Piedra verde Villahermosa Cerro Condémbaro Potrerillos Nuevo Cento Barajas Las Cuátaras Cupan del Río San Francisco de los Ranchos

Most of the mentioned locations are names of the towns which could be located on a map and overlaid with the land use map of 2006. From the total of 28 points, 18 are located on Rainfed agriculture and Grassland, three on Irrigated agriculture, five on Human settlement and only two were on Deciduous forest.

For the Infiernillo area the workshop revealed that the most important changes of land use change happened forty years ago when the Infiernillo dam was constructed, then ten or fifteen years ago when the electric line and the gas pipeline were constructed, and most recently with the construction of the highway.

- Types and causes of land use changes

In terms of the information about the types and causes of the land use changes, the information was shared in the three work groups with minor differences. Among the main type of land use changes that the people were able to recognize are the deforestation, land abandonment and the increase of the drought derived from the deforestation. Also mentioned was that the use of agrochemicals has created contamination and erosion.

As one of the causes of the deforestation, the belief that cattle ranching is more cost effective on human induced grassland than in the native forest was mentioned. Another cause is the illegal crops. Land abandonment is perceived to be related to the low prices of the agriculture products and the high rate of migration of young people to the United States. Those abandoned lands are now covered with mesquite *(Prosopis spp)* scrubs. The construction of infrastructure was identified as other cause of change, but as was mentioned before this is not a recent issue. For the Infiernillo area, another change was the promotion of the agriculture after the dam was built.

- Identification of possible areas for future change

The possible areas identified by the participants as likely to see change in the future are listed in Table 8.4. Noteworthy is the municipality's effort to reforest some areas.

8.4.2 Land Cover Mapping

Table 8.5 summarizes the area of each cover class along with the respective rate of deforestation. Close and semi-open dry tropical forests areas have significantly decreased. On the other hand, the category with significantly gained area is the rainfed agriculture, a category which includes pasture lands. The 2000 and 2003 land use/cover maps are shown in Fig. 8.5. The rates of deforestation found are in agreement with other estimations, although they can still be considered high (Trejo and Dirzo 2000, Bocco et al. 2001, Mas et al. 2004). It is also worth noting that the rate of deforestation increased dramatically during the second period (2003-2006). However, this can be partially attributed to the fact that cleared areas are more easily identified with the ASTER images used in 2006 than the Landsat images used earlier due to their higher spatial resolution. Therefore, some of the deforested patches detected in 2006 already existed, which can lead to an overestimation of the deforestation rate during the last period and an underestimation during the first one.

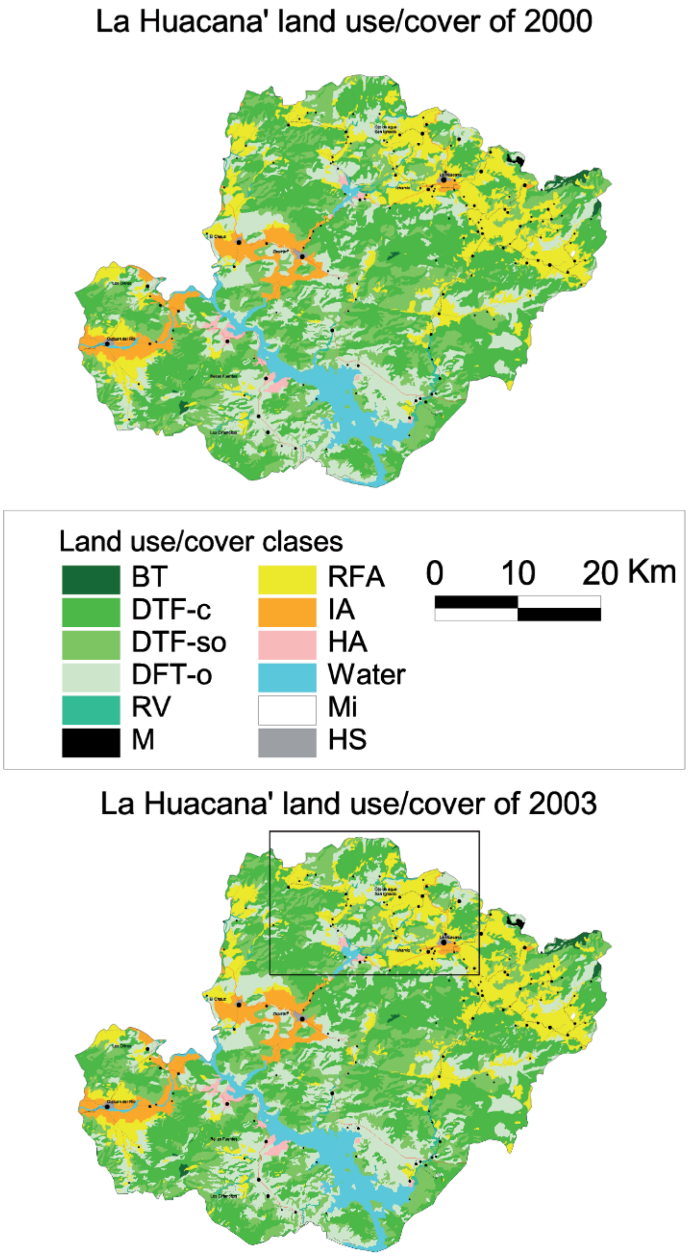

Fig. 8.5 La Huacana land use/cover map of 2000 (top) and 2003 (down)

Table 8.4 Areas with more possibilities to experience change in the near future according to the workshop's participants

Region Subject	La Huacana and surroundings	Zicuirán dam and surroundings	Infiernillo dam and surroundings
Future changes	Reforesting zones: Puerta La Playa, Zapote, Pedregosa, Salitrillo	If there is no conscience it will be more degradation and some species of trees and animal could be lost.	Strip from Potrerillos to Pocitos, towards the dam.
	Water: COINBIO's program	Less agriculture	Cerro Condémbaro (advancing of the agriculture border)
	Water pollution because the mines: Inguarán, Cuimbio, Pueblo Viejo	Less cattle	Infiernillo dam' border (reforestation planning)
		More migration	

Table 8.5 La Huacana' land use/cover areas in 2000 and 2003

Land cover class	2000 (Ha)	2003 (Ha)	2006 (Ha)	Rate 2000-2003 (%/yr)	Rate 2003-2006 (%/yr)
Temperate forest	902	902	890	0.00	0.46
Dry Tropical forest (closed)	66,118	65,720	62,441	0.20	1.69
Dry Tropical forest (semi-open)	36,512	36,375	35,604	0.13	0.71
Dry Tropical forest (open)	39,440	39,441	41,302	0.00	-1.55
Riparian Vegetation	1,770	1,770	1,707	0.00	1.20
Malpais	128	128	128	0.00	-0.05
Rainfed agriculture (inc. pasture lands)	30,572	31,097	33,326	-0.57	-2.33
Irrigated agriculture	7,757	7,763	7,800	-0.03	-0.16
Humidity agriculture	1,410	1,414	1,411	-0.09	0.06
Water body	8,889	8,889	8,888	0.00	0.00
Human settlement	32	32	32	0.00	0.13
Mine	405	405	405	0.00	-0.03

8.4.3 Change Analysis

The overall transition rates for the seven transitions analyzed are shown in Table 8.6. These were calculated by mean of a cross-tabulation operation between the initial (2000) and final (2003) land use/cover maps.

Table 8.6 Matrix for transition rates for La Huacana, 2000-2003

	DTF-c	DTF-so	DTF-o	RFA
DTF-c	0.9934	---	0.0025	0.0041
DTF-so	---	0.9945	0.0034	0.0022
DTF-o	---	0.0018	0.9912	0.0070
RFA	---	---	0.0023	0.9977

The results of the test for correlation between variables have shown that most of the values were lower than 0.3 for the Cramer's Coefficient (V). Only the correlation between land tenure and slope had a value of 0.7, but both variables were maintained.

Transition probabilities were calculated for each cell by means of the weights of the evidence method. Among the six factors defined, only the land tenure is in binary form. The other five are continuous data, which were transformed into ranked variables.

For the five transitions involving degradation, the distance to roads is the factor with the highest weights of evidence values, followed by the distance to urban areas. Roads appear as one of the strongest predictors of deforestation in dry regions, as it has proved to be in tropical deforestation as well (Kaimowitz 1998). Forest is converted to agriculture, plantations and cattle pastures where roads and rivers provide easy access.

The proximity to the main rivers also appears as an important factor that drives the deforestation and this makes sense if we consider that the availability of water in the study area is very important in determining land use. The low values of elevation and slope seem to be prone to deforestation because they are used for agriculture. The community land tenure (ejidos) tends to decrease the deforestation rate.

For the two transitions that imply a certain degree of forest recovery, which are concerned with land abandonment of land previously used for agriculture activities, the behaviour of factors analyzed changes completely. The areas, which exhibit recovering forest, appear to be far from urban areas and not very close to the roads. This transition also happened far from the main rivers, at higher elevations and in areas with steeper slope. The presence of ejidos is favourable to the vegetation regrowth.

8.4.4 Scenarios to 2015

Fig. 8.6 shows the 2006 land use/cover map, initial date of the simulation and the simulated 2015 maps according to the three scenarios respectively for a portion of the municipality (the square in Fig. 8.5 shows the location of this area). The more conspicuous difference between scenarios is the surface of rainfed/pasture cover.

8.5 Validation and discussion of results

The three land use/cover maps derived from remotely-sensed imagery were evaluated with the municipal staff, who have a good knowledge of the area. Also the classification of 2000 was evaluated using very high resolution digital aerial photography, while the classification of 2006 was evaluated with the field work information. Although these evaluation approaches did not allow for the obtaining of a statistically robust index of accuracy, the reliability of the maps was considered satisfactory.

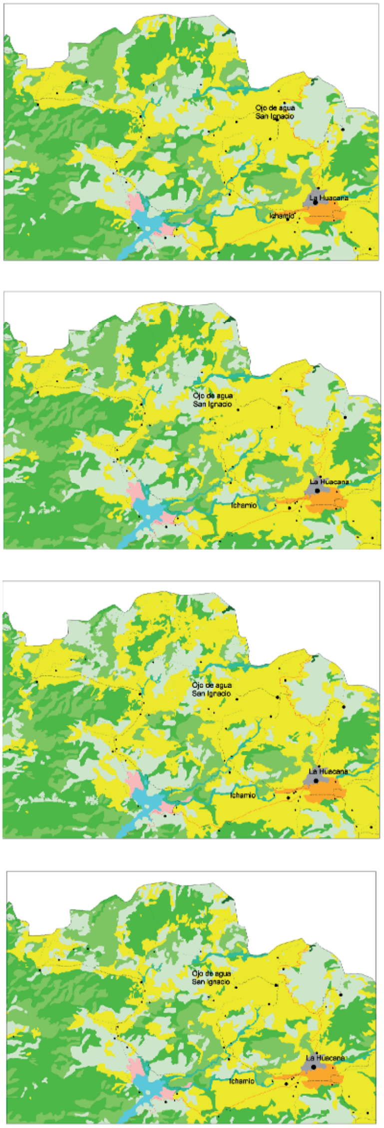

Fig. 8.6 Initial land use/cover map (observed 2006, top), trend scenario to 2015 (second from top), cattle scenario to 2015 (third from top) and sustainable scenario to 2015 (down)

In order to assess the simulations, we used the trend and the cattle model, calibrated using the 2000-2003 period, to produce two maps for 2006 (Fig. 8.7 shows the simulated map of 2006 using the trend model). These two simulations were compared with the observed 2006 land use/cover map (Fig. 8.8) with the fuzzy method of the reciprocal similarity map using windows from 1 to 73 pixels. Based upon one pixel window, this evaluation corresponds to a strict (no fuzzy) evaluation in which only exact coincidences of changes between the simulated and observed 2006 land use/cover maps are considered as correct. In juxtaposition, the accuracy assessment tolerates positional shift between the simulated and the observed patches of change, based upon a large window (73 pixels is equivalent to more than two kilometres). Fig. 8.9 shows the fuzzy similarity index as a function of window size (positional fuzziness) for 2006 maps derived from the trend and cattle scenario, respectively. No scenario was able to predict the exact position of change (with window size of one, the index is near zero). The explicative variables do not strictly control the spatial distribution of change and only a small part of the area which fulfils the conditions to change actually changed. When increasing the tolerance to positional error, the index augments importantly indicating that the model was able to identify coarsely the location of change. The cattle scenario has a better performance mainly because the quantity of change was higher and therefore closer to the observed change during 2003-2006 than the quantity computed by the trend scenario. Nevertheless, all the simulated landscapes are realistic in terms of the spatial pattern of changes: the size, shape and distribution of simulated patches of change are similar to the observed ones.

8.6 Conclusion and outlook

Simulated 2015 land use/cover maps derived from three scenarios of land use change were elaborated using a spatially explicit model in the municipality of La Huacana, a dry tropical forest region of Mexico. They show the plausible distribution of land use/cover in the municipality taking into account three configurations of possible future trends: i) the trend scenario (amount and patterns of change are the same as during 2000-2003, the calibration period), ii) the cattle scenario (loss of the ejidos social cohesion and increasing conversion of dry tropical forest to pastures for the cattle) and, iii) the sustainable scenario (promotion of “sustainable cattle” and protected area implementation). The different scenarios do not present dramatic changes due to the short time of simulation (2006 to 2015) and because most of the area remains without change. Based upon the comparison between the simulations between 2003 and 2006 and the observed

2006 map, the model is not expected to predict the location of futures changes accurately, but rather to identify roughly the areas of change and simulate a realistic future landscape with regards to the spatial pattern of change. Overall generally underestimated, obtaining realistic simulated maps can be very important for certain simulation purposes, such as for the elaboration of scenarios presented to communities or the assessment of change on fragmentation habitats. The research done on the performance's evaluation of spatially-explicit models is mainly focused on the spatial co-incidence between simulated and observed maps.

Also further research is needed to evaluate the model for its capacity to predict the spatial patterns of future landscapes.

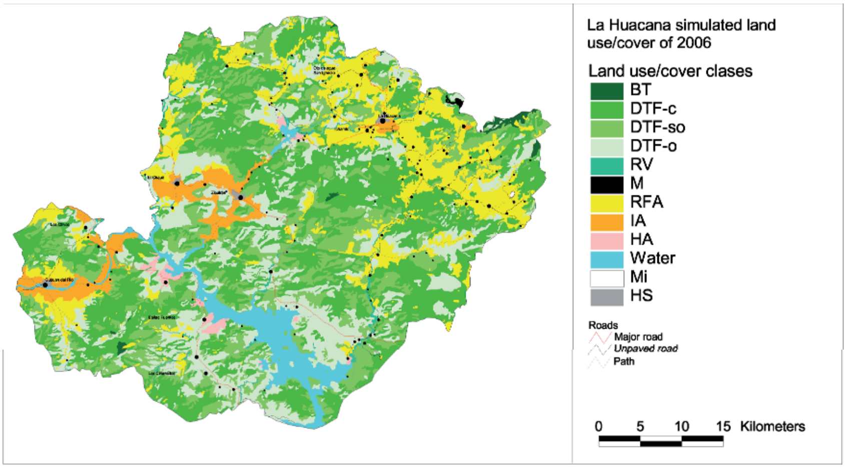

Fig. 8.7 La Huacana simulated land use/cover map of 2006

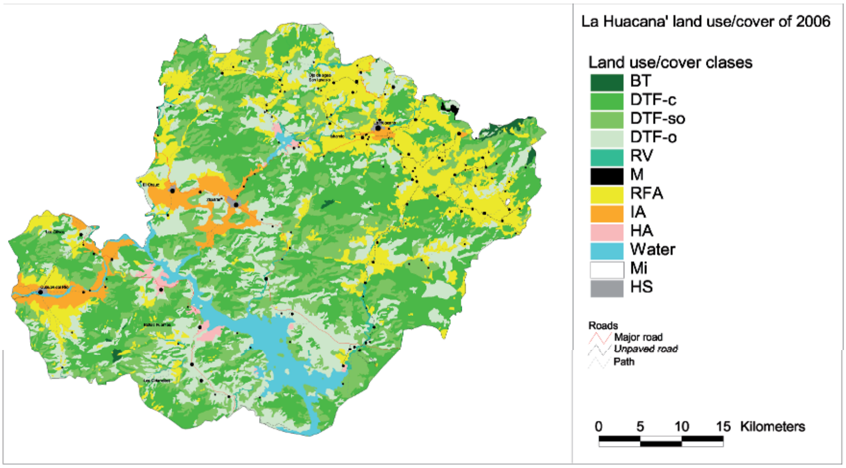

Fig. 8.8 La Huacana use/cover map of 2006

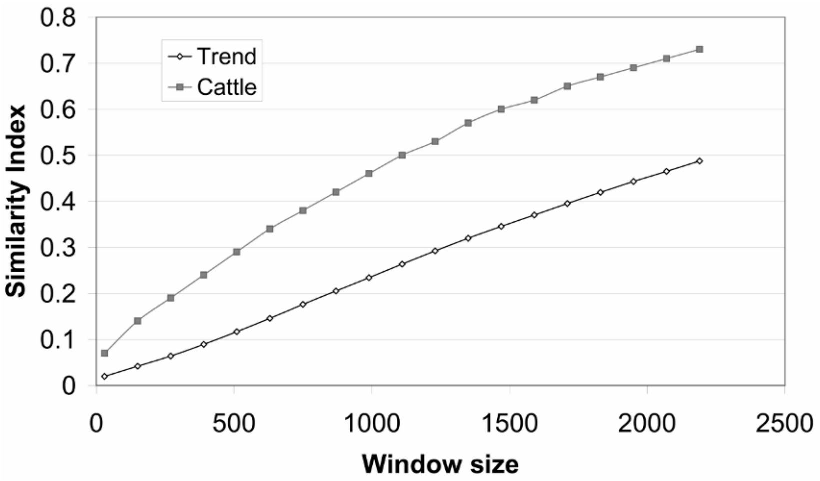

Fig. 8.9 Fuzzy Similarity Index as a function of window size (positional fuzziness)

The chosen approach to calibrate the model may be considered a trade-off between a "supervised" model with manual establishment of a knowledge base and an "automatic" approaches, which derive the relationships between changes and explicative variables only from the changes observed during the calibration period. As the model was calibrated upon a short period (3 years) the amount of change was minimal and therefore a purely statistically approach can be misleading due to its sensitivity to atypical events. For example, in a case in which a large clearing occurs at a certain distance from a road, a model based on the automatic approach will show that the probability of change at this distance is very high when a more progressive relationship between deforestation probability and distance is thought to represent better than the general trend. A manual editing of the weights of evidence allows for a reduction of the bias due to this lack of statistical representation. Moreover the editing of weights of evidence allows for the integration of expert knowledge and elaborating scenarios.

The simulated maps are presently under analysis by the municipal authorities and will serve as an input to promote discussion on environmental policy in the municipality. In order to improve the communication with communities, it can be useful to provide them with realistic landscape visualisations in a 3D environment, demonstrating how their landscape will change (Stock et al. 2007). Coupling land use/cover modelling and visual communication (i.e. realistic landscape visualisations), which engage the emotions, may substantially enhance awareness-building of the implications of land use/cover change, and may help motivate behavioural change at the individual to societal levels (Sheppard 2005).

Alternative futures derived from land use/cover modelling, and mediated by landscape visualisation-based tools is therefore a promising tool, which will be explored in further research.

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Retrospective modelling

9 Retrospective geomatic landscape modelling. A probabilistic approach

Camacho Olmedo MT, Paegelow M and García Martínez P

Abstract
Geographic information systems include, among a variety of analytical functions, those intended for spatial-temporal modelling and decision support, particularly multi criteria evaluation and multi objective evaluation. These tools are particularly useful for simulation scenarios because of their reproducibility of results and the possibility to define the amount of trade off and risk exists in the decision process. This paper focuses on the methodology and results obtained for retrospective land use modelling in the Alpujarra Alta Granadina (Andalusia, Spain) for the 16th, 18th and 19th century.

A multi criteria evaluation produces many land use potential maps, also called suitability maps, one for every objective (land use category). It is based on a chronological set of land use maps and the criteria, which are considered responsible for the observed changes and their estimates for agricultural use. After that, the multi objective evaluation resolves the incompatibilities between the potentials uses for the chronological set (1572, 1752, 1855/61), and rebuilt probabilistic historical maps based on the statistical known area. The results show the probable location for a specific use and allow the testing of the methodology and the specification of some contributions and limits. A complete validation, however, is not possible due to a lack of comparable historical documents.

Keywords: Geographic information systems, modelling, historic landscape, multi criteria evaluation, multi objective evaluation.

9.1 Introduction

During the last 10-15 years, scientists have made significant advances in modelling environmental dynamics (Coquillard and Hill 1997). Despite this progress, only a few modelling tools are available in the common GIS software (Banos 2001).

Usually applied prospectively, the modelling (it would be more exact to use the term *simulation* insofar as the behaviour is modelled through time) tools use different methodological approaches: stochastic based models like Markov chain analysis or logistic regression (López et al. 2001, Stefanakis 2003), artificial intelligence like cellular automaton (Barredo et al. 2003, Soares-Filho et al. 2006), multi-agent systems (although more frequently used in urban studies) and neural networks (Li and Yeh 2002, Mas et al. 2004). Often these approaches are mixed and coupled with fuzzy logic (Soares Filho et al. 2005).

The authors applied the majority of these modelling approaches to create an integrated and sturdy model for prospective land cover simulation (Ferraty et al. 2005, Follador et al. 2006, Paegelow and Camacho Olmedo 2005). The comparison of results performed by different models, applied to different test areas (Paegelow et al. 2004), shows that the association of Markov chains for temporal transition prediction with multi criteria evaluation (MCE) to assist manually the spatial assignment gives the best prediction rates on areas with an important land cover change (Villa et al. 2007).

Multi criteria evaluation (MCE) is a commonly used method for decision support (Gómez-Delgado and Tarantola 2006, Malczewski 2006) and considered by some authors as the most important method (Jiang and Eastman 2000).

In this contribution, authors employed MCE and MOE (multi objective evaluation which is only an extension of the MCE concept with multiple and concurrent objectives) techniques to retrospective landscape modelling. Only a few publications deal with retrospective modelling (Murphy and van der Vaart 2001). As for MCE, it is generally confined to creating suitability maps, which are used in a wide range of domains. The authors have not found publications in the international scientific literature about the use of MCE in retrospective modelling studies. Therefore the interest of this innovative work is basically methodological, focussing on the advantages and limits of applying MCE and MOE to modelling of historical landscapes.

This work is based on earlier studies (Camacho Olmedo et al. 2004, 2007) and only focus on the retrospective modelling aspect about the landscape and land use of three communes located in the Alta Alpujarra Granadina (Figure 9.1). The model is applied to a historical period exempt of map support, in order to permit the spatial assignment of land use: three dates since the early 16^{th} century to the middle of the 19^{th} century. This allows for some methodological and validation restrictions. Most commonly used models request a spatial data base of the modelled variable to calibrate the model, while we only deal with the historical statistical sources. Therefore we only use MCE and MOE techniques. Another restriction is the impossibility of validating the model results. In the context of prospective modelling one may validate the simulation, based on a known training period, by the comparison with the latest known date (unknown by the model), this is impossible, however, due to a lack of information. The first land use map of the region is from 1957 (aerial photographs), and a century after the last modelled land cover state (circa 1860). Knowing that the land cover of 1957 corresponds to the maximal extent of crops, we used this map to configure the model. In spite of a validation, we can only make comparisons between historical modelled land use and this reference map from 1957. The comparison may be considered distorted because the land use of 1957 is known by the model, even if its weight is small. So the comparison intends to show primarily the advantages and limits of the approach. In fact, the authors consider that the most interesting aspect is what alludes the model – in other words, the areas and dynamics for which the model doesn't have an answer and the reason why.

The model uses an important number of spatial criteria, which influence land use and is therefore able to resolve conflicts between different potential land uses (Barredo 1996). In this way, the created land use maps only express a certain degree of probability for the land use categories in time and space, depending upon statistical data and a lot of spatial criteria, which is constant over the modelled period. Modelled results are stochastic suitability maps. It follows that the created historical maps had to be interpreted as an approximation of historical land use rather than a faithful reconstruction of a spatially unknown historical reality.

The point of departure for this modelling attempt is the earliest known land use (1957) and statistics that have been extracted from different historical sources of the 16^{th}, 18^{th} and 19^{th} centuries (García Martínez 1999). These data show with what precision several land use categories for each common are known. Nevertheless, the sources present different lists of land use categories. Some of them are more detailed than others. The data collection is also incomplete and their reliability varies. Coupled with the impossibility –of perfectly modelling the important diversity of crops and fruit, the authors focus on the two main land use categories in this arid region: irrigated and non-irrigated land, for which they use the original Spanish terms: *regadío* (irrigated) and *secano* (non-irrigated land).

9.2 Test area and data sets

9.2.1 Test area

The study area corresponds to three communes of the Alta Alpujarra Granadina in the higher and middle sections of the Trevélez River (Fig. 9.1).

They are representative for the region and, contrary to other surrounding communes, their historical sources are complete for crops and fruit-growing (García Martínez 1999).

The geographical data base contains land use maps of 1957, 1974, 1987 and 2001, based on the interpretation of aerial panchromatic photographs, existing thematic maps and on site work. To these we added maps, which may help to explain (hypothesis) the spatial assignment of land use documented in the statistical series: DEM, slope, aspect, hydrography and irrigation canals, roads, rural housing, propriety, crop terraces, etc. These data (1 to 25,000) were rasterised with a pixel resolution of 25 meters and then used with Idrisi Kilimanjaro software to create the suitability maps.

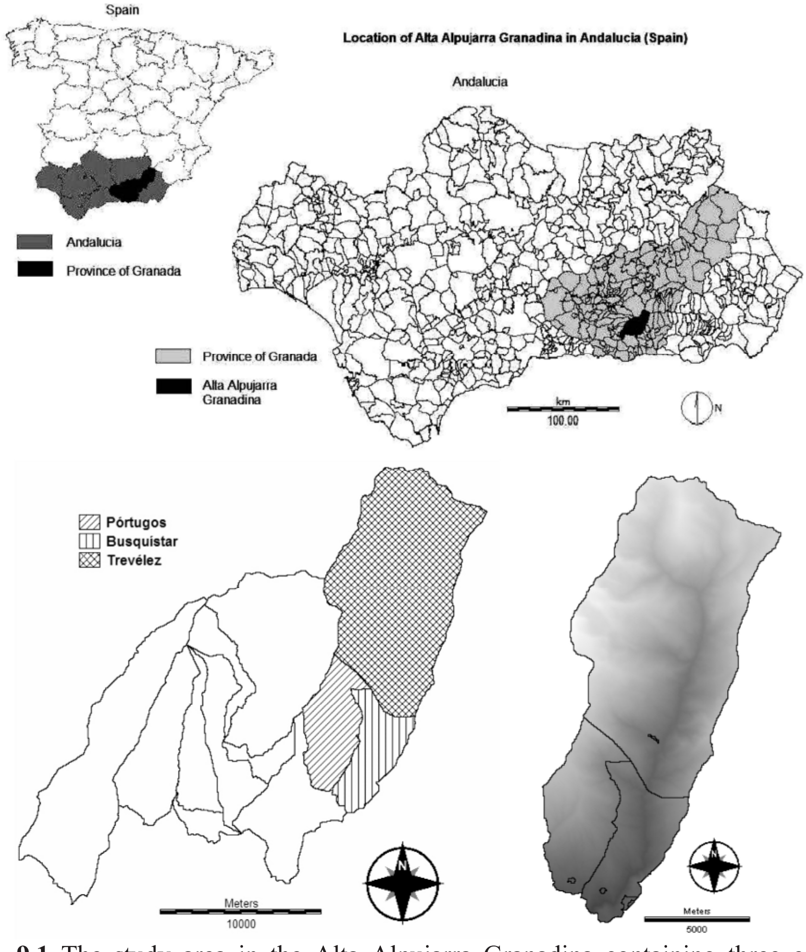

Fig. 9.1 The study area in the Alta Alpujarra Granadina containing three communes: Trevélez, Pórtugos and Busquístar (bottom left). Bottom right: DEM of the study area (from 927 to 3,482 meters at peak Mulhacen) with location of villages

9.2.2 Historical statistics: land use in the 16th, 18th and 19th century

The data for crops and general land use for communes of the Alta Alpujarra Granadina concerning the 16th, 18th and 19th century were extracted from different sources (García Martínez 1999) with a very detailed nomenclature. The diversity, but also the degree of reliability of the used sources, required the comparison and close scrutiny prior to its use for modelling. It is the reason why we resume the different categories into the two main classes: irrigated land and non-irrigated land (*regadío* and *secano*). This simplification makes it easier to compare created suitability maps to actual nomenclature of land use. On the other hand, we have to deal with significant heterogeneity within these two classes, as the aim is to perform only one suitability map for each class. The data about non agricultural land use are very vague. So we reduced all the other categories to only one: non agricultural use.

The document of 1572 (*Libros de Apeos y Repartimientos*) contain the number of settlers after expulsion of the Moors, the number of claims (*suertes*) and their characteristics (composition and surface). The communal extent of the crops, but also of irrigated and non-irrigated land is the result of multiplying the number of claims and their characteristic surface (Table 9.1). However, these data should be interpreted with caution because the antique registers contain some annotations, which create greater perspective. First, the land belonging to the church was not always inventoried. Second, one can see some unassigned claims (three in Busquístar, one in Trevélez). This fact may be explained in different ways. It may be that some Christians already lived in the two communes before the colonization and therefore they had to be compensated for. Another interpretation is that the claims belonged to the church or that they were used to compensate owners, whose claims were smaller than expected. Finally, during the definitive land attribution in Pórtugos some claims became a little bit bigger (marshes and woods). However these areas are not significant.

Table 9.1 Land use in 1572 (ha)

Commune	*Regadío*	*Secano*	Total agriculture area	Non agricultural area	TOTAL
Busquístar	25.38	0.00	25.38	-	-
Pórtugos	27.93	0.00	27.93	-	-
Trevélez	112.71	0.00	112.71	-	-
TOTAL	166.02	0.00	166.02	-	-

Source: Libros de Apeos y Repartimientos (1572). Elaboration: García Martínez (1999), modified. Note: no data for non agricultural area

For the 18th century, the cadastre (*Ensenada*) of 1752 shows the exact distribution of the crops, which were taxed (Table 9.2) while the rest (broom land, non-agricultural land, etc.) is less exact. This explains the difference between the actual cadastre area and the one in 1752, which is distinctly smaller particularly in Trevélez, where the major area is located at high altitudes.

Table 9.2 Land use in 1572 (ha)

Commune	*Regadío*	*Secano*	Total agriculture area	Non agricultural area	TOTAL
Busquístar	178.88	152.53	331.41	1402.44	1733.85
Pórtugos	70.25	365.05	435.30	14.63	449.93
Trevélez	75.50	580.64	656.14	64.93	721.12
TOTAL	324.63	1098.22	1422.85	1482.00	2904.90

Source: Catastro del Marqués de la Ensenada, Respuestas Particulares (1752). Elaboration: García Martínez (1999). Note: incomplete cadastre data for non agricultural area.

The cadastre data registered between 1855 and 1861 (Table 9.3) show the extension of crops, but do not include non-agricultural land. The principal objective of the cadastre is to tax the owners. In this way, some crops (particularly non-irrigated land or impermanent crops) were not registered and the real total area of agricultural land would be a little bit greater (García Martínez 1999).

Table 9.3 Land use in 1855/61

Commune	*Regadío*	*Secano*	Total agriculture area	Non agricultural area	TOTAL
Busquístar	261.70	212.50	474.20	-	-
Pórtugos	107.34	108.48	215.82	-	-
Trevélez	224.88	899.05	1123.93	-	-
TOTAL	593.92	1220.03	1813.95	-	-

Source: Amillaramientos (1855/61). Elaboration: García Martínez (1999). Note: no data for non agricultural area

9.3 Methodology and practical application to the data sets

9.3.1 Multi criteria evaluation (MCE): suitability maps for land use

Among the available variables included in the data base, the authors chose those that give information about the spatial assignment for each of the two mains categories of land use to be modelled: *regadío* and *secano*. MCE integers these variables. They are called *criteria*. Among criteria one can distinguish between *constraints* with Boolean character (an objective is possible or not) and *factors*. Factors express a variable degree of suitability. Factors may be weighted and their trade can be configured so that the user can choose the amount of risk in decision-making along an axis of fuzzy logic AND (Paegelow and Camacho Olmedo 2005). The result of MCE is a suitability map for each state of the modelled discrete variable (land use categories).

For the modelled period no map exists to assess spatial distribution of land use inside the communes. Therefore the authors used only time independent criteria like altitude, slope (physical criteria) and distance to irrigation canals derived from the Arabic occupation and the presence of crop terraces still visible today (anthropogenic criteria). Another used anthropogenic factor is the distance to villages Authors are aware that this is only a small portion of the criteria able to explain spatial distribution of land use, but other important criteria like social data or soil classes are not available. Also we consider only a small number of criteria in order to make the application of the model easier. The list of criteria is completed by the land use map of 1957. The middle of the 20th century corresponds to the maximal agricultural use in Alta Alpujarra Granadina (Camacho et al. 2004). The location of *regadío*, *secano* and fallows is the principal mapped reference for the above-mentioned criteria. This map is also a fully qualified criterion. Agricultural land, or land already abandoned, in 1957 have a higher probability of having been used for agriculture in the past as other land use categories such as broom land.

Comparing the statistics of 1855/61 with data from 1957, one may consider the stability of agricultural land in the study area: 1,813.95 ha in 1855/61; and 1,803.08 ha in 1957, to which we have to add 89.94 ha of semi-abandoned or mosaic of cropland and fallows (Camacho et al. 2003). However, this stability is not real. On the one hand, the situation is changing from one commune to another and on the other hand the *secano* regresses for the benefit of the *regadío* – two evolutions concerning, generally, distinct geographic areas.

As already mentioned, the land use map of 1957 was compared with different criteria, which are invariable in time in order to select the most significant among them (Pearson's coefficient of correlation and Cramer's V) and to transform them into constraints and factors. Binary constraints mask areas that will be excluded from further analysis (high altitude broom land, rocky areas, etc.). Factors express a (theoretically continuous) degree of suitability. They are standardized on a suitability index scale from 0 (no suitability) to 255 (maximal suitability). Quantitative factors are transformed by linear reclassification or by a fuzzy logic membership function. The only qualitative factor (land use in 1957) was reclassified manually.

The standardized factors then are weighted by the technique of pair weighting using the Saaty matrix (Saaty 1977). The weights result from previously performed association indexes (Pearson's coefficient of correlation and Cramer's V). The Saaty matrix is used to perform the eigenvector as a final weight for each factor. Finally, an ordered weighted averaging (OWA) (Eastman 1993) fixes the degree of trade off between the Saaty weighted factors. This process also fixes the degree of risk in decision-making on an axis, whose ends are the fuzzy Boolean operators AND and OR.

9.3.2 Multi objective evaluation (EMO): reconstruction of historical land use

Once the two suitability maps are calculated, the final step is to resolve conflicts between the competing objectives (*regadío* and *secano*). The EMO technique is based on the created suitability maps and assigns to each pixel the optimal objective. To do this, EMO considers the degree of suitability for each objective and an objective of area based on the historical data for each commune (Tables 9.1, 9.2 and 9.3). The computation is made for each commune and for each date with the same parameters except the area objective.

9.3.3 Practical application to the data sets

The computation is performed by Idrisi Kilimanjaro software. The authors chose a risk adverse strategy (Figure 9.2) allowing an average trade off during the ordered weighted averaging (OWA) step.

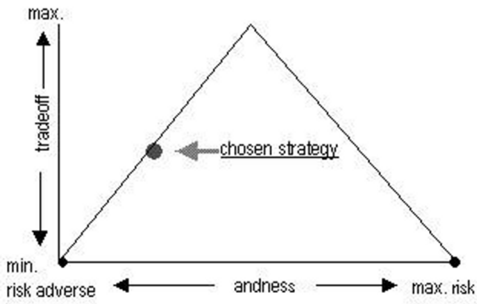

Fig. 9.2 Decision strategy space and chosen approach in MCE-OWA

The following two sections show the configuration of MCE used to create suitability maps for *regadío* and *secano*.

9.3.3.1 Suitability map for regadío

The practical configuration of constraints and factors for *regadío* is summarized in Tables 9.4 and 9.5. The constraints are surfaces outside of the study area, villages in 1957 and high altitude and Alpine level area. The factor's weights reflect the mentioned statistical tests. This emphasizes the weight of altitude (40.4%). The other important factors are proximity to crop terraces (22.07%) and to irrigation canals (17.08%). The two land use based factors weigh up to 18%, while the impact of distance to villages is very weak (2.45%).

Table 9.4 MCE contraints for *regadío*

Criteria	Constraints (0/1)
Limit of communes	Value 0: outside
Land use in 1957	Value 0: village
DEM	Value 0: higher then 2,500 m
Bioclimatic level	Value 0: Alpine level

Table 9.5 MCE factors for *regadío*

Criteria	Used function to Standardize	Factors (0-255)	Weight
DEM	Linear classification	Value 255: lowest altitude	0.4040
Distance to crop terraces	Fuzzy logic membership function: j-shaped, symmetric	Value 255: lowest distance to terraces	0.2207
Distance to irrigation canals	Fuzzy logic membership function: j-shaped, symmetric	Value 255: lowest distance to irrigation canal	0.1708
Land use in 1957	Linear classification	Value 255: regadío in 1957	0.1319
Land use in 1957	Linear classification of distance map	Value 255: lowest distance from abandoned crops (fallows) to regadío	0.0481
Distance to villages	Linear classification of distance map	Value 255: lowest distance to villages	0.0245
TOTAL			1.0000

Figure 9.3 shows the suitability map for *regadío*. Areas with high suitability form a continuous zone corresponding to low altitude, presence of terraces and proximity to irrigation canals and villages.

9.3.3.2 Suitability map for secano

The used constraints for *secano* are identical to that of *regadío* except with a higher altitudinal limit (bioclimatic constraint removed) (Table 9.6). The most influential factors are altitude (37.16%), the two 1957 land use based factors (25.46%) and distance to crop terraces (20.29%). Slope (10.05%) is also influential, while the distance to villages (5.17%) and the distance to irrigation canals (1.88%) have only a minor impact (Table 9.7).

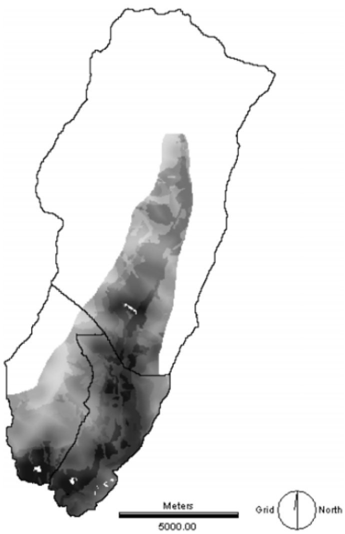

Fig. 9.3 MCE suitability map for *regadío*. White areas correspond to land excluded by constraints; Bright areas mean low suitability while dark areas signify high suitability

Table 9.6 MCE constraints for *secano*

Criteria	Constraints (0/1)
Limit of communes	Value 0: outside
Land use in 1957	Value 0: village
DEM	Value 0: higher then 2,500 m

Table 9.7 MCE factors for *secano*

Criteria	Used function to standardize	Factors (0-255)	Weight
DEM	Linear classification	Value 255: highest altitude	0.3716
Distance to crop terraces	Linear classification	Value 255: average distance to terraces	0.2029
Distance to irrigation canals	Fuzzy logic membership function: j-shaped, symmetric	Value 255: average distance to irrigation canals	0.0188
Land use in 1957	Linear classification	Value 255: secano in 1957	0.2029
Land use in 1957	Linear classification of distance map	Value 255: lowest distance from abandoned crops (fallows) to secano	0.0517
Distance to villages	Linear classification	Value 255: highest distance to villages for all agricultural land use	0.0517
Slope	Linear classification	Value 255: highest slope	0.1005
TOTAL			1.0000

Figure 9.4 shows the suitability map for *secano*. The terrain with high suitability scores are mid-side and comparatively far from villages and irrigation canals.

It is advisable to mention that some factors were used to model both: suitability for *regadío* and *secano,* but with different configurations (altitude, distance to irrigation canals, terraces and villages). In this way, areas with the highest suitability for *regadío* (particularly low altitude terraces) and for *secano* (higher altitude) seem to be juxtaposed.

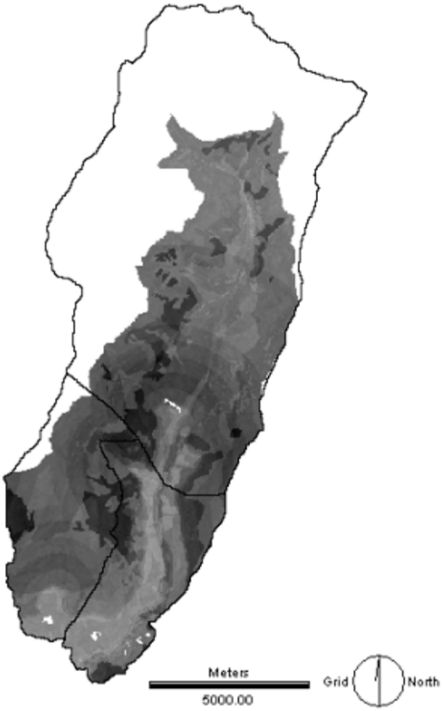

Fig. 9.4 MCE suitability map for *secano*. White areas correspond to land excluded by constraints; Bright areas mean low suitability, while dark areas signify high suitability

9.4 Results

Figure 9.5 shows the results of retrospective modelling of land use for 1572, 1752 and 1855/61 by adding the maps performed for each commune. In the legend, mentioned areas correspond to the areas indicated in Tables 9.1, 9.2 and 9.3, which are summarized in Table 9.8.

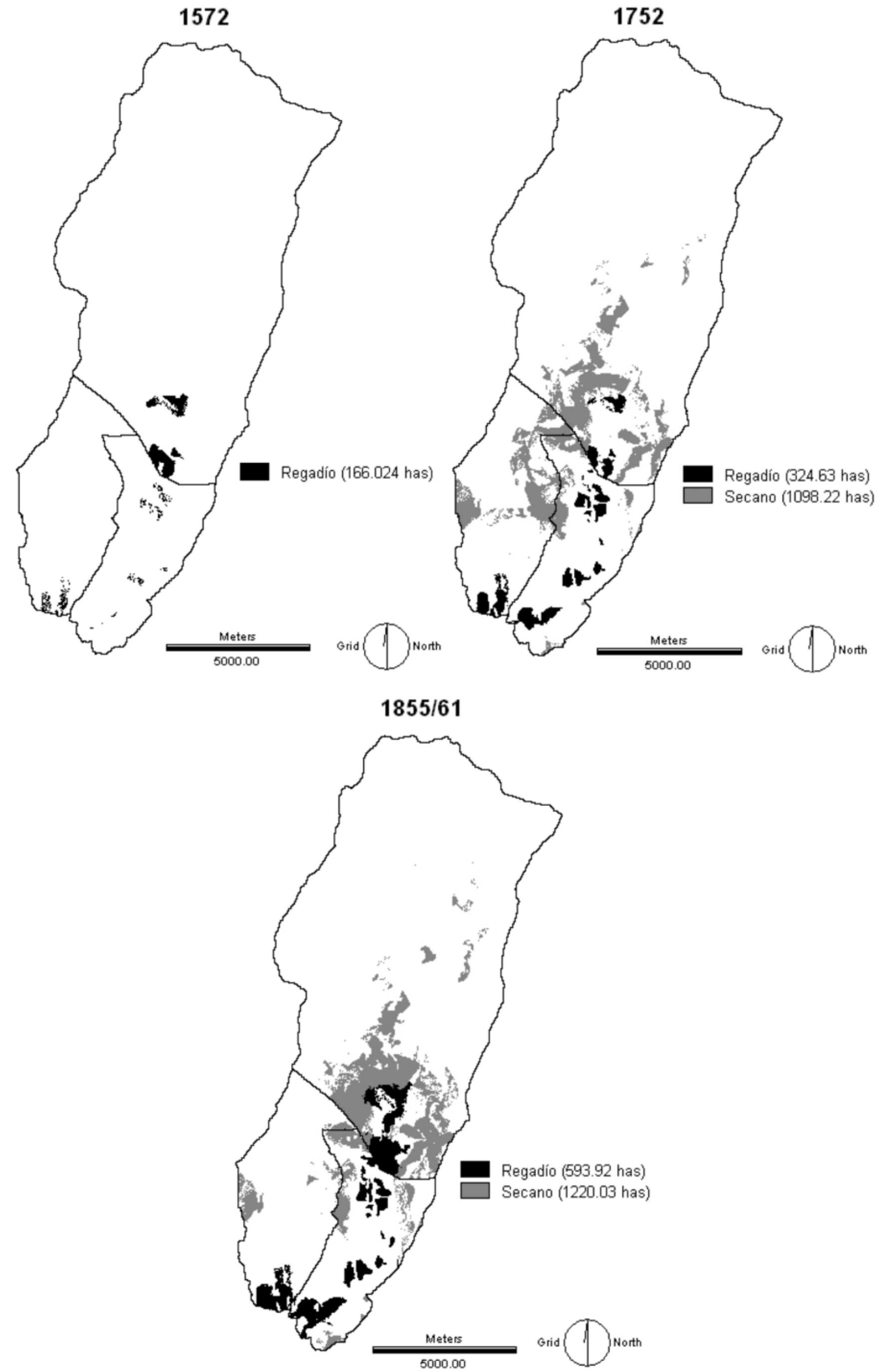

Fig. 9.5 Retrospective modelling of land use: 1572, 1752, 1855/61

Table 9.8 Areas of *regadio* and *secano* in 1572, 1752 and 1885/61 (ha)

Commune	1572		1752		1855/61	
	Regadío	*Secano*	*Regadío*	*Secano*	*Regadío*	*Secano*
Pórtugos	27.93	0.00	70.25	365.05	107.34	108.48
Busquístar	25.38	0.00	178.88	152.53	261.70	212.50
Trevélez	11.71	0.00	75.50	580.64	224.88	899.05
TOTAL	166.02	0.00	324.63	1,098.22	593.92	1,220.03

Sources: Libros de Apeos y Repartimientos (1572), Catastro del Marqués de la Ensenada (1752), Amillaramientos (1855/61). Elaboration: García Martínez (1999), modified.

9.5 Validation and discussion of results

The modelled historical land use maps are a stochastic approximation of the real spatial distribution for the two main land use categories in the past. Their extent is correct, but their spatial distribution can not be validated. We will use physical constraints and relationship between the modelled land use maps to the real land use map of 1957 to help us to estimate and interpret the results. However, a neutral comparison of these maps is also impossible. 1957 land use belongs to the criteria set used to model historical land use. This apparent tautological aspect is only partial. The cumulative weight of factors using land use in 1957 is about 18% for *regadío* and 25.5% for *secano*. Conscious of the limits of this exercise and without the possibility of validating the results by another source, we will first discuss them before relating them to the nearest known historical map: that of 1957.

9.5.1 Discussion of results and comparison with land use in the 20th century

Figure 9.6 shows land use in 1957, 1974, 1987 and 2001. Their legend is simplified so as to correspond with those of modelled historical land use. However, the maps of real land use during the second half of the 20th century contain one more category important to understanding the current land use dynamics: *semi abandon*. This category includes agricultural parcels used semi-permanently (a practice promoted by very slow vegetal recolonization) and a mosaic of micro-parcels, in which size can not distinguish between agricultural use and fallows. Table 9.9 is a table summarizing the previous mapped information.

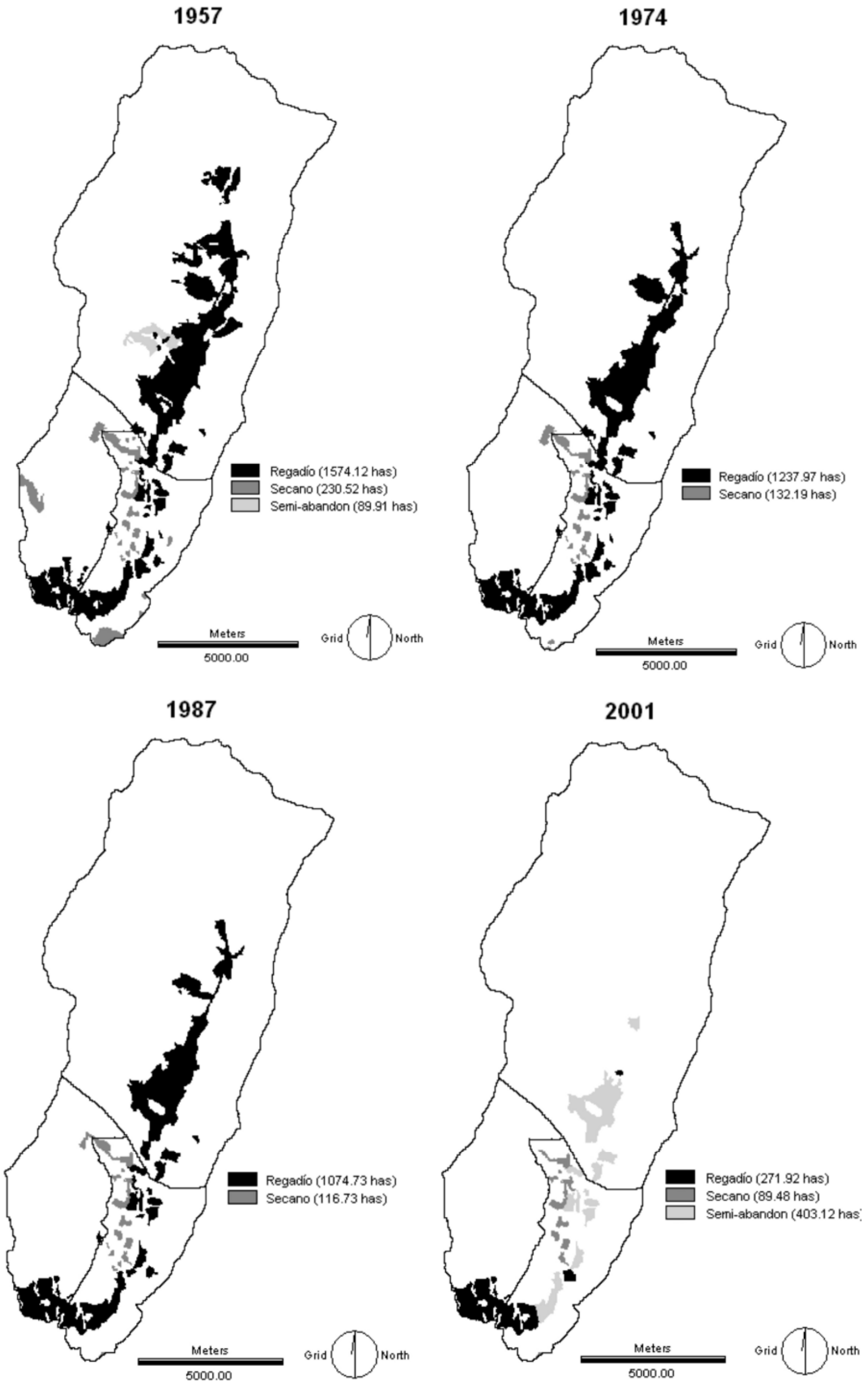

Fig. 9.6 Land use maps for 1957, 1974, 1987 and 2001

Table 9.9 Land use (ha) in 1957, 1974, 1987 and 2001

	1957			1974		
	Regadío	*Secano*	Semi abandon	*Regadío*	*Secano*	Semi abandon
Pórtugos	181.11	66.35	-	164.66	20.50	-
Busquístar	320.28	164.04	-	309.94	111.58	-
Trevélez	1027.43	-	89.91	762.30	-	-
TOTAL	1574.12	230.52	89.91	1237.97	132.19	-
	1987			**2001**		
	Regadío	*Secano*	Semi abandon	*Regadío*	*Secano*	Semi abandon
Pórtugos	163.04	10.34	-	157.74	-	-
Busquístar	276.67	106.28	-	110.39	89.40	155.00
Trevélez	634.09	-	-	3.55	-	247.77
TOTAL	1074.73	116.73	-	271.92	89.40	403.12

At first glance, the modelled historical land use (Figure 9.5) seems similar considering the spatial patterns over time. It shows also an extension of the agricultural land use from the 16th to the 19th century. This increase is much more evident between 1572 and 1752 as for the next period, which is more contrasting. Pórtugos *secano* even declined between 1752 and 1855/61. Except for this case, the increase of agricultural area concerns both: *regadío* and *secano*. According to modelled results, this increase happens by contiguous extension or near to the initial agricultural cores (a phenomenon particularly visible between 1752 and 1855/61). The mentioned decrease of *secano* in Pórtugos also took place in the same way: a spatial retraction, in which the process is similar to the general extension according to neighbourhood effects.

A first visual comparison between land use maps from the 20th century (Figure 9.6) and the modelled previous land use (Figure 9.5) shows that the highest suitability zones for *regadío* from the 16th to the 19th century correspond, generally, to those really used as *regadío* in 1957. The situation for *secano* is different. It seems that the criteria that are not available have an influence on its spatial assignment. This would explain the location of some high suitability level areas mid-side or the track of the distance factor in the north of Trevélez in the maps of 1752 and 1855/61.

A complete analysis of the full chronological set, from the 16th century to today, emphasizes that the most adequate dates for land use studies are, on the one hand, the second part of the 19th century, which correspond to the "ceiling of vital possibilities" of the traditional agri-pastoral system (Bosque 1969) and, on the other hand, the 1950's, which corresponds to the maximal agricultural land use in the second half of the 20th century. After that the process of land abandonment began, and continues to this day. However, an analysis at the communal scale brings out that the agricultural used area in Trevélez is more important in 1957 than in 1855/61, while one can notice a quasi-stability in Pórtugos and Busquístar during the same period, while the more detailed situation (*regadío* and *secano*) is even more complex.

9.5.2 Crossing modelled land use in 1855/61 with real land use in 1957

We crossed the modelled land use map of 1855/61 with the real land use map of 1957. Both dates correspond to a maximal agricultural land use for the concerned period and economic operating system. As already mentioned above, the map of 1855/61 depends partially on land use in 1957 used as criterion in MCE with a weight of 18% for *regadío* and 25.46% for *secano*. However, this comparison helps to demonstrate the methodological limits in modelling and the limits of used data by analysing the residues: areas and dynamics defying the model. Also conscious that a century separates the two dates and aware of the statistical limits of the used historical documents, this overlay is helpful to estimate the quality of modelling results.

Figure 9.7 shows the Cartesian product of modelled land use (1957) and real land use (1957). To acquire more information about land use dynamics we used a more detailed legend for the situation in 1957. This way non-agricultural land was split into three categories: 1. forest, scrubs and pasture; 2. coniferous reforestation; 3. fallows. Fallows are very expressive for agricultural transformations because it is the spatial track of former agricultural land use.

The most evident changes visible in the map (Figure 9.7) are the increase of *regadío* and the decrease of *secano* between 1855/61 and 1957. The increase of *regadío* creates an area with high suitability level for *regadío* in 1855/61 that in reality is assigned to *regadío* in 1957. The cross matrix (Table 9.10) quantifies this observation. 87.55% of modelled *regadío* in 1855/61 (593.10 ha) still have the same land use in 1957 (519.27 ha); 100% in Pórtugos. The rest (73.83 ha) became coniferous reforestation (45.73 ha) and forests, scrubs or pasture (21.74 ha). Only 4.55 ha were transformed to *secano*.

The important increase of *regadío* (165%), principally centered in Trevélez near to the upper section of the river, is due first to development of non-agricultural land (873.20 ha) and for a minor part to transformation of *secano* into *regadío*.

The process of *secano* dynamics is the reverse of that of *regadío*. Only a small part (6.32%), located in Busquístar, of the most suitable areas for *secano*, also modelled as *secano* in 1855/61, still remained *secano* in 1957. *Secano* quasi disappeared in the two other communes. The major part (93%) of lost *secano* became non-agricultural land: forest, scrubs and pasture (27.8%), coniferous reforestation (11.4%) and fallows (41.1%). 15.8% were transformed to *regadío* (a land use change completely located in Trevélez) and only 3.9% became semi-abandoned land.

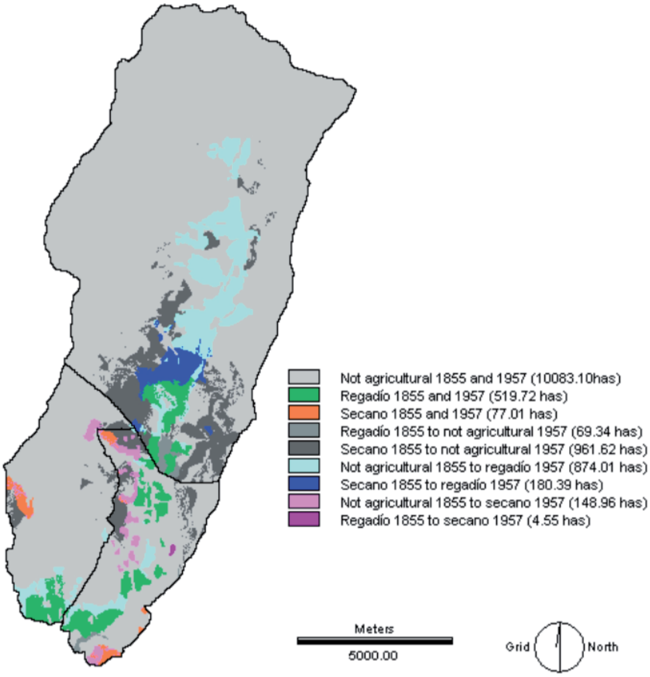

Fig. 9.7 Crossing modelled land use in 1855/61 and real land use in 1957

Table 9.10 Matrix of modelled land use in 1855/61 x real land use in 1957 (ha)

			1855/61			
	Land use		Not agricultural	*Regadío*	*Secano*	Total 1957
1957	Not agricultural	Forest, scrubs, pasture	9,402.19	21.74	317.16	9,741.09
		Coniferous, reforestation	315.11	45.73	129.65	490.49
		Fallows	311.87	1.81	469.37	783.05
	Semi abandon		45.23	0.00	44.61	89.84
	Regadío		873.2	519.27	180.23	1,572.76
	Secano		148.83	4.55	76.94	230.32
	Total 1855/61		1,1096.49	593.10	1,217.96	230.32

The most important difference between modelled land use in 1855/61 and real land use in 1957 concerns the supposed evolution of non agricultural used land. According to data of Table 9.10, resulting from a pixel by pixel crossing of the two maps, 311.87 ha of the non-agricultural land became fallows one century later and 45.23 ha semi-abandoned land. This means that these areas, non-agricultural in the middle of the 19th century, would be used for agriculture after this date but were abandoned until 1957. In addition to that, almost two-thirds (148.83 ha) of *secano* in 1957 (230.32 ha) would have been non-agricultural land a century ago. This modelled evolution is concentrated in Busquístar. This may have happened as a spatial swap of *secano* caused by coniferous reforestation. The forest campaigns also affected irrigated crops and a part of them have been relocated near the river (Figure 9.7).

These doubts about the spatial assignment in modelled land use, partially different from the real land use distribution in 1957, may signify that the agricultural strategies of the three communes vary and thus using a uniform set of criteria to model the communes creates inaccuracies. This is proven by global data at the communal scale. One can note the quasi disappearance of *secano* in Trevélez and an important increase of *regadío* at the same time (Tables 9.8 and 9.9). In Pórtugos, the decline of *secano* is also visible, while *regadío* expanded moderately. In Busquístar, the evolution is once more different: a moderate increase of *regadío* and a decrease of *secano*.

Another factor responsible for a part of the land use changes is the degree of reliability of the historical sources (García Martínez 1999) in which the definition of *regadío* and *secano* is not even clear but also the distinction between continuous irrigation and occasional irrigation.

9.6 Conclusion and outlook

Retrospective modelling opens a large field of applications for historians dealing with text documents and statistics as maps. Spatialization is also a challenge for paleo-environmental studies, which tries to reconstruct - land use/land cover changes during earlier periods.

The limits of retrospective land use modelling depend on the reliability of statistical sources and methodological restrictions.

The authors commented in detail on the used historical sources containing variable definitions. Also the registered area does not always correspond to the surface obtained in our geographical data base.

The main methodological problem is that authors used actual criteria in MCE to model historical land use for a lack of historical maps. Also some criteria changed over time, but authors created one suitability map for each category, which is supposed to match with the suitability conditions from the 16th to the 19th century.

The second methodological problem is the fact that the authors created only one suitability map for all communes (and not one per commune). This may explain a part of the mentioned inadequacies. Analyzing the suitability maps for *regadío* and *secano*, one can note a certain convergence in the spatial assignment criteria, the main effect of which is spatial contiguity of *regadío* (on low altitudinal terraces) and *secano* (located at higher altitude). The reality is more complex and farmers distinguish between irrigated land close to villages and the rest, but also between continuous and occasional irrigation. These conditions vary from one commune to another. This is mainly the case of *secano,* which is localized also mid-side as low altitude area (like *regadío*) but farther from rivers. However the modelling intends to integrate this by directly relating factors (areas identified for each category) and indirectly relating factors like specific distance for each category to fallows and villages in 1957.

The use of the 1957 land use map as criteria to model historical land use creates the need for a certain conditioning of the results and restricts the validation possibilities. However, the situation is more differentiated at the communal level. In communes with an important land use change like Trevélez, authors note a stronger correlation with factors which are independent from the 1957 based criteria. The changes that are the most difficult to explain are transformations between *regadío* and *secano*. This clearly limits the significance of the modelled results at the communal level.

A last methodological limitation is caused by the multi objective evaluation that intends to resolve conflicts between concurrent objectives by using the suitability level of each MCE created categorical land use map, in which the criteria are limited by availability.

However, keeping in mind the available data and their quality, MCE and MOE techniques supply an innovative method for stochastic-based modelling of historical land use with spatial assignment able to deal with a large number of criteria. The method is transposable and offers a solution to a frequent case: availability of statistical data without maps of the modelled phenomenon. To improve the model it would be important to model separately each commune (in more generally terms each spatial unit with a specific behaviour) in the MCE and MOE steps. This also allows the integration of the variable degrees of knowledge and reliability. Finally, the necessity of model calibration by a document containing finer spatial distribution of the modelled variable as the communal level is dependent upon the availability of data.

Acknowledgements

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Multi objective conflicts and environmental impact of intensive agriculture

10 Simulating greenhouse growth in urban zoning on the coast of Granada (Spain)

Aguilera Benavente F, Matarán Ruiz A, Pérez Campaña R and Valenzuela Montes LM

Abstract
Within the last 30 years, greenhouse growth on the coast of Granada has become an environmental and territorial process of extraordinary significance, which has caused a huge transformation in the landscape and the traditional irrigated crops existing in this Mediterranean area. The creation of simulation models for generating future scenarios is focused on the evaluation of the environmental consequences of the increasing greenhouse use, mainly on non-urbanizable land according to coastal urban planning. Commonly, this land has higher environmental and heritage values. A simulation model based on cellular automata has been created, similar to those widely utilized in urban processes modelling. The agricultural use of the simulation model has followed the dynamics of urban process models of recent years, for their industrial and intensive character-istics and the significant process of diffusion and spatial contagion, with hardly taking into consideration the urban planning mechanisms.

Keywords: Greenhouses, changes in the land use, scenarios, cellular automata, urban zoning.

10.1 Introduction

The coast of Granada is located in southeast Spain. In this area, similar to the rest of the Mediterranean coast, the use of land for agricultural purposes and the consequent anthropization have historically been very significant (Fernández Ales et al. 1992). The transformation in land use, which has occurred during the last 50 years, is well known agriculturally as wells as for urban uses (Matarán and Valenzuela 2004). The first farms appeared in the 1950s; after 20 years there was broader development, and the biggest transformation has occurred since the 1970s. Nevertheless, the greenhouse growth process is clearly a new type of territorial transformation, similar to those occurring in dynamic areas such as strawberry intensive farms in Huelva (Spain) or tourism development along the coast.

In the particular case of greenhouses, the impressive expansion is mainly the result of the successful initiatives carried out by the local producers. Greenhouses are very profitable because of the climate conditions that make a year-round (non-seasonal) production possible (Castilla 2004). This new agro-industrial land use consumes high quantities of resources and produces several waste fluxes (Matarán 2005). It is also causing dramatic landscape changes because urban and spatial planning regulations are not taken into consideration and are occupying non-urbanizable land. In this land, most of the environmental and heritage values are found. However, new planning criteria are urgently needed. Moreover, the spatial and environmental conflicts could increase if the growth process continues, and this will be analyzed in this article using the implemented model and the created future scenarios.

In order to define these future scenarios for greenhouse expansion and according to many previous urban expansion research studies (White and Engelen 1997, White et al. 1997, Stefanov and Christensen 2001, Barredo et al. 2003, Cheng and Masser 2003, Aguilera 2006), this article will present an ex post predictive analysis of greenhouses on the coast of Granada, based on the spatial and temporal description of greenhouse dynamics between 1977 and 2007.

The first step of this study will be to describe the most important factors involved in this complex process by developing a simulation model based on cellular automata, similar to those widely utilized to model urban processes. For this reason, greenhouse growth processes are considered similar to urban growth processes, since this is an industrial agriculture with similar patterns of spatial dynamics such as spatial diffusion and contagion.

Using this model, a set of ex post simulations have been generated for the period of 1990 through 2007. This has allowed us to carry out a calibration of the model. Subsequently, future simulations of the possible expansion of greenhouses have been generated based on three scenarios until the year 2025. Results of such simulations can be the base for a decision-making process designed to overcome an unsustainable situation through new planning and management criteria.

10.2 Test areas and data sets

The studied area is located on the Granada coast, which is characterized by a length spanning 71 km and a particular (distinct) landscape: several deltas, hills, and huge slopes. The absolute distance from sea level to 1,000 meters altitude is 10 km. And the highest mountain of the Iberian Peninsula (Mulhacen Peak, 3,482 meters) is only 30 Km away from the coastline. This situation reduces the influence of the northern winds, which results in a subtropical microclimate unique in Europe and suitable for both subtropical farming and greenhouses (Frontana González 1984).

Since the 1970s, the mild climate situation for horticultural crops combined with the emergency use of cultivating under plastic allowed, an expansion of low cost greenhouses, utilizing low (delete space) levelled technology in comparison to other parts of the world (Castilla 2004).

From the entire, above-mentioned coastal strip of land, a constrained section of 180 km² has been selected to represent the overall situation of greenhouses, which is the main process affecting expansion and the geographical diversity of the coast (Fig. 10.1). Three units (West, Central, and East), each with their different particularities, can be distinguished in this field in order to give a representative view of the greenhouse expansion process and dynamics in any of the characteristic spatial situations of greenhouses: West Unit- greenhouses in a fertile agricultural plane, Central Unit- greenhouses in a non-fertile agricultural plane, and Eastern Unit- greenhouses in a rough valley.

Cartography for this area has been created in order to demonstrate the evolution of greenhouses throughout the last 30 years (the period of the most important growth), also to show a set of territorial variables that have influenced the expansion process of greenhouses based on previous studies (Matarán 2005, Aguilera et al. 2005, Matarán et al. 2006). Both will be used to carry out the elaborate model in the different simulations. They are shown in the following figures.

10.2.1 Greenhouse growth cartography

To begin with an analysis of the greenhouse dynamics over the last 30 years has been carried out using the growth cartography developed for the years 1977, 1984, 1990, and 2007 shown in Fig. 10.2. For the years 1977 and 1984 the cartography is based on aerial photographs. For the year 1990 it is based on the satellite image Landsat TM, we applied a non-supervised classification using the ISODATA (Chuvieco 2002) algorithm and we have also compared our results with the land use cartography of the year 1991 (Consejería de Agricultura y Pesca 1991). Finally, for the year 2007 the cartography is mainly based on a Landsat ETM+ satellite image of January 2003 corrected with the orthophotos from the Junta de Andalucía (2004) and Google Earth (2007).

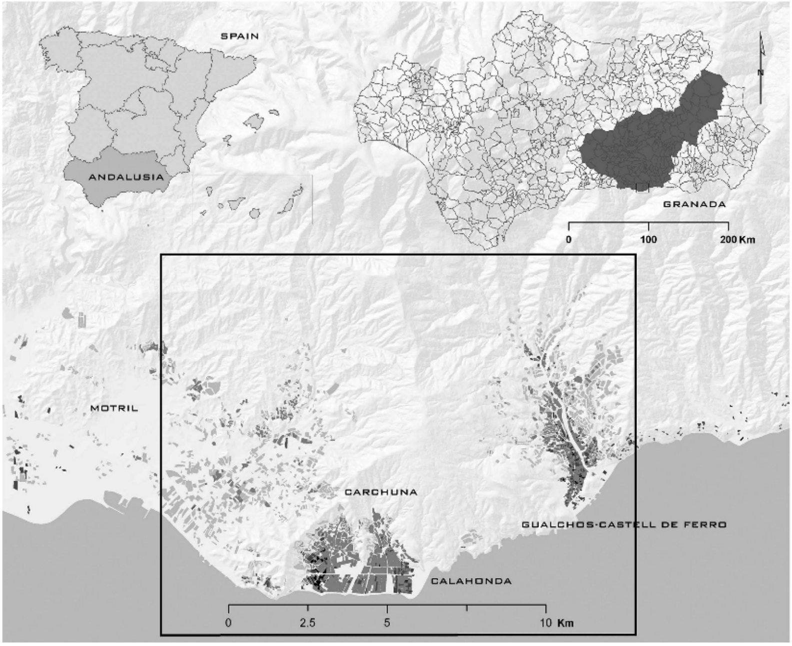

Fig. 10.1 The Coast of Granada: studied areas

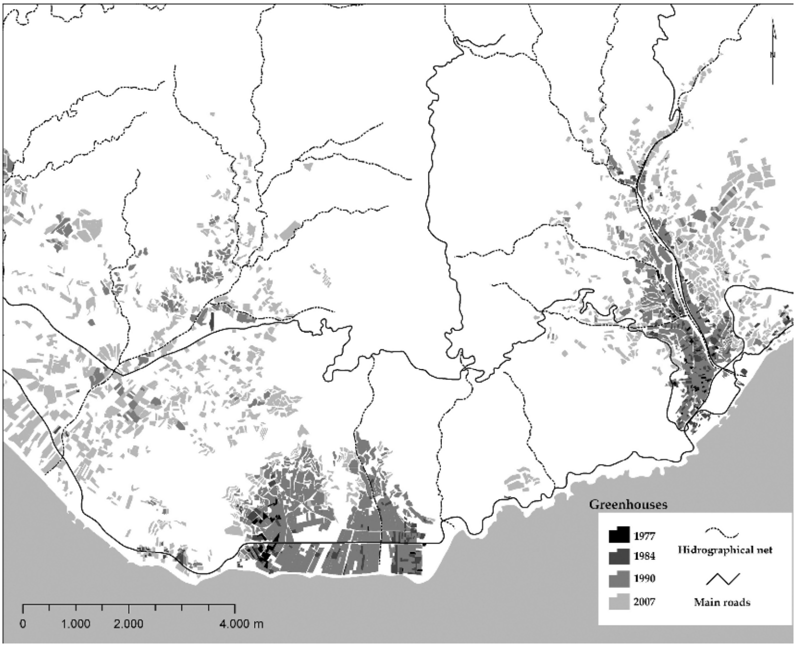

Fig. 10.2 Greenhouse growth cartography 1977-2007

As shown, the greenhouse surface development over the last 30 years has been extraordinary. The first greenhouses appeared in the 1950s, and since the 1970s greenhouse crops have gradually replaced irrigated low-land crops and non-irrigated coastal land crops.

In 1977, only 20.17 hectares existed within the studied area, and by 1984, the greenhouse surface had undergone a major growth process resulting in five times the original surface to approximately 95.44 hectares. Since 1990, as a consequence of this extraordinary growth, the greenhouse surface has reached 464.68 hectares, which will result in the saturation in most of the plane lands situated below the altitude of 100 meters along a significant part of the coast (Matarán 2005).

During the 1990s, the greenhouse surface continued expanding at a significant growth rate, especially in the West unit (Rambla del Puntalón). After the 1990s, this growth slowed down due to the stabilization of market prices and the emergence of plagues that affected the production (Matarán 2005). This has resulted in the current uncertain situation with a greenhouse surface of 1,664.26 hectares, posing the creation of scenarios that may shed light on possible future consequences of this process.

10.2.2 Territorial variables cartography

According to previous studies on the geography of greenhouses (Matarán 2005), and together with the greenhouse evolution cartography the following group of environmental and spatial factors have been charted. These factors have been considered to be the most influential in greenhouse development in a study based on logistic regression (Matarán et al. 2005, Matarán et al. 2006). The factors are as follows:

– *Land uses:* This factor represents the importance of the previous landscape structure and growing pattern.
– *Distance to central places:* The "central areas" are the centers for commercial purposes and provision of services for farmers (Matarán 2005). The distance to these places influences the set up of new greenhouses.
– *Distance to roads:* accessibility affects the expansion of greenhouses as it reduces the costs for building new lanes for the setup of greenhouses and it also facilitates the access to merchandising centers.
– *Distance to hydrographical net:* distance to the irrigation channels defines the costs of the irrigation and is the only restriction concerning water, as the new Rules dam and its irrigation net has introduced in the XXI century enough water resources for greenhouse growing. In addition to this, a price policy approach coming from the application of the

Water Framework Directive (2000) will not affect the greenhouse agriculture as it consumes less water and produces bigger benefits than the rest of agricultures (Matarán 2005).

- *Topography:* height above sea level determines the temperatures and the pumping needs for irrigation.
- *Slopes:* high slopes imply greater set up costs, whereas areas with low slopes cost less.
- *Orientation:* relates to sunlight and temperatures. Northward-orientated areas imply lower temperatures, fewer sun hours and less marine breeze.
- *Protected areas:* In Natural and National Parks, it is forbidden to build greenhouses, other regional or national restrictions are not considered in the anarchic greenhouse planning described by Matarán (2005). In addition to this, as we state in the article, in local protected areas we have found fewer restrictions.

10.3 Methodology and practical application to the data sets

The characteristics of the greenhouse expansion process described above, and the significant territorial and environmental consequences that result from these characteristics make the process quite comprehensive. The creation of future simulations from these considerations create an approach of alternative expansion scenarios in order to compare and weigh spatial possibilities. The predictive capacity of the model alone would in vain if it did not contribute to the decision process.

Our interest for modelling lies not only in knowing or creating a gradually more precise model, but also as an instrument for planning through the identification and the anticipation of possible spatial consequences that could allow us to suggest new planning criteria.

In order to carry out this task, the creation of a simulation model of greenhouse expansion has been proposed. Similar to those widely utilized in the listed bibliographies, it is based on cellular automata (CA), which is used for the simulation and evaluation of urban growth; including greenhouse expansion and many previous urban expansion research studies (White and Engelen 1997, White et al. 1997, Stefanov and Christensen 2001, Barredo et al. 2003, Cheng and Masser 2003, Aguilera 2006) as well as other natural processes, in which spatial contagion is very significant, such as in forest fires.

Applying these types of models in the field of agricultural growth could seem strange or unjustified at first glance since these tools have been widely utilized for the analysis of the spreading of urban processes. Due to the spatial characteristics of these processes, they can be "well reproduced" by the models based on CA (Batty 1997, White et al. 1997, Torrents 2000, Barredo et al. 2003, Barredo et al. 2004). These characteristics, such as the similarity through scales, spreading processes, spatial autocorrelation, contagion, attraction, repulsion, etc. can also be identified and modelled through CA for the use with greenhouses. In addition to their agricultural use, greenhouses have an intensive characteristic, which converts them into agro-industrial soil, and therefore acquire certain urban properties (Matarán 2005). These properties influence the variables that set the spatial nearness and spreading. Consequently, these properties make applying CA ideal for the construction of a predictive model (Matarán et al. 2006).

The methods used for creating simulations consist of building a model that allows the creation of an ex post simulation for the situation in 2007 using the greenhouse surface cartography from 1990, thus including the most important period of greenhouse growing and based on the knowledge of the growing process since the 1970s. Generating simulations for 2007 and comparing them with the actual situation at that time will allow the progressive calibration of the model eventually obtaining the most accurate simulations compared to the actual data in 2007 beginning with the available data for 1990. Calibrating and adjusting the model will result in the comprehension of the spatial process previously defined as the main objective of this study.

Once the ex post simulations are carried out, some perspective simulations will be generated for 2025 using the most up-to-date cartography, the map of 2007, as the base year, thus we are considering a similar interval for the calibration process (17 years) and for the modelling (18 years, not 17 years in order to round up to 2025). The proposed simulations for the same year (2025) will be based on the approach of three greenhouse expansion scenarios that consider 15 to 20 years as the best period to assess greenhouse dynamics (see Sect. 10.3.2). These simulations allow an analysis of the effects of the possible expansion of greenhouses on non-urbanizable land included in the planning.

10.3.1 The model based on cellular automata

The model based on cellular automata is theoretically inspired by those developed for urban environment by White et al. (1997). At a practical level, the model has been completely developed using IDRISI Andes. This model has been used as a base for the studies of different authors (Barredo et al. 2003, Aguilera 2006, etc). Some modifications have been introduced to this theoretical model.

From a theoretical point of view, the model is composed of three different parameters. By combining these components, a transition potential for greenhouse use will be obtained.

The three parameters are:

1. A *neighborhood parameter*, consistent on the cellular automaton, which has been defined for a regular grid whose elements or cells are represented by the cells on a raster GIS using a pixel of 50x50 meters, selected according to the average size of greenhouse farms (around 0.8 to 1 ha).
2. *A territory aptitude* value, or parameter, for each cell built by combining the set of charted territorial variables and those previously described.
3. Finally, it is also composed by the stochastic, or randomness, parameter. The objective of this parameter is to generate a "real" degree of disorder, similar to the parameter that roughly characterizes the distribution and change in spatial urban processes.

Since previous studies (Aguilera et al. 2005, Matarán et al. 2006) have revealed a low correlation between this factor and greenhouse growth[1], in this version of the model used for this case study, the accessibility parameter of the transition potential calculation is not considered (as it is in the urban theory purposed by White et al. 1997).

These parameters are combined according to the following equation:

$$P_I = v \times (1+s) \times (1+n) \tag{10.1}$$

Where:

- P_I is the transition potential of each cell in greenhouse use. It is the result of the combination of all the parameters previously described.
- n is the neighborhood parameter, also referred to as the parameter of cellular automata.
- s is the territory aptitude parameter for greenhouse use. Created using the set of charted factors, this parameter, for which correlation analysis exists from previous studies, will be presented below (Aguilera et al. 2005, Matarán et al. 2006), and has shown a significant relation to greenhouse growth. These correlation values given by the ROC (Pontius and Batchu 2003) statistic are presented in Table 10.1.

  The group of factors include: topography, slopes, orientations, uses of soil, distance to the road networks, distance to the commercialization centralities, distance to the hydrographic network, and protected areas.

[1] The values for the ROC statistic for the accessibility existing in previous studies (Matarán et al. 2006) were 0.63

They have been combined resulting in the aptitude parameter as shown below.

- v is the stochastic parameter, also referred to as the parameter of random perturbation. This parameter is used in order to try to replicate the degree of randomness inherent to social processes.

Table 10.1 ROC Values

Factors	ROC
Topography	0.8555
Distance to greenhouses	0.8355
Distance to centralities	0.8299
Slope	0.7982
Land Use	0.7257
Distance to roads	0.6291
Distance to hydrographical net	0.6106
Protected areas	0.5601
Orientation	0.5302

A detailed description of the parameters follows.

10.3.1.1 Neighborhood parameter

n refers to the neighborhood parameter, being in itself a CA parameter. The automaton is considered to work in a relatively simple way; for each cell, it obtains a value of change potentiality depending on the present greenhouses in the adjacent cells that compose its regular grid. The closer cells will attract the new greenhouses stronger than the farther cells. This decrease effect of attraction-repulsion is known in the literature as "distance-decay effect" and, as pointed out in White et al (1997), appears as a common characteristic in most of the cities.[2]

In order to be able to implement the model, a filtering matrix (9x9 cells) is used (Fig. 10.3). This matrix calculates the potentiality value for each pixel of the raster grid, depending on the number of pixels that represent the greenhouse use around it and on the distance between them. Using this matrix, the value of the neighboring pixels are multiplied by a certain factor (0 represents the absence of a greenhouse, 1 represents the existence of a greenhouse) that represents the attraction capacity of the new greenhouses

[2] This behavior is generic, and does not apply in all cases. It is possible that certain uses can show a growth in attraction after some distance, as it can occur in industrial uses, repelling in close distances to residential uses, and at longer distances can attract.

generated by the surrounding, or neighboring pixels, and shows a decay effect with distance. According to this parameter, it is assumed that those pixels, having other pixels with greenhouse use in their vicinity, will have a higher trend to turn into new greenhouses.

1	1	1	1	1	1	1	2	1
1	2	2	2	2	2	2	2	1
1	2	3	3	3	3	3	2	1
1	2	3	-50	-50	-50	3	2	1
1	2	3	-50	0	-50	3	2	1
1	2	3	-50	-50	-50	3	2	1
1	2	3	3	3	3	3	2	1
1	2	2	2	2	2	2	2	1
1	1	1	1	1	1	1	1	1

Fig. 10.3 Filtering matrix

Therefore, the definition of the filtering matrix is crucial, in other words, it determines up to which range of distances the pixels will be considered as neighboring, just as in the assignment of the factor of the model calibration process. This process assigns values to the neighborhood parameter. These values determine the attraction that the greenhouse areas generate on the adjacent areas. This calibration process is carried out using approximation through different trials, until certain values are set, which al-low obtaining results as close as possible to the actual results.

Finally, all the values are summed and the resulting value is normalized between 0 and 1.

10.3.1.2 Aptitude parameter

The aptitude parameter refers to the intrinsic capacity of the territory to accommodate greenhouses. It has been defined by combining the variables, or territorial charted factors, and those variables which the existing correlation value of greenhouse growth has previously shown. In order to combine these factors, each one of them has been converted into an aptitude factor on a scale from 0 to 1, in such a way that the values close to 1 represent the most optimal values of the factor for the establishment of greenhouses. The values close to 0 represent the worst values of the expansion variable. For instance, for the slopes, the higher values will have an aptitude value close to 0 and the lower values will have a higher aptitude value.

Utilizing IDRISI Andes software, the factors expressed in aptitude values from 0 to 1, and the correlation values for each one of them, have been combined using the methodology of multi-criteria evaluation (Malczewski

1999, Gómez and Barredo 2006) in order to determine the global aptitude factor. By means of a pair comparison matrix, in which the different factors have been prioritized according to the correlation values previously obtained (Aguilera et al. 2005, Matarán et al. 2006), the different weights assigned have been determined in order to carry out the weighting system of the multi-criteria evaluation.

Table 10.2 shows the correlation values obtained from the ROC statistic, as well as the value of the weight assigned in the MCE for the different factors, used in the determination of the aptitude.

Table 10.2 ROC and MCE weight values

Factors	ROC	MCE weight
Topography	0.8555	0.40
Distance to greenhouses	0.8355	-
Distance to centralities	0.8299	0.25
Slope	0.7982	0.13
Land Use	0.7257	0.12
Distance to roads	0.6291	-
Distance to hydrographical net	0.6106	-
Protected areas	0.5601	-
Orientation	0.5302	-

Once these factors are combined depending on the weights presented in the previous table, the aptitude factor is obtained and used as a raster surface that shows the territorial aptitude for the location of the new, intensive agricultural crops. This surface is shown in the Fig. 10.4.

Areas having a higher aptitude (depending on the available variables) for the occupation of agricultural areas used for greenhouses are shown in lighter tones.

10.3.1.3 Randomness parameter

As pointed out previously, v is the stochastic or random perturbation, parameter. This parameter is used to try to replicate the randomness degree inherent to social processes. It is obtained for each of the pixels in the studied area applying the equation proposed by White and Engelen (1997).

$$v = 1 + (-ln(rand))^{\partial} \tag{10.2}$$

rand is a random number between 0 and 1.

∂ is a parameter that permits the adjustment of the degree of perturbation. After carrying out different simulations, with varying calibrations of this parameter, we have adjusted the value of α to 0.55 in this study. As this parameter increases, a larger degree of disorder is introduced. The simulations generated with high values of this parameter will tend to show more scattered forms of occupation than those simulations generated with lower values of this parameter.

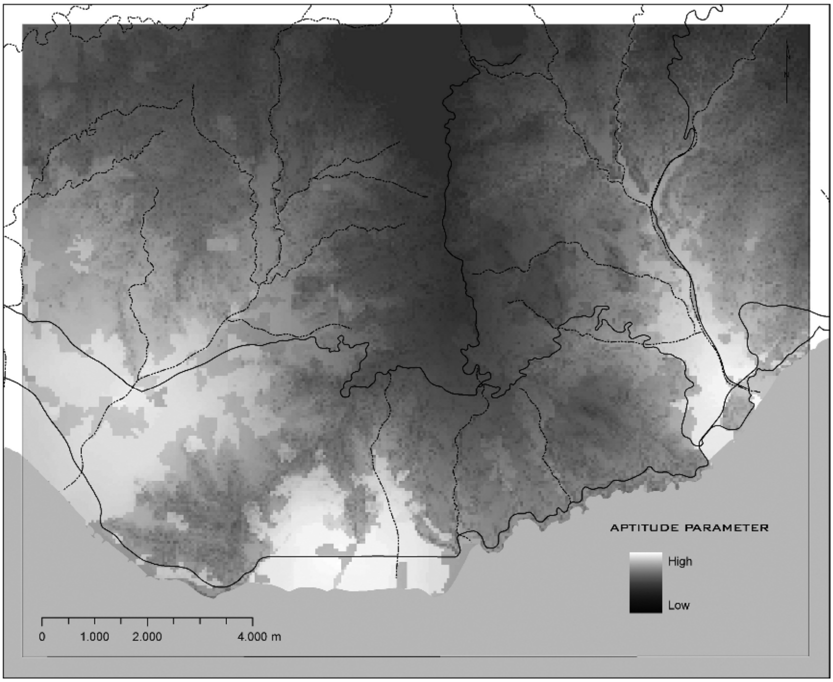

Fig. 10.4 Aptitude parameter

10.3.1.4 The implementation of the model

After the different parameters had been theoretically defined, they were implemented in the model constructor IDRISI Andes resulting in the greenhouse growth model. It is worth noting that the model has been completely implemented in a widely extended GIS, without having to resort to connections between geographic input data stored in the GIS and an external model. This has the advantage of not having to carry out programming tasks, which makes the model easily reproducible. It also eases its use for geographic fields, once it is calibrated. In this sense, this fact is a breakthrough, since the models proposed in previous literature consist of specific software and are usually complex. These previous models are developed just for this purpose and are highly complex when implementing their use.

The model works through a series of iterations, each iteration corresponding with a year in the simulation, and obtains a transition potential for each one of the pixels of the studied area and selects those with the highest potential. These pixels will be included as new greenhouses for the next iteration of the model.

The amount of pixels which are selected by the model in each iteration for the ex post simulation for the period of 1990-2007 will correspond with the annual growth rate of the greenhouses for that same period of time. For future simulations created and based on the 2007 greenhouse cartography; the selected surfaces in each iteration of the model as new greenhouses will be established by 3 future growth scenarios. These scenarios will be explained below and will take into consideration different situations of occupancy demand for new greenhouses.

10.3.2 The calibration of the model

As previously explained, the simulations carried out for the future, using the 2007 cartography as the base year, will require the establishment of certain surfaces and growth rates in order to allow the model to select a specific set of pixels with the highest potential. This occurs because the model can only spatially identify those pixels with the highest potential, but can not identify how many must change.

Three scenarios for the possible evolution of greenhouse agriculture in future years have been created, taking into account the socio-economical factor which determine greenhouse surface growth. These scenarios have been created in order to raise different future growth hypotheses, each hypothesis with certain demands for growth of greenhouse surface, which can be included in the model. Each one of these scenarios will be projected to the year 2025, starting from the existing situation in 2007. This 18-year interval has been chosen in order to maintain some similarity between the studied intervals in the period of 1990-2007 and, likewise, in order to consider enough time as to make it representative of the average values for factors that affect the localization of greenhouses.

Among the main factors that determine the dynamics of the 3 proposed scenarios, there is the profitability of crops, dependent on the market prices of these crops, based on the analysis carried out for the period of 1990-2003, obtained from Matarán (2005).

Dynamics will also be affected by other factors such as urban planning. According to what has been observed in the analysis of the last 30 years in the coastal region of Granada, urban planning is substantially modified at least every 15 years (and at most every 20 years), unless political decisions set different regulations. Up to the present, it has been observed that the greenhouses located on urbanizable land tend to be abandoned. This process has gone almost unnoticed in the recent years. However, the new planning in the early 21st century and the extraordinary dynamics of urban growth in this decade may lead to a significant transformation of some of the lands that are currently occupied by greenhouses.

Finally, the environmental factors and the availability of natural resources remain more or less constant in time, in other words, there is an amount of resources suitable to maintain different growth rates; for instance, what happened with water after the Rules Dam started working in the river Guadalfeo, (Valenzuela and Matarán 2008), the main river in the studied area.

Hence, according to these factors, 3 future growth scenarios have been proposed:

– *Stabilization*: This scenario represents stagnation in the greenhouse growth process, which would yield to the pressure of the incipient tourist sector. For this reason, the greenhouse surface remains more or less constant. However, a relocation process in which greenhouses are being urbanized occurs. Therefore, a growth in the greenhouse surface in the non-urbanizable areas has occurred, occupying about 208.35 hectares. This means a transformation of almost 1% per year, which is equivalent to the percentage of greenhouse areas that will be used for urbanization.
– *Tendential Growth:* In this scenario the average growth rates in the last 23 years (1984-2007) remain constant. In these years a process of occupation has taken place and it has resulted in the current saturated landscapes. This is related to the relocation process due to urbanization of existing areas, and to the existence of an average profitability similar to the average of the last 23 years that guarantees new growths at the previous pace. Therefore, the growth of the land occupied by greenhouses has increased by 1,274 hectares, representing an annual growth rate of over 4%.
– *Moderate growth:* In between the two extreme scenarios described, there is a scenario of moderate growth in which the average growth rates of the last 23 years (1984-2007) are reduced. It is related to the relocation process, because of the expansion of urban areas, and related to overcoming the current crisis scenario. This favors the existence of the average profitability, which could be lower than those of the last 23 years, lowering the capacity of the farmers´ ability to occupy new lands. The annual growth rate in this case could reach 2% (around 29 hectares per year), representing around 524.29 hectares of growth. This number and the total 208.35 relocated hectares, through the 18 years, add up to 732.94 hectares.

10.4 Results

Results for the ex post simulations used in order to carry out the calibration of the model during the period 1990-2007 and the future scenarios for the year 2025 will be presented next. The results for the ex post simulations will be presented first, followed by the results of the prospective simulations.

10.4.1 Results of the ex post simulation process in period 1990-2007

In order to calibrate the model, many ex post simulations have been carried out for the period 1990-2007 using the presented model. Hence, the feedback mechanism allows for the optimization of the results, narrowing in on the situation in 2007. Three of the simulations obtained, which were used in the model calibration process will be presented next in Fig. 10.5.

Through each simulation, a model that better resembles the current situation is obtained. In order to obtain better results in each of the simulations, the calibration values for the filtering matrix of the neighborhood parameter have been modified, as well as the randomness degree obtained from the stochastic parameter.

Simulation 6, visually, has the highest degree of similarity with the existing situation in 2007. This is corroborated by different tests used and described in the validation and discussion of the results epigraph. In this simulation, the existing "disorder" degree is lower than in previous simulations, which appear to have a dispersion degree higher than the actual one. This fact gives it a less "real" aspect due to the presence of multiple dispersed pixels. Other simulations, when trying to attenuate this effect, created masses in the areas planned as new greenhouses, which also reduced the ¨reality¨ effect. On the contrary, in simulation 6, a distribution of the greenhouse growth much more similar to the actual one can be observed. It has some "packages" that are not as compact as in some of the first simulations or as dispersed as in the other simulations.

For the Central unit, the result resembles the actual existing situation, although with a slightly higher degree of saturation. The West unit shows a similar structure, although the actual situation seems to show a lower degree of aggregation, tending to occupy areas of higher altitude than in the situation simulated by the model. Finally, the least similarity is found in the East unit. In this studied area, the obtained results are less satisfactory since the simulation shows a much more compact situation than the reality. These results show different situations in the different units, which suggest that the three can be found in different stages of the expansion dynamic, making it difficult to calibrate them simultaneously. In any case, simulation 6 shows that it is possible to generate a simulation that can be similar to the actual situation, as will be discussed in the validation of results.

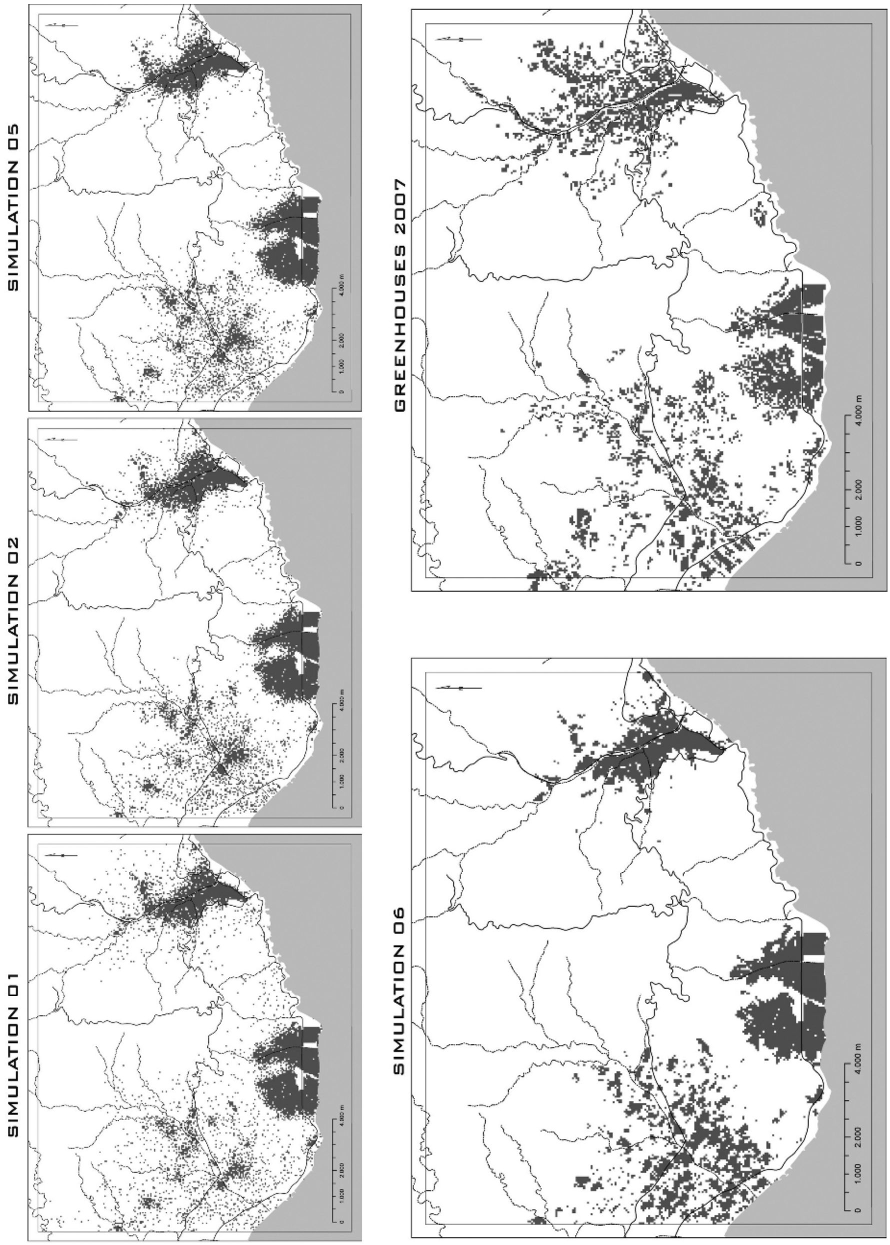

Fig. 10.5 Simulations obtained using the model

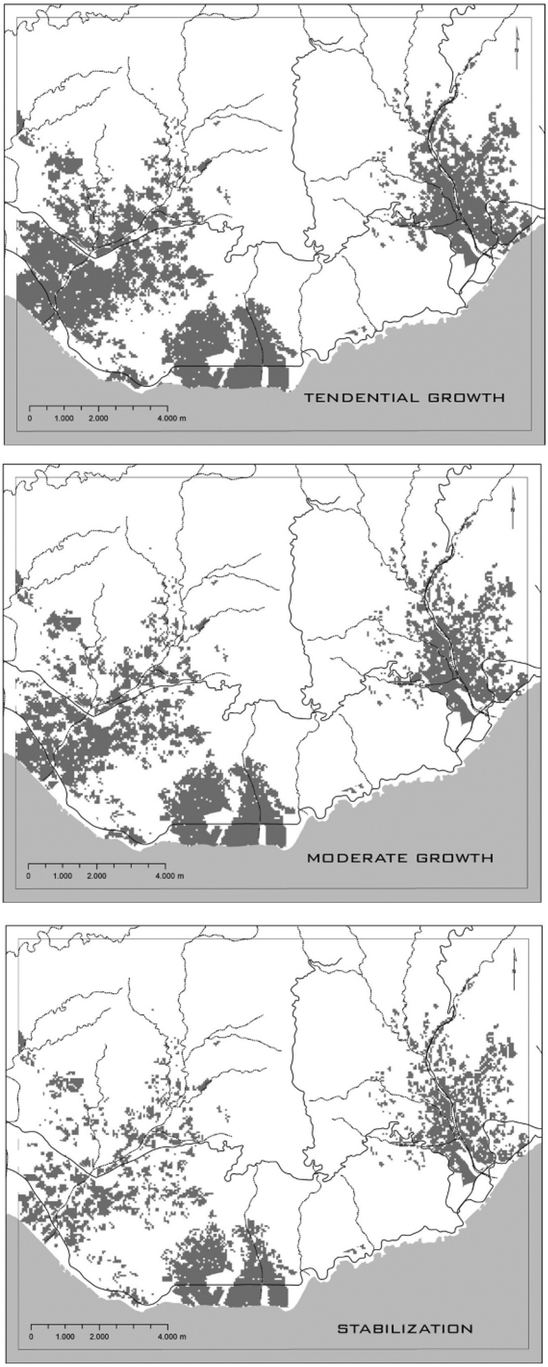

Fig. 10.6 Future scenarios generated

10.4.2 Results of the future scenarios

After the model has been calibrated according to the ex post simulations and the calibration used to generate simulation 6 (identified as the one which best represents the growth patterns of greenhouses, according to the tests applied in the next epigraph) has been applied, simulations for each one of the three proposed scenarios were carried out (stabilization, tendential growth, and moderate growth). The results for each one of these generated scenarios, using the base of the 2007 cartography, are shown in Fig. 10.6

From the top to the bottom, the figure shows the scenarios for tendential growth, moderate growth, and stabilization. The first scenario shows a greenhouse growth process that maintains the pace of the last years, which generates a massive occupation of the coastal plains, with a significant aggregation of new growth. The scenario for moderate growth shows a growth that is mainly the result of the relocation of greenhouses, which will be replaced by new tourist development, which does not cause such a pronounced saturation as in the first scenario. The stabilization scenario shows how only a slight relocation of some surfaces, that would transfer greenhouses to areas of lower tourist demand, would result in little change in the existing situation.

In the three scenarios, the occupation structure is very similar, changing generally the degree of saturation that reaches those areas which show acceptable aptitude values for being cultivated. This occurs because the areas of higher capacity are already occupied; hence the new growths have to compete for those areas that are not suitable for being occupied with new greenhouse agriculture.

In any case presented below, the different scenarios described show different possible degrees of development for the expansion processes of greenhouse agriculture along the coast of Granada.

10.5 Validation and discussion of results

After describing both the ex post simulations generated in order to calibrate the model and the different future simulations of the greenhouse expansion scenarios, a validation of the results of the ex post simulations for 2007 was carried out. Different comparison techniques have been applied, as well as an evaluation of the future scenarios and consequences that those scenarios could imply for the non-urbanizable lands, included the planning.

10.5.1 Validation of ex post simulations

Firstly, the validation of the ex post simulations generated through the cellular automaton model, should be considered. In order to do this, several methods for comparison have been selected to evaluate the different simulations with the existing situation in 2007. Besides the visual comparison previously shown, these methods include the already classic, pair comparison matrix, as well as a comparison through landscape ecology metrics, such as the patch number (PN) and their average size (MPS) (Botequilha and Ahern 2002, Botequilha et al. 2006). The pair comparison matrixes have been widely utilized as a method of comparison in simulations and actual situations, as in the models based in cellular automata used in the simulation of urban processes (White and Engelen 1997, Barredo et al. 2003, Aguilera 2006). However, these matrixes have been criticized for not being able to compare patterns at a landscape mosaic structure level (White et al 1997). Hence, a set of landscape ecology metrics that allows a comparison of the situation in the greenhouse landscape mosaic, has been selected. Since it is not so important to determine whether one or the other pixel will turn into a greenhouse, the use of this type of landscape and spatial pattern metrics as a measurement of validation of the simulations is much more valuable. This type of test is much more valid for the objective of this study because it can better identify the patterns and shapes of future occupations.

10.5.1.1 Comparison through matrixes; cross tabulation

Validation through pair comparison matrixes shows, by using the kappa index, the degree of similarity between two images by comparing pixel by pixel. Each one of the simulations can be compared to the actual situation, hence a coincidence value can be obtained for the paired maps. The main problem of this comparison method, as previously pointed out, is that is not able to identify occupation patterns. In any case, the following table (Table 10.3) shows the values for the kappa index for the next 4 selected simulations.

Table 10.3 Value for Kappa index for the selected simulations

SCENARIO	Kappa index
Simulation 1	0.5062
Simulation 2	0.5195
Simulation 5	0.5208
Simulation 6	0.5368

The previous table shows how the values are very similar for all the simulations and it can be noted that they are low values. In other words, pixel by pixel, the simulations do not correspond very accurately with the results (reality). For the first three simulations, which visually do not accurately resemble the actual situation, the results do not seem to be too illogical. However, for simulation 6, which at least at a visual level seemed to resemble the actual situation, the results are not very encouraging, since the values for the kappa index are only slightly higher. The different behaviours of the different units distinguishable in the studied area explain these results (Fig. 10.7). For the West and Central units, at a visual level, the results seem to be satisfactory. However, for the East unit the results are less satisfactory. It is possible that the results of the East unit affect the kappa index by lowering it for all the studied areas.

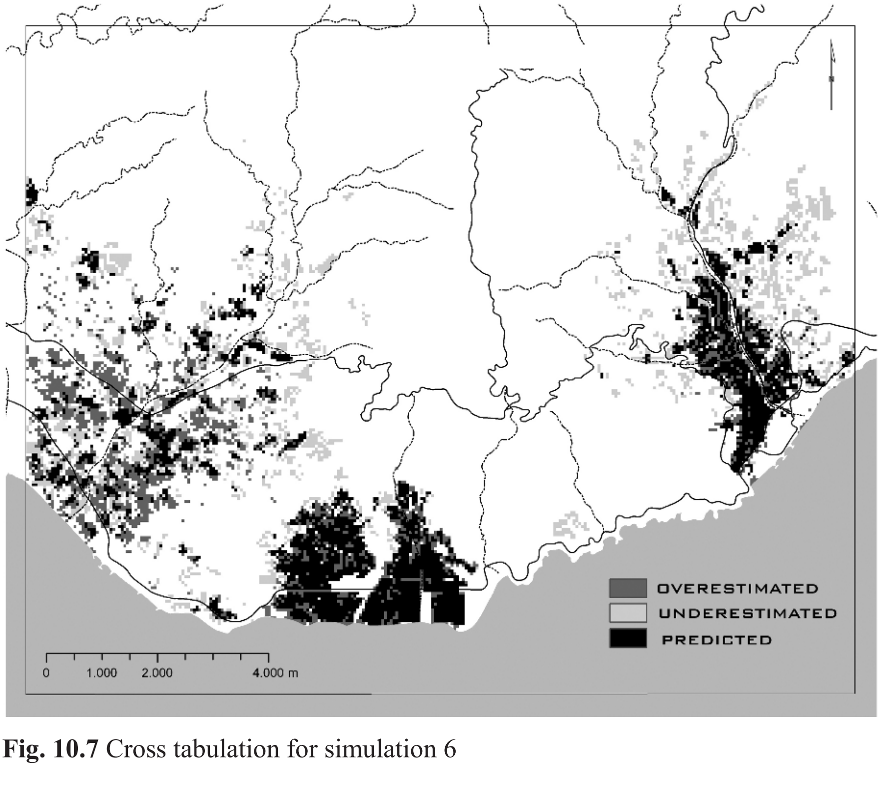

Fig. 10.7 Cross tabulation for simulation 6

An individual calibration would probably show more accurate results, taking only one of the three units as a field of study. In order to consider the possible particularities of each of the existing units (West, Central and East), subsequent developments of the model and its calibration could work in this way, as it was developed for a logistic regression model (Aguilera et al 2005). Regardless of calibration type, in this article we wanted to assess the process at a subregional scale, which means that we have to consider at least an area large enough to represent the main situations.

10.5.1.2 Comparison through landscape ecology metrics

The other method selected in order to validate the results, consisted of the comparison through landscape ecology metrics. These are non-dimensional (only comparable) metrics (Table 10.4, Fig. 10.8), whose exhaustive description can be found in McGarigal and Marks (1995) and in Botequilha et al. (2006), and among them we have selected the following:

PN: The *patch number* is the simplest metric in the landscape ecology and can hint to how much a use is divided or fragmented.

MPS: From *the medium patch size*, the average surface of individual spots of a certain use will be obtained (McGarigal and Marks 1995). In this study, the average values of the different patches will be obtained.

Table 10.4 PN and MPS value for the 4 simulations and the real situation

SCENARIO	PN	MPS
Simulation 1	833	2.00
Simulation 2	903	1.84
Simulation 5	1,238	1.35
Simulation 6	238	6.79
Greenhouses 2007	356	4.70

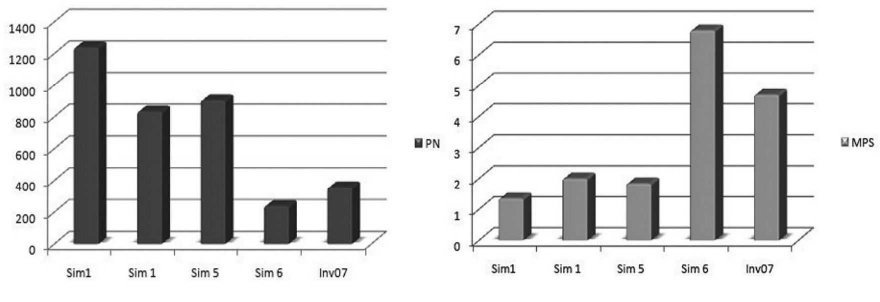

Fig. 10.8 PN and MPS result

In accordance with this comparison method, simulation 6 shows values much more similar to the actual situation than the previous simulations, despite having similar values for the kappa index. These values show that simulation 6 is able to roughly reproduce the occupancy structures that greenhouses showed for the period of 1990-2007. The comparison through matrixes and kappa index is less suitable in trying to identify those simulations that show a pattern similar to the actual one.

Likewise, in spite of the fact that there is not a total degree of coincidence (perfect agreement), this simulation is considered capable of generating future scenarios fairly representative of the greenhouse growth dynamic that might occur. Hence, it has been selected for the simulation of the previously described simulations.

10.5.2 The valuation of future scenarios; the growth on non-urbanizable land

Finally, generated future scenarios have been valued, with special attention to the occupancy of the lands included in the planning. In this sense, the location of the greenhouses would take place on non-urbanizable land in the tendential and moderate growth scenarios, in which a net increase of the greenhouse surface occurs, as well as in the relocation scenario.

The higher growth in the tendential scenario represents a densification of the greenhouse surface in the studied area. This compactness mainly appears in both the West and East units.

The other two scenarios, the moderate and the stabilization scenarios, involve a higher presence of areas free of greenhouses in an interstitial manner in the three units. Lower compactness represents better drainage and water infiltration, especially for the aquifer located in the West unit, as well as a more distant location from the dry watercourse that lowers the risk of flooding.

Other consequences of lesser compactness in greenhouse use would be environmental infiltration related to ecologic connectivity, the possibility of diversification of uses, and the decrease of the visual impact of greenhouses.

Because of the intensive use, which is closer to the industrial use than to the traditional agricultural use, municipal planning should establish certain control mechanisms regarding the different categories that can be established for non-urbanizable land. In the example of Motril, located in the West unit, the greenhouse expansion would be restricted to two areas (in gray) located in Fig. 10.9 (according to the municipal town planning of from 2003).

Fig. 10.9, corresponding to the tendential scenario, shows how a large quantity of greenhouses would be located in non-urbanizable land, especially when protected because of its forest and archeological values or its high slopes.

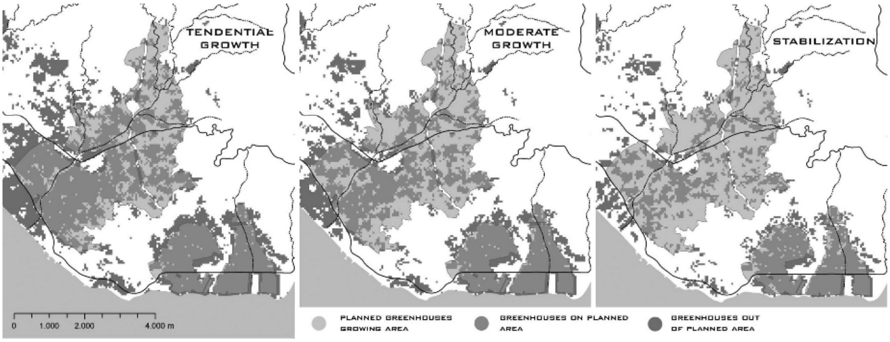

Fig. 10.9 Future Scenarios and Non-urbanizable land

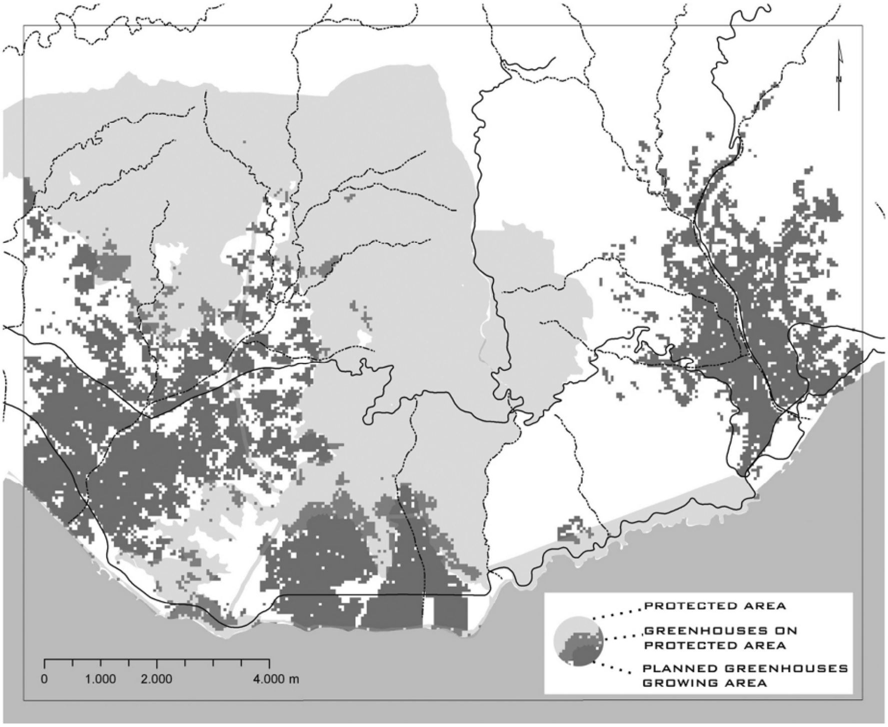

Fig. 10.10 Greenhouses located in protected areas. Tendential scenario

Therefore, it is necessary to establish adequate control mechanisms for greenhouse growth, taking into consideration the criteria based on environmental and landscape functions in the planning of non-urbanizable land. Using these functions, the suitability of certain areas for organized greenhouse growth can be established.

10.6 Conclusion and outlook

Analyzing, modelling, calibrating, predicting, interpreting, planning, and managing spatial change should represent a constant and unitary sequence in planning, feeding back models and territory management systems. In such a manner that predictions can be used in order to make informed decisions and not the other way around. Models should adapt to territories, helping to understand and describe complex processes with a clear territorial significance, such as this case of intensive greenhouse agricultural growth on the coast of Granada (Matarán 2005). In this case the model developed, although it did not obtain spectacular values of similarity (average values for the kappa index and approximated values for the spatial ecology metrics) in the ex post simulations, fulfills the desired objectives. It advances knowledge both in the comprehension of the greenhouse expansion territorial process, as well as in the creation of future scenarios, which could be incorporated into the planning and decision-making process. Since 2004 a sub-regional plan has been in development, unfortunately the regional authority in charge of this plan is currently the sole user of the model. Local authorities could also use the model, seeing as they are in charge of urban planning and zoning, and greenhouses need to be included in these regulations as they are considered an agro-urban land use. Finally, other administrations such us the environmental and the water administrations (both regional and national) could use the model, for example to assess the possible environmental impacts produced by greenhouse wastes (Matarán 2005) or to predict the increasing hydrological risk due to the impervious surface of new greenhouses.

On the other hand, results obtained from future scenarios, with significant growth of non-urbanizable land (some under special protection), raise some questions about planning, optimizing the use of the results of the simulations.

- Which significant parameters exist in order to identify the environmental and financial impacts originated from the spatial diffusion of greenhouses?
- Which monitoring instruments exist that can utilize parameters, or indexes, capable of planning and managing the diffusion of a certain activity?
- Is it possible to generate environmental and territorial suitability criteria for the greenhouse spatial diffusion process?

These questions arise as consequence of: the analysis of the process, the attempt of modelling of the process, and the creation of possible future scenarios that start to take into consideration the planning process. For that precise reason, the modelling and comprehension process of the greenhouse diffusion per se, should be advanced. In this sense, some of the proposed challenges are:

– *Incorporating new factors which can effect the process.*

Many of the factors analyzed and utilized in the model described are territorial factors that are easy to chart and obtain information from. However, other factors are more diffuse and difficult to value, such as landscape inertia (Matarán 2005). This concept is related to the existence of changing motor forces in the land use, linked to facts including social, financial, cultural, and spatial origin of the conditioning processes. These other factors can be decisive, because lands that have conditions suitable for expansion a priori, will remain unaltered and vice versa.

– *The space-time perspective of the model and future scenarios.*

Regarding the time and space scale, predictive dependency should be mentioned first. The field, the selected variables, and the understanding of the process end up conditioning the results, also conditioned by the chosen technique (Verburg et al. 2004). In this sense, new proposals must be developed in order to improve the modelling process. In any case, an added complexity such as the spatial process should be considered. It responds to an original and accelerated expansion process (around 30 years), unprecedented in the international literature or in analysis on this spatial process.

– *Validation methods and use of spatial ecology metrics.*

Validation methods are an additional main challenge that arises from the design of these models. Spatial ecology metrics can end up representing not just an alternative method, but also a complementary method to other classic methods, such as the comparison matrixes method. These classic methods have been criticized for not being able to take the spatial pattern into account (White et al. 1997). In this sense, the exploration of other metrics that have understanding of compactness and shape can be, and must be, explored in future studies.

These metrics can also be utilized in order to value possible future scenarios and determine environmental consequences of growths that are more disperse, compact, aggregated, etc.

All these factors must be explored in new studies in order to maintain the advancement in the knowledge of the greenhouse expansion process on the Mediterranean coastal areas and to incorporate the results of the simulations created in the decision-making process, with the objective of planning and valuing consequences of possible future situations.

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11 Greenhouses, land use change, and predictive models: MaxEnt and Geomod working together

Benito de Pando B and Peñas de Giles J

Abstract
We have developed a methodology which predicts the expansion of greenhouses and evaluates the results, combining a species distribution model (MaxEnt) and a simulator of land use change (Geomod). In the simulations, we take into account not only the effect of different environmental variables governing greenhouse expansion but also the spatial distribution of the error. The method has been tested on a region of SE Spain to establish future greenhouse-expansion scenarios. The results indicate that the combination of MaxEnt and Geomod improves the predictive capacity, as well as the functional interpretation of the land use change models.

Keywords: Geomod, MaxEnt, land use, distribution model.

11.1 Introduction

In the context of global change, the study of land use change takes on great relevance because small changes at the local scale (plots of a few ha), added together, can exert an impact on the scale of the entire planet. An example is the deforestation of tropical jungles, which diminishes atmospheric carbon fixation, imposing long-term consequences on global climate (Dixon et al. 1994). An analogous problem of emerging importance involves the expansion of greenhouses, a form of industrial agriculture that is developing on a grand scale in certain regions of the planet. In 1999, an estimated 682,000 ha were occupied by greenhouses throughout the world, especially in China (380,000 ha), followed by Mediterranean countries (161,300 ha in France Italy, Spain, Greece, Turkey, Morocco, and Algeria (Takakura and Fang 2002).

The problems arising from the spread of greenhouses are directly related, on the one hand, to the natural resources available in the affected region (biodiversity, natural habitats, water resources, etc.) and, on the other hand, to human resources (nearby populations). The construction of greenhouses covers the soil, depriving it of its ecological functions (evapotranspiration, infiltration of precipitation, supporting habitats, etc.), and it degrades the dynamics of natural habitats by fragmenting and destroying them. Greenhouse crops, though designed to make maximum use of irrigation, nevertheless demand huge quantities of water, altering the regime of aquifers. Other problems associated with greenhouses that can concern human health are plastic waste and organic debris contaminated by pesticides and fertilizers.

In the last two decades, the European food market has generated a high demand for fresh vegetables and fruits, triggering the uncontrolled proliferation of greenhouses in productive regions. The growth rate of greenhouses and the lack of a territorial management policy have wreaked havoc, inflicting grave environmental repercussions. In this context of uncontrolled land use change, management plans are indispensable for balanced regional development in which the economy and natural conservation are in balance.

Some GIS-based methods are useful to design and improve land use management plans, such as the land use and cover change simulations (LUCCs) (e.g., cellular automata, Geomod or Markov chains), which experimentally replicate the transition between land uses (Pontius et al. 2001, Jantz et al. 2003, Pontius and Pacheco 2004, Aguilera 2006). Other applicable methods are the species distribution models (SDMs) (e.g. Bioclim, GARP, MaxEnt), which provide knowledge on the potential distribution of targeted species and are increasingly in use for the design of conservation plans (Guisan and Zimmermann 2000, Posillico et al. 2004, Johnson and Gillingham 2005).

In this paper, we propose a method to predict land use change based on the integration of SDMs and LUCCs. The main idea is to use MaxEnt to compute distribution models, and use them in Geomod as suitability maps to perform better land use change simulations.

The main objectives of this paper are:

- Compare simulations performed by Geomod used in stand alone mode with the combined simulations performed by Geomod and MaxEnt, to test the feasibility of integrating the two methods.
- Introduce Procrustes analysis as a tool to evaluate the spatial agreement between simulations and ground-truth information.
- Introduce an easy method to compute the spatial distribution of certainty in Geomod simulations in order to generate certainty maps for assessing simulation accuracy.
- Test the proposed method in the period 1987-2001 (using 1987 data to calibrate and 2001 data to evaluate) to perform simulations for the period 2001-2010, in order to provide and explore three future scenarios of spreading of greenhouses.

11.2 Test area, data sets and tools

11.2.1 Test area

The test area selected was the province of Almeria (SE Spain, see Fig. 11.1), located between 3.14ºE and 1.62ºE longitude and 36.6ºN and 37.46ºN latitude (Fig. 11.1). The surface area analysed is 7,171 km². The climate is Mediterranean, with rainfall of 200-300 mm and means annual temperatures of 16-17ºC. Geologically, post-orogenic sedimentary materials predominate, and the landscape is dominated by a mosaic of chamaephyte plant communities, xerophytic grasslands and varied communities of annual plants. Greenhouses have been spreading in the area since 1960, occupying around 37,000 ha in 2001.

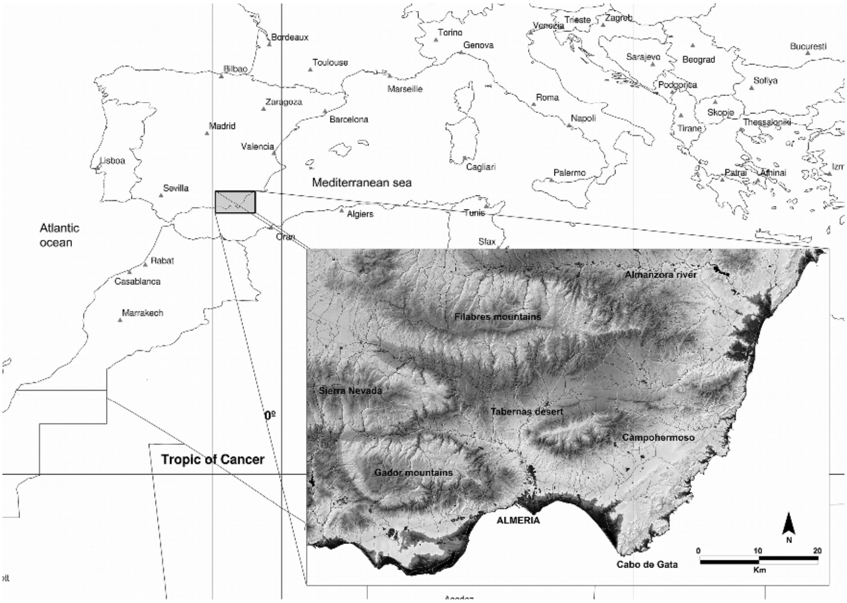

Fig. 11.1 Situation of the test area in the Mediterranean geographical context

11.2.2 Data sets

11.2.2.1 Environmental and geographical variables

From a digital elevation model of 20 m resolution (provided by the Environmental Information Network of the Andalusian Regional Government) a total of 11 topographical variables were derived: elevation, slope, northness, southness, eastness, westness (in gradient from 100 to 0), direct solar radiation (mean, minimum and maximum computed by the Solar Analyst extension for ArcView 3.2), topographical wetness index (TWI) and sediment transport index (STI) (both computed in ILWIS 3.4 Open using the Flow_indices script available at http://spatial-analyst.net).

From road maps from 1987, 2000 and 2006 (2006 map includes roads under construction expected for 2010), we mapped the distance to roads of 1st, 2nd, 3rd, and 4th order (motorways and national highways, regional roads, provincial roads and local roads, respectively) for years 1987, 2001 and 2010. For each year, an "accessibility index" coverage was built, computed by a weighted mean of the distance coverages. Weights were: 1 for 1st order roads, 0.75 for 2nd order roads, 0.50 for 3rd order roads and 0.25 for 4th order roads. The weighted sum was scaled into values from 0 to 100 using the module Stretch of the Idrisi Andes software.

Coverages of distances to water resources in years 1987 and 2001 were drawn using the cartography of water infrastructures of the regional government of Andalusia. Distances to water resources in 2010 were computed using the locations of future desalination plants projected by the Water Plan of the Ministry of the Environment of Spain. Areas not suitable for greenhouses (towns, lakes, natural parks) were masked in the datasets so as to be excluded from the analysis.

To avoid high correlation between variables in the dataset, we used Biomapper 3.0 (Hirzel et al. 2006), which computes UPGMA (Unweighted Pair-Group Meted with Arithmetic Mean) trees using Pearson's correlation index as the distance between variables. With 0.75 being selected as the maximum correlation threshold, from each group of highly correlated variables, one was retained. The remaining variables (elevation, slope, topographical-wetness index, mean solar radiation, accessibility index, distance to water resources, and the distances to roads of 1st, 2nd, 3rd and 4th order) were used to compose three data sets corresponding to the years 1987, 2001 and 2010, which had in common topographic variables but differed in the values of the distance variables (see Fig. 11.2).

11.2.2.2 Greenhouse coverages and presence records

For the calibration and evaluation of MaxEnt suitability maps and Geomod simulations, presence records and greenhouse coverages are needed. For calculating greenhouse coverages for 1987 and 2001, digital land use maps from the years 1991 and 1999 (stored as polygon layers) were manually corrected using Landsat images (RGB composites) of years 1987 and 2001 as reference. The resulting polygon layers were rasterized to determine greenhouse (absence/presence) Boolean coverages. From these coverages, 340 and 471 presence records of greenhouses were collected, respectively, by random sampling, establishing a minimum-distance criterion (at least 1000 m between records) in order to avoid spatial autocorrelation effects from using samples too close together (pseudoreplication).

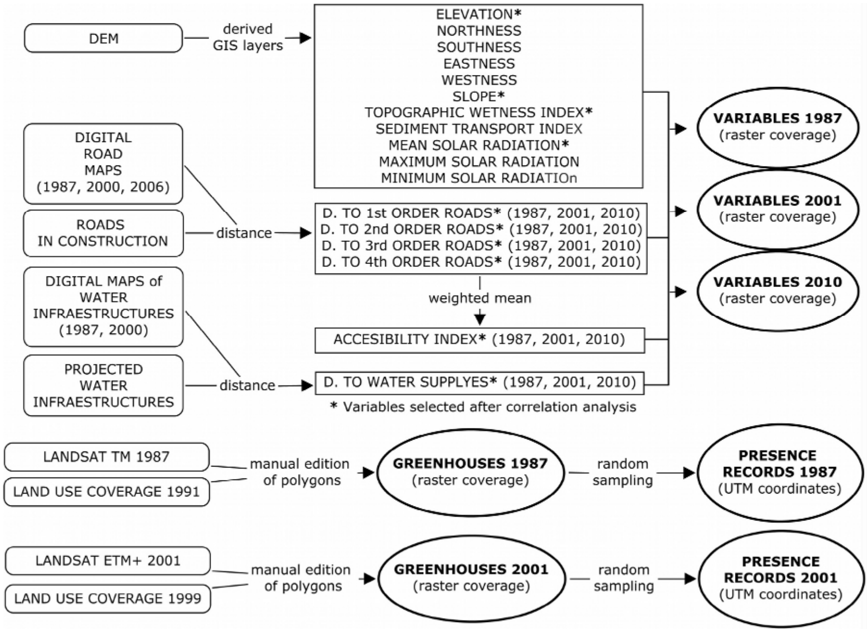

Fig. 11.2 Flowchart I. Making of the environmental datasets and presence samples

Although the initial resolution of both data sets (variables and greenhouse coverage) was 20 m, the process that we wished to model occurred at a lower resolution, related to the dimensions of the greenhouses (Hengl 2006). A study of the mean area of the greenhouses indicated that a pixel size of 80 x 80 m would properly represent the land use change, and therefore all the spatial data were rescaled to this resolution using the module Contract included in Idrisi Andes (pixel aggregation for continuous data and pixel thinning for categorical data).

11.2.3 Modelling and evaluation tools

11.2.3.1 MaxEnt

MaxEnt (Maximum Entropy), a general purpose method for making predictions from incomplete information, has recently been applied to modelling biological species distribution (Phillips et al. 2006). Successful tests have demonstrated that its results are among the best possible within the broad set of algorithms for distribution modelling (Elith et al. 2006).

The algorithm needs a sample of presence records of the organism and a set of environmental variables of the entire study area to compute the distribution model. The environmental variables and functions representing the interactions among them are called “features”, from which the ecological niche of the species is defined. Using presences, features, and a background sample (locations taken randomly from the entire study area) MaxEnt searches iteratively for the probability distribution of the maximum entropy (the closest to uniform), but subject to one condition: the expected value for each feature under the estimated distribution matches its empirical average (calculated from the values of the feature in the presence records). The probability is computed in terms of “gain” (log of the number of grid cells minus the average of the negative log probabilities of the sample locations), which starts at zero and increases in each iteration, until differences between iterations fall below a predefined “convergence threshold”, or the “maximum iterations” number is reached (Phillips et al. 2006).

The probability distribution is projected onto the geographical space, resulting in a distribution model with a range of values of between 0 and 100, which expresses in relative terms the suitability of the habitat for the species (suitability map). MaxEnt can also project the model over variables representing a different time, to explore simulated past or future scenarios. In order to provide a better understanding in the relationships between variables and presence records, MaxEnt performs a Jackknife test to measure variable importance, and plots the log response curves for each variable.

Greenhouses require a combination of environmental variables (temperature, solar radiation, etc.) and geographical ones (distance to roads, water resources) that influence its productivity. These requirements determine the greenhouse construction site selection in the same way as a biological species selects an appropriate habitat. This quasi-biological behaviour permits the application of MaxEnt to calculate the potential distribution of greenhouses, using the same method as applied to biological species. According to this idea, high suitability values in a greenhouse MaxEnt distribution model indicate areas adapted for the construction of greenhouses.

11.2.3.2 Geomod

Geomod (Pontius et al. 2001) is a land use change simulator implemented in Idrisi Andes (Clarklabs 2006). It simulates the land use change between two categories (e.g. from unoccupied to occupied by greenhouses) using as start-up information the beginning and ending time of the simulation, a coverage with the initial state of the two categories, the land area changing in use (indicated by the number of cells), a series of environmental variables from which a suitability map is drawn (determining the areas most prone to use change), and a stratification map (enabling the area to be divided into regions that behave differently).

The simulation is based on certain decision rules:

1. Land use change is simulated in only one direction, from occupied to unoccupied or vice versa, but not both simultaneously. If a stratification map is used, Geomod can simulate changes in different directions for different strata.
2. A neighbourhood rule should be defined: in the constrained mode, a radius is established for the edge of the initial use patches within which Geomod will search for the areas prone to change. In the unconstrained mode, it searches for transition areas without restrictions on the radius, throughout the entire territory being analysed.
3. The suitability map for land use change. Geomod computes a suitability map from a set of environmental variables (that influence land use change) and a coverage of the initial state of land use. The computing method reclassifies each variable into categories, assigning to every new category the value of the percentage of cells occupied by the land use towards which the change is going to be simulated. Finally, a weighted sum of the reclassified variables is used to compute the suitability map. The weighting factor may be equal for all the variables or defined for each one by the user. The values of the suitability map are called "lubrication values": larger lubrication values implies high suitability for land use change (for more details, see Pontius and Chen 2006).

11.2.3.3 Procruster analysis

Sensitivity (S) is the conditional probability that a presence cell in the reference image is predicted correctly in a simulation. It can be calculated from the confusion matrix provided by de Crosstab module of Idrisi Andes, dividing the true presences (correctly simulated cells) by the sum of true presences and false presences (incorrectly simulated presence cells). The result (the true positive fraction) is a measure of agreement between a simulation and a reference image in terms of quantity, without bearing spatial differences in mind. We use this additional evaluation measure to support the results of the Procrustes analysis.

11.3 Methodology and practical application to the datasets

Two simulation phases were executed using Geomod: to test the performance of MaxEnt suitability maps and select the decision rules that best represent the spreading of greenhouses, nine simulations using different combinations of decision rules were performed and evaluated for the interval 1987-2001 (1987 data to calibrate and 2001 data to evaluate simulations). Then, using the selected rules, Geomod simulations considering three different land use change scenarios were performed for the interval 2001-2010.

11.3.1 Simulations 1987-2001

The aim is to select the decision rules available to calibrate Geomod simulations that best describe the spreading of greenhouses in the study area. Suitability maps computed by MaxEnt and Geomod, and different neighbourhood rules were combined in nine performed simulations:

- Suitability maps: Three suitability maps were used: *1)* M1, (computed in MaxEnt) model calibrated with the training sample and variables of 1987. *2)* M2, (computed in MaxEnt) model calibrated with the training sample and variables of 1987 and projected over variables of 2001 (using the Projection feature available in the software). Suitability maps computed with MaxEnt were calibrated using the default settings (Phillips et al. 2006). *3)* G1, computed in Geomod with the greenhouse's coverage and variables of 1987 (using the same weighting factor for all variables).
- Neighbourhood: settings used were 80 m (1 cell around), 2,000 m (25 cells around) and unconstrained.

The simulations were calibrated setting the starting time at 1987, initial area of the greenhouses coverage of 1987 (38,743 cells, 24,795 ha.), ending time at 2001 and final area of the greenhouse coverage of 2001 (58,097 cells, 37,182 ha). All simulations were stratified by municipality limits, representing the diversity of land-management policies in different towns. An extra simulation (unstratified, without suitability map and unconstrained neighbourhood) was performed in order to simulate the random spreading of greenhouses, calling this the Random Simulation (hereafter, RS; to clarify this explanation, see Fig. 11.3).

11.3.1.1 Evaluation and spatial certainty of the simulations

It is important to consider that, on comparing a simulation with the reference image, both share the entire area occupied by greenhouses at the starting time (1987). Consequently, any comparison index that we apply will interpret an inflated degree of agreement between the simulation and the reference image. To avoid this inflation, we eliminated (in all the simulations, the RS, and the reference image) the area corresponding to greenhouses in 1987. Therefore, the evaluation took into account only the area of the new greenhouses.

Results were evaluated by Procrustes analysis and sensitivity using the greenhouse coverage of 2001 as the reference image. The simulation with the least m^2 and greatest S with respect to the reference image will determine the decision rules that best describe the spreading of greenhouses. Results were tested separately for Procrustes analysis and sensitivity by factorial ANOVA, establishing a "suitability map" (levels: G1, M1 and M2) and "neighbourhood" (levels: 80 m, 2,000 m, and unconstrained) as categorical predictors. The relationship between m2 and S were assessed by linear regression.

Usually, when evaluating a simulation by calculating its sensitivity, a homogeneous spatial distribution of certainty must be considered, assuming that all the simulated cells have the same likelihood of being correctly classified. In the real world, if greenhouses are constructed preferably in areas of high suitability (according to the suitability maps) because it favours greenhouse productivity, and Geomod selects as a priority these areas to simulate land use change to greenhouses construction, we can assume that the certainty of the simulation will vary according to the values of the suitability map. Following this reasoning, in the areas of greatest suitability, the probability of finding cells where the presence of new greenhouses has been correctly simulated is higher than in the areas of lower suitability. To test this idea, a joint analysis was made of the best simulation, its suitability map and the reference image (coverage of greenhouses in 2001), in order to: *1)* describe graphically the relationship between the suitability map and the total amount of hits (correctly simulated cells) and errors (incorrect simulated cells) in the simulation, plotting the number of hits and errors against suitability values; *2)* find a suitability-certainty function that relates each suitability value to a given probability for a cell to be correctly simulated, which is useful to compute a simulation certainty map. For this, the percentage of correctly simulated cells was plotted against suitability. The plot represents the specific behaviour of the best simulation, but we are looking for a more general function, capable of predicting approximately the behaviour of different simulations. With this aim, the data was smoothed by means of a moving average (using 25 as span size), and analysed by a polynomial-curve fitting using Octave.

11.3.1.2 Simulations 2001-2010

The spreading of greenhouses in the study area has been continuous from 1954, and today the construction of greenhouses is booming, due to the construction of new infrastructures oriented to increase water supply. But the greenhouses are involved in a dynamic market, and the profitability of the crops depends on multiple economic and social factors difficult to predict. Another emerging factor adding uncertainty in the last years is the competition with other Mediterranean countries with cheaper production. To confront this uncertainty we propose three simple scenarios of spreading of greenhouses for the period 2001-2010:

a) Linear greenhouse area growth with the trend identified for 1987-2001.
b) Accelerated growth (20%) over the linear trend due to increased demand.
c) Slowed growth (20%) under the trend due to increased competition from countries with cheaper production (e.g. Morocco and Algeria).

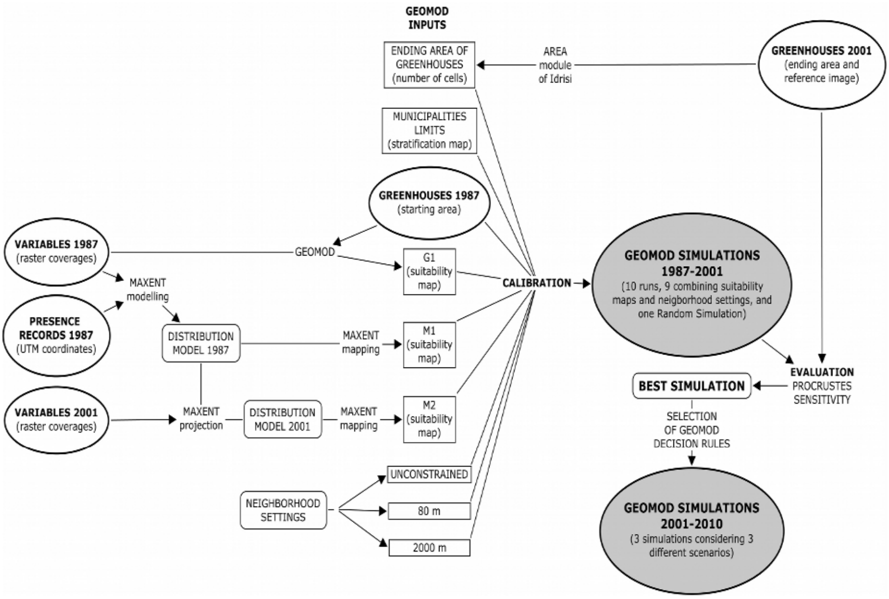

Fig. 11.3 Flowchart II. Steps followed to select the suitability map and the neighbourhood setting most appropriate to simulate the spreading of greenhouses

To be used a suitability map in the projections, a MaxEnt (M3) distribution model was calibrated using the training sample and variables of 2001, and projected over the variables of 2010. Differences in suitability between M2 and M3 were computed by map algebra. Using the 2001 greenhouse coverage as the starting image, the suitability map M3, and the projected areas in the different scenarios, three Geomod simulations for the period 2001-2010 were performed. To assess the spatial certainty of the simulations, the computed suitability-certainty function (see Sect. 11.3.1.1) was applied to the M3 suitability map (replacing M2 values by M3 values and dividing the result by 100 to translate percent values into probabilities).

11.4 Results

11.4.1 Simulations 1987-2001

Fig. 11.4 shows the coverage of greenhouses (1987) and the suitability maps used as inputs to calibrate Geomod simulations. Fig. 11.5 summarizes the influence of the modelling variables in the MaxEnt distribution model (suitability maps M1 and M2) and shows the log-response curves of the most relevant variables.

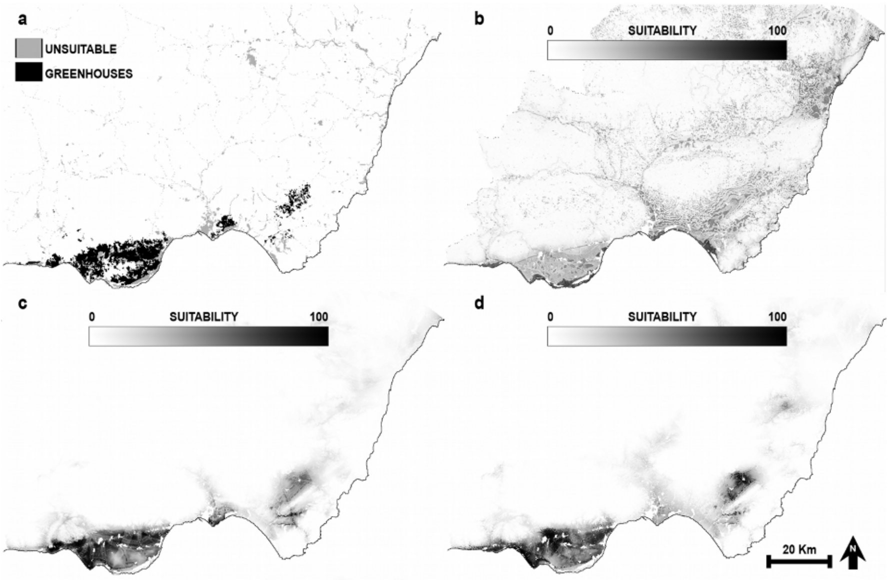

Fig. 11.4 Greenhouses in 1987 and suitability maps. a) Coverage of greenhouses in 1987 (starting time) used to calibrate simulations and non-suitable areas excluded from the analysis; b) G1 Suitability map, computed by Geomod; c) and d) M1 and M2 suitability maps calibrated in MaxEnt using presence records and variables of 1987 (M1), and projecting the model over variables of 2001 (M2). Dark colours indicate high suitability for the construction of greenhouses

The results of the Procrustes analysis and sensitivity for the nine performed simulations are shown in Fig. 11.6. All the simulations performed better than the RS (m^2=0.04; S=0.02), the results of which are not shown in Fig. 11.5 due to problems of scale. Two simulations calibrated with the suitability map M2 worked better than the remaining ones: the unconstrained neighbourhood simulation (m^2=0.0062; S=0.4060), selected as the best simulation and the 2,000 m neighbourhood simulation (m^2=0.0063; S=0.4050). Factorial ANOVA test found significant differences in simulations performance between suitability maps, but not between neighbourhood rules (see Table 11.1 for a summary of factorial ANOVA results). Procrustes and sensitivity values were closely correlated (adjusted R^2=0.947; p-level=0.000006). Unconstrained neighbourhood and MaxEnt suitability map (but replacing M2 with M3) were the settings selected to calibrate and simulate the three future scenarios of land use change.

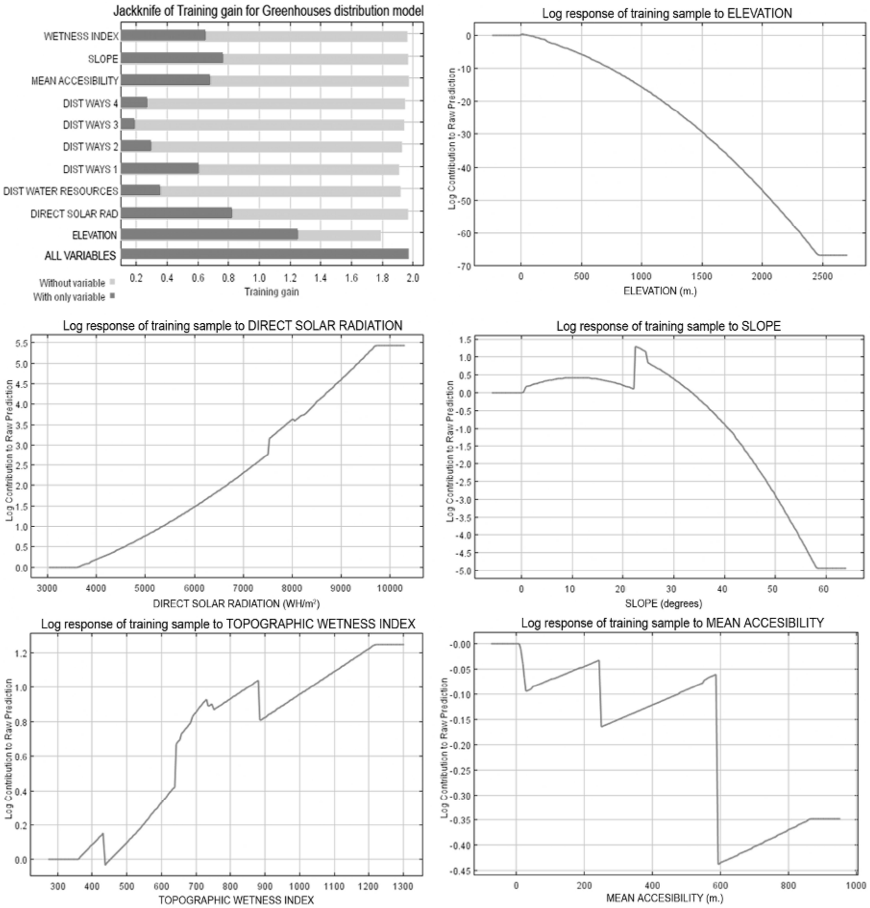

Fig. 11.5 Jackknife test and response curves of MaxEnt distribution model. Bars plot: dark grey bars indicate model gain when computed with only the variable, and light grey is the model gain when computed with the other variables. Minor differences between the two bars indicate major importance of the variable in the model. Log-response curves: the five most important variables are shown. Values over 0 indicate suitable conditions for greenhouses, whereas the values below zero indicate unfavourable conditions

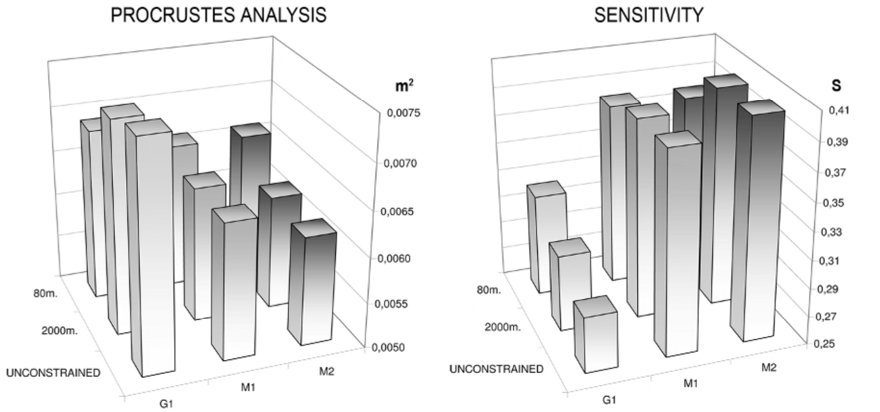

Fig. 11.6 Evaluation results. Evaluation of 9 simulations performed in Geomod combining three neighbourhood rules (80 m, 2,000 m and unconstrained) and three suitability maps, one computed in Geomod (G1), and two computed in MaxEnt (M1 and M2). Each bar corresponds to a performed simulation. The reference image is the real coverage of greenhouses in 2001 (ending time in the simulations). Low values of m^2 are indicative of a good spatial agreement between a simulation and the reference image. Higher values in S indicate a good agreement between a simulation and the reference image in quantity of correctly predicted cells. The best simulation was performed with an unconstrained neighbourhood and the suitability map M2.

Table 11.1 Summary of results of factorial ANOVA. Significant values in bold

Dependent variable	m^2		S	
Categorical predictor	suitability map	neighbourhood	suitability map	neighbourhood
F	**9.132**	0.009	**29.158**	0.108
P	**0.032**	0.990	**0.004**	0.900

Fig. 11.7 (left) shows the graphical analysis of correctly and incorrectly simulated cells of the best simulation. Fig. 11.7 (right) shows the polynomial relationship between the suitability values (of the M2 suitability map) and the percentage of cells correctly predicted for that suitability value, calculated from the best simulation. Eq. 11.1 expresses the suitability-certainty function (R^2=0.99; RMSE=1.24).

$$\% \text{ HITS} = 1.186 \cdot 10^{-13}\, M2^9 + -4.729 \cdot 10^{-11}\, M2^8 + 7.417 \cdot 10^{-9}\, M2^7 + -5.681 \cdot 10^{-7}\, M2^6 + 2.08 \cdot 10^{-5}\, M2^5 + -0.0002511\, M2^4 + -0.003183\, M2^3 + 0.1024\, M2^2 + -0.3118\, M2 + 0.3413 \quad (11.1)$$

M2: values for every pixel of the M2 suitability map.

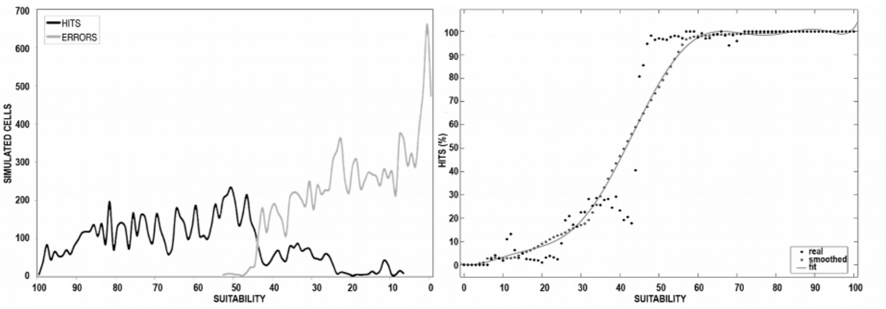

Fig. 11.7 Certainty against suitability in the best simulation. Left: the plots describe the behaviour of the best simulation in terms of total amount of correctly (hits) and incorrectly (errors) predicted cells against suitability. Right: 9th order polynomial relationship between the percentage of correctly predicted cells and suitability (M2 suitability map). The black plots represent the real data, and the grey dots the smoothed data. The curve represents the curve fitted to the smoothed data

11.4.2 Simulations 2001-2010

Fig. 11.8 shows the differences in suitability between M2 and M3. The construction of new infrastructures (roads and desalination plants) boosts the suitability for greenhouses in areas that already were fulfilling suitable topographic conditions. The relative importance of the variables and the response curves in the M3 distribution model were similar to those of the M2 distribution model, confirming that both models had close similarities.

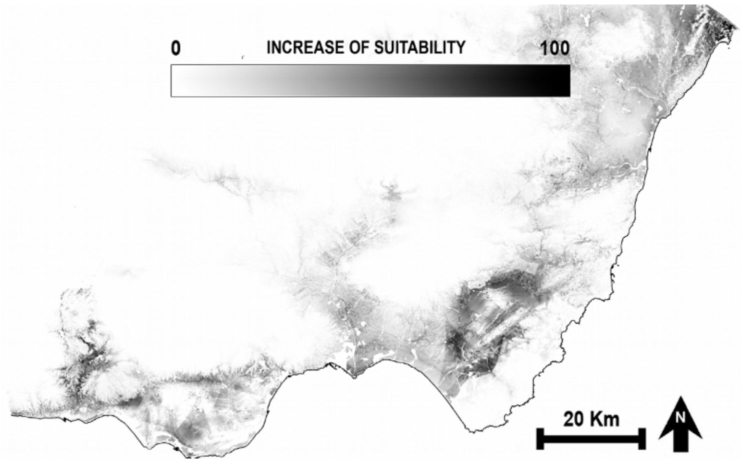

Fig. 11.8 Differences in suitability between M2 and M3. Differences in suitability between M2 and M3 were computed as M3-M2 in the raster calculator of Idrisi Andes. Higher values are indicative of new suitable areas for the spreading of greenhouses

Fig. 11.9 shows the simulations corresponding to the proposed scenarios A, B, and C, compared to the real greenhouse-occupied area in 2001.

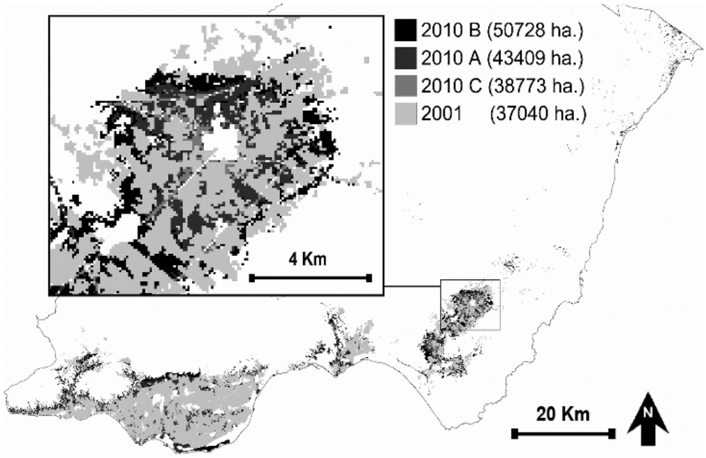

Fig. 11.9 Simulations of scenarios A, B, and C. Scenario B is the sum of 2010 B, 2010 A, 2010 C, and 2001 occupied areas. Scenario A is the sum of 2010 A, 2010 C, and 2001 occupied areas, etc. The zoomed area is a detail of Campohermoso (see Fig. 11.1), a locality with an intense growth of the area occupied by greenhouses in recent years

Fig. 11.10 shows the certainty map of the simulations of scenarios A, B, and C for the year 2010.

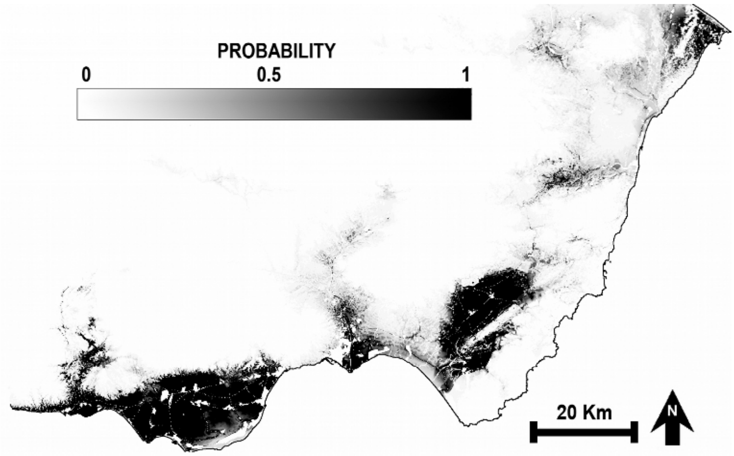

Fig. 11.10 Certainty map for simulations of scenarios A, B, and C. The certainty map computed from Eq. 11.1 applied over the M3 suitability map. The values indicate the probability that a cell with presence of greenhouses simulated by Geomod will really be occupied in 2010

11.5 Validation of the results and discussion

11.5.1 Simulations 1987-2001

The ANOVA analysis of the evaluation values indicate that the simulations performed with MaxEnt suitability maps work better than those performed with Geomod ones (in terms of S and m^2). While MaxEnt uses scattered presence points as input, Geomod uses the complete land use coverage. If, for reasons other than the suitability of the territory, there is a great concentration of greenhouses in a given area (e.g. historical causes), the combination of variables present at this site takes on relatively high importance with respect to the other combinations of variables in the rest of the territory, resulting in a misleading suitability map. The same can happen in the MaxEnt models when the presence records provided as input were very close together, but the initial treatment that we applied (minimum distance between presence points greater than 1,000 m) diminish any possibility that aggregation effects could affect the quality of the models. Another difference between the two methods to calculate suitability maps is based on the relative weight given to the variables. Geomod does not use any algorithm to compute weights, and they have to be established by the user (by subjective criteria, or criteria based on previous statistical analysis). MaxEnt includes a Jackknife test, which automatically computes the relative contribution of every variable to the model. Another advantage of the MaxEnt algorithm successfully explored in this paper is the "Projection" feature, capable of projecting a distribution model over variables with values expected for the future. It is a useful tool to explore alternative land use change scenarios bearing in mind expected changes in the values of the variables (accordingly to known information, such as projected roads). Our results support the idea that the MaxEnt algorithm can generate useful suitability maps applicable to Geomod simulations, outperforming the results given by a stand-alone use of Geomod.

The results for the importance of the variables in the suitability maps computed by MaxEnt (Fig. 11.4) and of their response curves (Fig. 11.5) indicate that the fundamental factors influencing greenhouse distribution in the study area are related to topography and distance to roads. The open plains (which coincide with the areas having high indices of topographical moisture) at low altitudes have the temperature, slope, and solar radiation appropriate for greenhouse operation. The factors related to the distances to roads do not appear to be limiting, although the longest distance to first-order roads (motorways) are related to a lower presence of greenhouses. The variable "accessibility index", the fourth in importance, accurately summarizes the distances to different types of roads, and it is useful to predict the spreading of greenhouses. Interpretation problems arise with the variable Distance to Water Resources, because the great majority of greenhouses do not depend on centralized resources such as reservoirs or desalination plants, but rather use their own wells, which pump water from aquifers. This variable is the only one that has lost relevance over time among the 1987-2001 and 2001-2010 models, since desalination of sea water has proliferated on the Almería coast. Even so, the low gain shown by all the models indicates that the contribution of desalination does not significantly affect the results.

In the evaluation of the simulations, we considered two sides: agreement in number of predicted cells, expressed in terms of S, and spatial agreement, tested by Procrustes analysis and expressed in terms of m^2. Both measures were correlated, but not perfectly because, for two simulations with the same sensitivity (compared with a reference image), there may be differences in the location of the errors detected by the Procrustes analysis. Procrustes analysis is a quick and simple way to assess spatial agreement between simulations and real land use coverages.

The analysis of hits and errors of the best simulation (Fig. 11.7, left) shows that it works better in the section of higher values of the M2 suitability map (especially in the range 100-50), and the errors increases when suitability trends toward zero. When the percentage of hits against suitability values is smoothed by a moving average (Fig. 11.7, right), the pattern remains quite clear, making it possible to find, by means of curve fitting, a function (9th-order polynomial, see Eq. 11.1) describing the behaviour of the simulation.

11.5.2 Simulations 2001-2010

The construction of new roads and desalination plants can increase the area suitable for greenhouses, as shown in the map of differences between M2 and M3 suitability maps (Fig. 11.8). Apart from the increase of suitable area, both models show identical behaviour regarding the relative contribution and the response curve that every variable presents. During the studied periods 1987-2001 and 2001-2010, the relationships between the presence of greenhouses and the variables that influence their distribution did not significantly change.

Geomod is designed to predict the locations of land use change, not the quantity of area that changed. Therefore, the validity of the simulations is based on a solid interpretation of the data for surface-area growth of greenhouses. Using only the two available sets of temporal data (1987 and 2001), we used a linear estimation to calculate the amount of occupied area in the scenarios A, B and C, but it would be more appropriate to use data from temporal series with a greater number of control points. The problem arises when inflexion points are foreseen in the growth curves of the occupied area, a possibility in the study areas because there is a high degree of saturation (a large area of land that can be occupied by the greenhouses is already occupied) and the resources supporting the greenhouse industry (mainly soil and water) are being depleted. Thus, to our knowledge, scenarios A and C are probably the closest to reality (see Fig. 11.9).

The certainty map (Fig. 11.10) can be useful to assess the expected accuracy of the simulations when it is not possible to validate them with ground-truth information. Nevertheless, the function used to compute the certainty map of the simulations 2001-2010 has been calculated for a simulation performed for the period 1987-2001 and the suitability map M2, there are at least two ideas that may justify its application:

– M2 and M3 distribution models are quite similar, and therefore a significant behavioural change in the suitability-certainty function between models is not expected.
– The smoothing of the data by moving the average prior to the curve fitting removes bias and generalizes the function, allowing its application to other simulations performed under the same conditions.

However, it is important to bear in mind the limitations of this application: the function does not take into account the effect of the area that will predictably undergo land use change. This effect is important because it tends to increase the percentage of correctly predicted cells of the simulation and can influence the relationship between certainty and suitability, altering the shape of the curve and changing the coefficients of the function. This can lead to an erroneous interpretation of the probability values of the certainty map. It would be useful to make an in-depth study of the relationship between suitability and certainty for different simulations to find an equation that can function in a general way in order to associate each simulating cell with a particular certainty value.

11.6 Conclusion and perspectives

11.6.1 Conclusions

The combined use of MaxEnt and Geomod provide a series of significant advantages with respect to the stand-alone use of Geomod in land use change simulations:

• Geomod simulations using MaxEnt distribution models as suitability maps significantly outperform simulations calibrated with suitability maps computed by Geomod. In addition, the "projection" feature of MaxEnt makes it possible to explore alternative scenarios by changing the values of the variables used to calibrate the model.

- It is possible to predict accurately the spreading of greenhouses using only topographic variables and distances to roads. In this sense, the proposed "accessibility index" is a useful variable that summarizes distances to different types of roads.
- Relationships between greenhouses and variables are stable in time for the periods studied, allowing the exploration of future scenarios.
- Procrustes analysis is a powerful tool to assess spatial similarity between simulations and ground-truth information, and provides a simple and easily interpretable measure of agreement (m^2).
- The certainty of Geomod simulations is not spatially uniform. There is a strong relationship between the amount of correctly simulated cells and suitability. This relationship is useful to compute certainty maps to assess the spatial accuracy of simulations.
- The proposed methodology can be applied to territorial management of areas in which greenhouse expansion can represent an environmental problem, as in the Mediterranean countries mentioned in the present work. From the simulations, it is possible to identify the hotspots on which to focus environmental management and conservation efforts.

11.6.2 Perspectives

In the context of global change, the studies on land use change are becoming as relevant as those related to climatic change. Though we have specifically oriented tools, the complexity of the web of factors affecting land use is such that it is difficult to develop highly accurate techniques. It is necessary to continue to delve into the possibilities offered by geographic information technology to formulate predictions that enable us to face coming changes.

The present study seeks to combine two different perspectives: ecological species-distribution models used in biology, and land use change models used in geography. Both approaches combined can generate powerful tools to analyse our changing world and to explore alternative scenarios.

Although the analysis proposed for land use change is applied only to greenhouses, it has other potential applications (perhaps irrigation, urbanization, tourist facilities, etc.). This implies another alternative to the different use of change models currently being used.

Acknowledgements

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Urban environment and urban growth

12 Modelling intra-urban dynamics in the Savassi neighbourhood, Belo Horizonte city, Brazil

Godoy M and Soares-Filho BS

Abstract
We have developed a space-time model to analyze and simulate the land use changes from 1985 to 2004 in the Savassi neighbourhood, Belo Horizonte, Brazil. The study area represents an important commercial reference to the city of Belo Horizonte, although it currently needs a new model for revitalization of its economic sector. We analysed two periods: 1985 to 1996, the rising of a burgeoning street commerce in the region, and 1996-2004, the decline of this commerce and intense transformation of Savassi into a service zone. The conceptual basis for the development of the spatial simulation model was the technique of cellular automata, implemented on the software DINAMICA. Results from simulations for the 1996-2004 period approached the historical spatial patterns of change and projections to 2020 demonstrated the trend of this neighbourhood, continuing its transformation into a major service zone, thus concentrating commercial establishments into a few shopping malls. Therefore, the utilization of this land use simulation model showed its potential as a tool for urban planning, aiming to foresee urbanistic implications due to land use dynamics.

Keywords: land use analyses, dynamic model, urban simulation, cellular automata, intra-urban dynamics

12.1 Introduction

The city is a live phenomenon, in which interactions between the economics, societal pressures and politics drive its permanent transformation and growth. Hence, the urban changes consist of a process driven by demographic and economic growths, as well as public policies, which is stimulated by the commercial, industrial and services activities. These are the sectors that determine the city's dynamism, growth and the adaptation of the urban space as well as the urban daily routine. A better understanding of the urban evolution process requires the development of methods capable of representing this constant urban mutation (Batty et al. 2004), which, in fact, poses a major challenge to Geographical Information Systems (GIS), still strongly based upon a static vision of the geographic realm.

The advent of space-time models, in which the state or attribute of a certain spatial location changes over a period of time as a response of particular drivers (Burrough 1998) creates a new field of possibilities for urban dynamics representation. Amongst these models lie the systems based on the cellular automata technique. This model envisages the space as an array of cells on which each cell assumes a different state based on the other cells' states within a certain cell neighbourhood and according to a specific set of transition rules (White and Engelen 2000). All the transitions occur simultaneously as time advances in small discrete steps. Although this concept is very simple, it emerges as a very powerful tool for modelling urban phenomena, because of its tractability and flexibility to adapt to different geographical abstractions. This is the reason why this concept is often used by several researchers for urban dynamics representation, e.g. Engelen et al. (1997), Wu (1998), White et al. (2000), Li and Yeh (2000), Almeida et al. (2003), and Almeida et al. (2008). These models aim to subsidize urban and regional planning, considering that information on land use change trend is necessary for the decision-making process. For example, the trend of land use dynamics consists of an important criterion to select areas needing urban renovation, improvement on transportation services and environmental quality, as well as installation of urban equipment, and revitalization of the commercial and residential sectors.

In this work, we applied the software DINAMICA, a generic type of cellular automata (Soares et al. 2002, Soares et al. 2005, Hermann et al. 2007), to develop a space-time model for the analysis and simulation of land use changes that occurred in the Savassi neighbourhood, Belo Horizonte, within the periods of 1985-1996 and 1996-2004. DINAMICA considers the 2D urban landscape represented as a fine grain matrix, in which each cell has a state that can be changed to another state depending on pre-quantified dynamics and the configuration of the cell neighbourhood. The influence of the cell neighbourhood is given by a set of territorial variables that control the land use transitions and the spatial pattern of changes. In a general way, the setup and operation of the simulation model consisted of: 1) the organization of a multi-temporal cartographic database for the land uses; 2) transition rates quantification; 3) selection of variables that, as urban and architectural references, influence land use changes; 4) calibration of the simulation system to achieve the best performance and validation aiming at assessing its ability to reproduce the intra-urban dynamics observed within the modelling time-period, and 5) prognostic for near future (2020) using the land use change trend of the most recent analysed period (1996-2004).

As a result, the present model aims to show not only the recent urban dynamic spatial patterns for Savassi, but also how this trend can provide insights to foresee possible near future spatial configuration as well as its urban implications. As a contribution, this tool will allow the assessment of outcomes of prospective scenarios for urban revitalization, something the residents of Belo Horizonte have been looking forward to for so long.

12.2 The Savassi Neighbourhood

The foundation of the Belo Horizonte city, in 1897, was a response to the need for a new state capital that could exert a regional political balance and minimize the economic differences that existed in the state of Minas Gerais at that time. This event also reflected a new era, which began with the proclamation of the republic, since Ouro Preto, the old capital, was seen as a symbol of colonial domination and monarchist power. Belo Horizonte creation was based upon the positivism concept, an outcome of the Illuminist manifestation at the end of the XIX century. The original project organized the city space in three different categories or zones: Firstly, at the centre, a zone was planned with meticulous orthogonal streets and large, treed avenues. The second category comprises the suburb (separate from the urban zones by a large circular avenue called Contorno, which means boundary in Portuguese) and the third were the agricultural zones (intended to serve as a greenbelt around the city). Both the second and third categories presented more flexible urbanization standards and were reserved for future urban expansion (Monte-Mór et al. 1994).

One of neighbourhoods within the Contorno avenue belt, known as Funcionários, was originally populated by public employees who had to move to the new capital. During the eighties and nineties this neighbourhood passed through an amazing valorisation process, resulting in the creation of the Savassi neighbourhood in 1991, a section of the original neighbourhood (municipal Law 5872), which by that time already consisted of an emerging zone of intense street commerce (Fig. 12.1).

The name Savassi came from a bakery located at 13 de Maio Square (current Diogo de Vasconcelos or Savassi square). In 1940, a trader Arthur Savassi, owner of a dairy, decided to open a bakery at 13 de Maio square, which soon became one of most popular places in Belo Horizonte city due to its delicious products.

In the eighties, several blocks were closed, resulting in the creation of paseos for strollers. The region around the paseos flourished with a prosperous commerce, especially for fine garments. However, in the beginning of the nineties, the street commerce, common in Savassi, declined due to the development in the city of several shopping malls that offered better parking facilities and more security for shoppers.

Amongst the transformations that occurred in the Funcionários neighbourhood to date, we distinguish the three most significant phases: The first is the creation and separation of the Savassi from the Funcionários neighbourhood. The second relates to the transformation from a traditional residential zone into an area of intense commerce of fashion and stylist garments. Around the commercial zone, the neighbourhood was also transformed into a place with bars and night clubs, gourmet restaurants, cafes and snack bars, therefore with intense social life day and night. Currently, the Savassi neighbourhood continues to present the same cultural and nocturnal emphases. There are abundant restaurants, bars, dance clubs, snack bars and everything that rhymes with fun. Recently, the commerce gave way to the services activities, with the establishment of several offices and headquarters for small business and even larger companies in the region. This span of vivid history occurred during the last two decades in Savassi will be the object for the simulation model presented below.

12.3 Methodology

12.3.1 Space-Time Model

Up-to-date GIS applications have focused mostly on static spatial models, for example, the land use zone proposition for urban or rural uses (Pedrosa and Chamber 2002). However, spatial phenomena, such as urban growth and land use change, are inherently dynamic and thus demand dynamic representations, uncommon to most traditional GIS (Batty et al. 2004).

Space-time models aim to analyse and simulate numerically real world processes that show territorial expression. Hence, one of the greatest challenges for Spatial Information Science is the development of abstraction methods capable of adequately representing such processes, and as a result, modelling the system changes with respect to quantity and location (Chamber and Hunter 2003).

For this study, we employed a simulation model based on a cellular automata system. The cellular automata concept encompasses a set of interacting cells that allows the establishment of bridges between macroscopic and microscopic representations. Because of their tractability, cellular automata models have been applied to several applications, e.g. fire spreading (Karafyllidis and Thanailakis 1997), epidemic propagation (Sirakoulis et al. 2000) and deforestation (Soares-Filho et al. 2004, 2006).

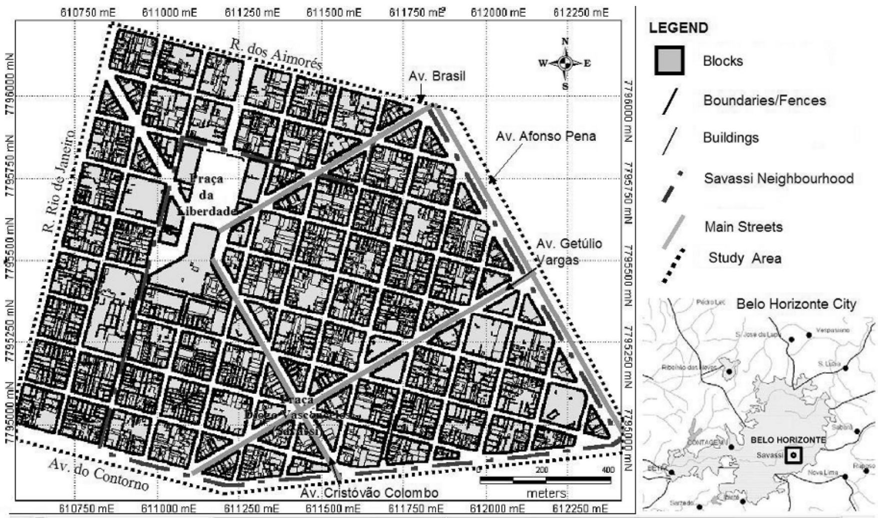

Fig. 12.1 The Savassi neighbourhood and its location with respect to the city of Belo Horizonte

In this study, DINAMICA software is used as a simulation platform for our urban dynamics model. DINAMICA employs, as input, a set of maps, including the initial and final map of land use, also known as landscape maps, considering that a landscape could be viewed as a bi-dimensional array of land use types; the sojourn time map that keeps track of the time since the last change, and two sets of ancillary maps: the static and dynamic variables, the latter named so because they are updated by the model iteration. These two sets of variables control the location of changes (Fig. 12.2). These variables are combined by summing their Weights of Evidences (Goodacre et al. 1993, Bonham-Carter 1994 and Soares-Filho et al. 2005), to produce a transition probability map, which depicts the most favourable areas for change (Soares-Filho et al. 2002, 2004 and 2005). Weights of Evidence consists of a Bayesian method, in which the effect of each spatial variable on a transition is calculated independently of a combined solution. The Weights of Evidence represent each variable influence on the spatial probability of a transition i $\Rightarrow$ j and are calculated as follows.

$$O\{D|B\} = \frac{P\{D|B\}}{P\{\overline{D}|B\}} \tag{12.1}$$

$$\log\{D|B\} = \log\{D\} + W^{+} \tag{12.2}$$

Where W^+ is the weight of evidence of occurring event D, given a spatial pattern B. The spatial post-probability of a transition $i \Rightarrow j$, given a set of spatial data ($B, C, D, \ldots N$), is expressed as follows:

$$\mathrm{P}\{i \Rightarrow j | B \cap C \cap D \ldots \cap N\} = \frac{e^{\sum W_N^+}}{1 + e^{\sum W_N^+}} \tag{12.3}$$

Where B, C, D, N are the values of k spatial variables measured at location x,y and represented by its weights W^+_N

The only assumption for the Weights of Evidence method is that the input maps have to be spatially independent. A set of measures can be used to assess this assumption, such as the Cramer test and the Joint-Uncertainty Information (Bonham-Carter 1994). Correlated variables must be disregarded or combined into a third that will be used in the model. As a result, the spatial relationships calculated by Weights of Evidence method are used to parameterize and calibrate the simulation model with respect to the spatial configuration of changes.

Another component of the model, the transition function, operates on the probability maps, and is constrained by the quantity of changes specified as input for each transition. This function draws the higher probability cells, after having ranked them in a vector file. The quantities of changes are determined a priori through the calculation of a historical transition matrix.

The transition matrix describes a system that changes over discrete time increments, in which the value of any variable in a given time period is the sum of fixed percentages of the value of the variables in the previous time period. The sum of fractions along the column of the transition matrix is equal to one (Eq. 12.4). The diagonal line of the transition matrix does not need to be filled in since it models the percentage of unchangeable cells. The transition rates are passed on to the model as a fixed parameter. For DINAMICA, time step can comprise any span of time, since the time unit is only an externally set reference parameter.

$$\begin{bmatrix} 1 \\ 2 \\ . \\ j \end{bmatrix}_{t=v} = \begin{bmatrix} P_{11} & P_{21} & P_{.1} & P_{j1} \\ P_{12} & P_{22} & P_{.2} & P_{j2} \\ P_{1.} & P_{2.} & P_{..} & P_{j.} \\ P_{1j} & P_{2j} & P_{.j} & P_{jj} \end{bmatrix}^{v} * \begin{bmatrix} 1 \\ 2 \\ . \\ j \end{bmatrix}_{t=0} \tag{12.4}$$

DINAMICA uses as a local CA rule, a transition engine composed of two complementary transition functions, the Expander and the Patcher (Soares-Filho et al. 2002). DINAMICA splits the cell selection mechanism into these two processes. The first process is dedicated only to the expansion or contraction of previous patches of a certain class, and it is called Expander. The second process is designed to generate or form new patches through a seeding mechanism, and it is called *Patcher*. For each transition, the percentage of transitions executed by the *Expander* function in relation to *Patcher* must be defined. The *Patch Isometry* is a number varying from 0 to 2. The patches assume a more isometric form as this number increases. The size of new patches and expansion fringes are set according to a lognormal probability distribution. Therefore, it is necessary to specify the parameters of this distribution represented by the mean and variance of the patch sizes to be formed.

As the quantity of changes is passed as fixed parameter to the model, its validation considers only the spatial locations of the changes. This is the last procedure before the model can be used for prognosis. It consists of a comparison between the model results and a reference map, in this case, the land use map at the simulation final time. To date, there are several map comparison techniques that have gained prominence as they apply multiple resolution windows to asses the spatial match between two maps, e.g. Costanza (1989), Pontius (2002), Power et al. (2001) and Hagen (2003). Nonetheless, there is neither consensus about which technique yields the most appropriate validation, nor what fitness value should be taken as a threshold to accept or reject the model. Of these techniques, the fuzzy comparison method by Hagen (2003) was adapted to be used in Dinamica, named therein as the "Reciprocal Similarity". This method employs a decay exponential function with the distance to weight the cell state distribution around a central cell. Generally, one can say that a simulated map presents good result when it has a fitness value higher than the one obtained through a comparison between the final and initial historical maps (Hagen 2003).

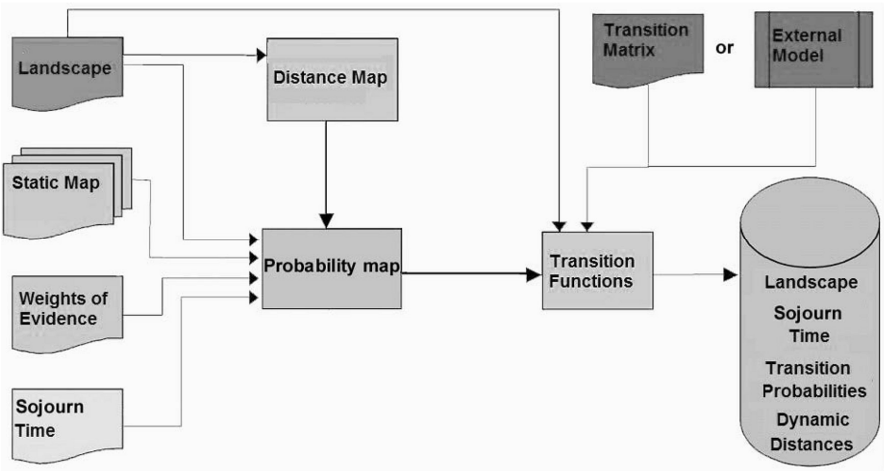

Fig. 12.2 A simplified view of DINAMICA simulation model.

Although this study involves two time periods (1985-1996 and 1996-2004), the simulation model was only implemented for the last period. Finally after the model calibration, the model was applied to project the Savassi spatial configuration by the year of 2020, using the 1996-2004 parameters.

12.3.2 Multi-temporal Database Setup

A municipal law defines the Savassi neighbourhood boundaries. However, for this particular modelling exercise, two blocks were added to the east side and another additional two blocks to the north side of its formal neighbourhood boundary (Fig. 12.1), considering that the Bahia street and the Brasil Avenue (original boundaries) do not represent urban barriers for the development and occupation of this region. The methodology applied in this study follows the flowchart presented in Fig. 12.3.

In this work, the modelling spatial unit is the urban land lot, with its boundaries defined from the original land parcelling map established by the municipality of Belo Horizonte. Land use can be defined as the utilization purpose given to a specific tract of land (Jensen and di Gregorio 2002). In this work, we used land use types defined by the municipality of Belo Horizonte city in its land use zoning law (PBH 1996) and mapped them for three specific years: 1985, 1996 and 2004.

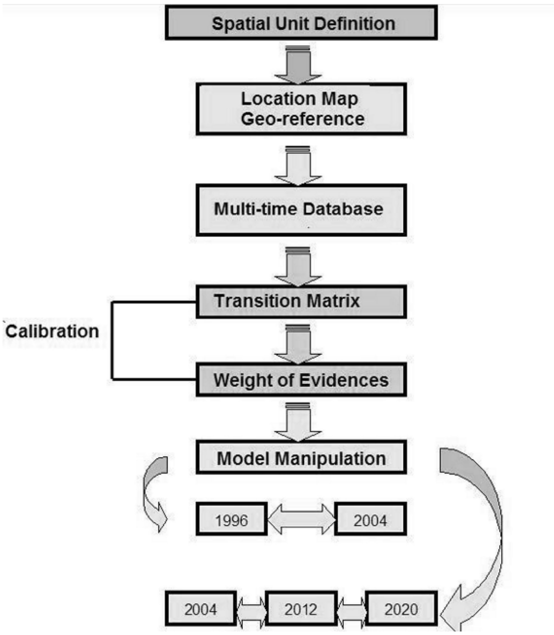

Fig. 12.3 Model development flowchart

For 1985 and 1996, information on land use was extracted from a research project called "Percurso" (Passage) developed and organised by Prodabel (Data processing company of Belo Horizonte). For those data, the collection methodology is not known or published, nor are the criteria for land use classification known. Since these data are only available in microfilms at Prodabel, we had to digitize them by means of a scanner and then geo-reference the data using the municipal map of land lots.

Information on land use for 2004 was gathered through a field work. We took photography of the façades throughout the study area and made some visits to clarify some doubts. In this research, 1681 properties were surveyed. The data collected were then assigned to the map of land lots already in vector format.

Considering that the data have come from several sources, a standardization process became necessary in order to establish a common land use classification system. As a result, the final land use classes encompassed the following types: 1 – Commercial (CO); 2 – Residential (RS); 3 – Services (SV); 4 – Institutional (IT); 5 – Empty Lot (LV). Also, as we can find more than one activity per land lot since some of the original land parcels contain more than one property, we included combinations of these individual uses and when they were superior to 03 (three) uses per spatial unit, they were reclassified as 6 – Miscellaneous (MI). The lots whose use could not be identified were classified as: 7 – Without Information (SI). Other mixed uses were: 8 – Commercial and Services (COSV); 9 – Residential and Services (RSSV); 10 – Commercial and Residential (CORS) (see Fig. 12.4).

12.4 Results

12.4.1 Change Analysis

Fig. 12.4 shows the distribution of land uses in the three observed times. One can observe an increasing diversification of the major land uses as a consequence of the new law on land use, approved and implemented in 1985, which reflects the concepts of pluralism and flexibility (PBH 1985, 1996). This tendency was also maintained for the period of 1996-2004.

In the first period, there was an expansion of the commerce and mixed use of commerce and services, which was concentrated around the Diogo Vasconcelos Square. The eastern Savassi, traditionally occupied by residences in 1985, passed through a profound transformation, initially with the establishment of shops and afterwards with the spreading of offices and other small services, such as restaurants and bars.

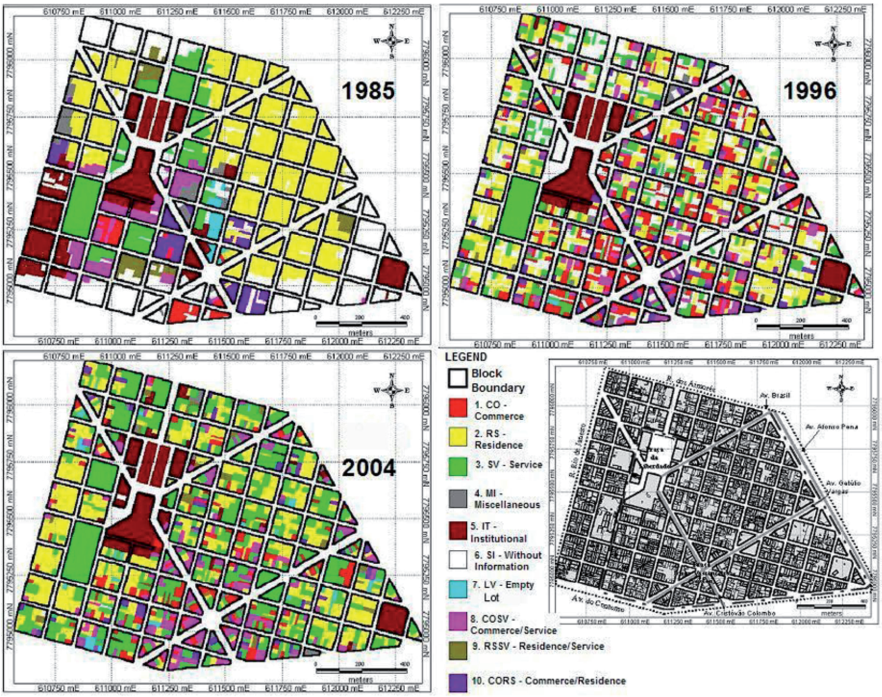

Fig. 12.4 Land use in the Savassi region in the three observed times

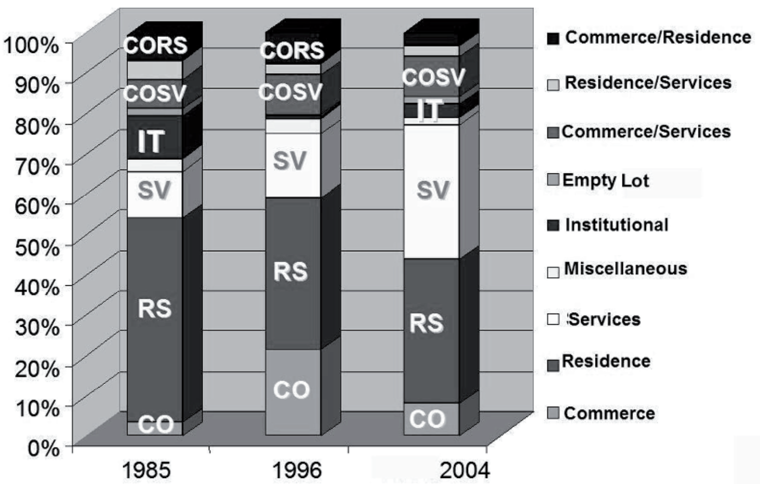

Fig. 12.5 Land use distribution in Savassi in the three observed times. Commercial (CO), Residential (RS), Services (SV), Institutional (IT), Empty Lot (LV), Miscellaneous (MI), Without Information (SI), Commercial and Services (COSV), Residential and Services (RSSV), Commercial and Residential (CORS)

This acute transformation is summarised in Fig. 12.5, which shows firstly the rise of the commerce between 1985 and 1996, and the resulting decline of the residential use. Over the 1996-2004 period, the recent trajectory of expansion of the service replaced some originally commercial areas, while the residential use remained practically unchanged.

The dynamics of empty lots must be regarded as a special phenomenon. A major decrease in their number can be observed until the middle of the nineties and an increase towards 2004. This can be explained by the real estate speculation. In this area, the properties have become extremely appreciated. As a consequence and common practice in the region, the real state market brought about the demolition of old houses to create space for apartment buildings, which led to an artificial increase of empty lots while these building were being designed. In turn, the oscillations in the institutional use can be attributed to the different methodologies employed in the data gathering processes.

The transition matrices were obtained by cross-tabulating the land use information per lot. They were useful to quantify the intra-urban dynamic tendencies over the two analysed periods (Fig. 12.6). Both matrices 1985/1996 and 1996/2004 represent the intense dynamism, which occurred in the Savassi region through these two decades, indicating that most of the lots changed their uses. Notice that the diagonal line of the transition matrix indicates the permanence of the uses, of which, during the first period, 32% of commerce, 44% of residences and 22% of services remained unchanged. In turn, for the second period, 17%, 60% and 44%, respectively, of the uses above have not changed.

Another important observation for the first period is that 27% of commercial use has changed to residence (maybe, a return to the original use), while 24% have changed into mixed use of commerce and service. More than 40% of the residences have changed into commerce or services and 32% of the services have changed to residential use, while 15% have changed into commerce.

The continuous changes for the commerce use were intense during the last decade, in which only 17% of it remains unchanged, 25% has changed into residences and 34% into services. During this period, the residential use was more constant, when only 10% changed into services and another 20% for other uses. The services showed the most constant use (45%), while 38% changed into the residential use and the remaining, approximately 17%, has changed into other uses.

The permanence of the miscellaneous use is meaningless, because of the several different uses (more then two) present at the same spatial unit. Between 1985 and 1996, the permanence of the institutional use was small; approximately 58% of it changed into residence and 15% into services use. The institutional use did not present any type of changes between 1996 and

2004. The empty lots presented 0% of permanence through the two analysed periods. In synthesis, the dominant land uses in the region over the study period have been the commercial, residential, services and mixed use of commerce and service. During the first period, the residential use increased, despite the advance of the commerce in the region. In the latter period, the services spread at the expense of commerce; even so the extent of the residential use has been practically constant.

1985 → 1996

1985 \ 1996	CO	RS	SV	MI	IT	LV	COSV	RSSV	CORS
CO	0.324324	0.27027	0.081081	0.054054	0	0	0.162162	0.027027	0.08108
RS	0.188596	0.445175	0.144737	0.037281	0	0	0.078947	0.019737	0.08552
SV	0.150538	0.322581	0.225806	0.053763	0	0	0.16129	0.043011	0.04301
MI	0.184211	0.315789	0.210526	0.026316	0	0	0.105263	0.026316	0.13157
IT	0.098039	0.578431	0.147059	0.019608	0.068627	0	0	0.029412	0.05882
LV	0.533333	0.133333	0.2	0	0	0	0.066667	0	0.06666
COSV	0.1	0.457143	0.157143	0.071429	0	0	0.114286	0.014286	0.08571
RSSV	0.228571	0.2	0.285714	0.028571	0	0	0.2	0	0.05714
CORS	0.389831	0.135593	0.101695	0.033898	0	0.016949	0.152542	0.016949	0.15254

1996 → 2004

1996 \ 2004	CO	RS	SV	MI	IT	LV	COSV	RSSV	CORS
CO	0.177143	0.245714	0.342857	0.022857	0.028571	0.022857	0.12	0.011429	0.02857
RS	0.060606	0.600551	0.203857	0.008264	0.013774	0.022039	0.035813	0.027548	0.02754
SV	0.048951	0.377622	0.447552	0	0.020979	0.013986	0.041958	0.041958	0.00699
MI	0.057143	0.228571	0.257143	0.028571	0	0	0.257143	0.085714	0.08571
IT	0	0	0	0	1	0	0	0	0
LV	1	0	0	0	0	0	0	0	0
COSV	0.05814	0.186047	0.290698	0.081395	0	0.011628	0.22093	0.046512	0.10465
RSSV	0	0.25	0.65	0	0	0	0.05	0.05	0
CORS	0.173333	0.226667	0.24	0.013333	0	0.013333	0.32	0	0.01333

1996 → 2004 Per cell

1996 \ 2004	CO	RS	SV	MI	IT	LV	COSV	RSSV	CORS
CO	**0,1612**	0,2176	0,3695	0,0242	0,0298	0,0267	0,1438	0,0099	0,0174
RS	0,0415	**0,4593**	0,2569	0,0065	0,1464	0,0172	0,0266	0,0226	0,0229
SV	0,0632	0,3420	**0,4407**	0,0121	0,0147	0,0251	0,0632	0,0346	0,0043
MI	0,0789	0,2434	0,2566	**0,0197**	0,0000	0,0000	0,2500	0,0724	0,0789
IT	0,0000	0,0000	1,0000	0,0000	**0,0000**	0,0000	0,0000	0,0000	0,0000
LV	0,3125	0,0000	0,6875	0,0000	0,0000	**0,0000**	0,0000	0,0000	0,0000
COSV	0,0573	0,1762	0,2421	0,0917	0,0086	0,015759	**0,2407**	0,0444	0,1232
RSSV	0,0000	0,2488	0,5493	0,0751	0,0000	0,0000	0,070423	**0,0563**	0,0000
CORS	0,1373	0,2246	0,2310	0,0468	0,0000	0,0097	0,3425	0	**0,0081**

Fig. 12.6 Transition matrices for 1985/1996 and 1996/2004, from cross-tabulating information per lot and 1996/2004 from cross-tabulating information per cell on the raster maps

The analysis of the maps of changes allows us to identify the hot spots of changes for each land use as well as its major urban attractors (Fig. 12.7). In this figure, one can notice that the commerce activity, initially located at the sector east of the region, tended to concentrate around Diogo de Vasconcelos Square (Savassi) and through Cristóvão Colombo and Getúlio Vargas avenues and adjacent streets. The residential use remained at the most peripheral portions of the region, both east and west of Savassi (next to the Liberdade Square), far away from the major access axes, i.e. avenues. The service use indistinctly occupies the whole region. This analysis allows us to identify the territorial variables that influence most the location of the changes: 1) distance to the Savassi Square; 2) distance to the Liberdade Square; 3) distance to the main avenues (Cristóvão Colombo and Getúlio Vargas avenues); 4) distance to the residential use and 5) distance to the commercial use. The inclusion of these two latter variables aims to add to the model the contagious effect present in the commerce development and in the permanence of the residential use.

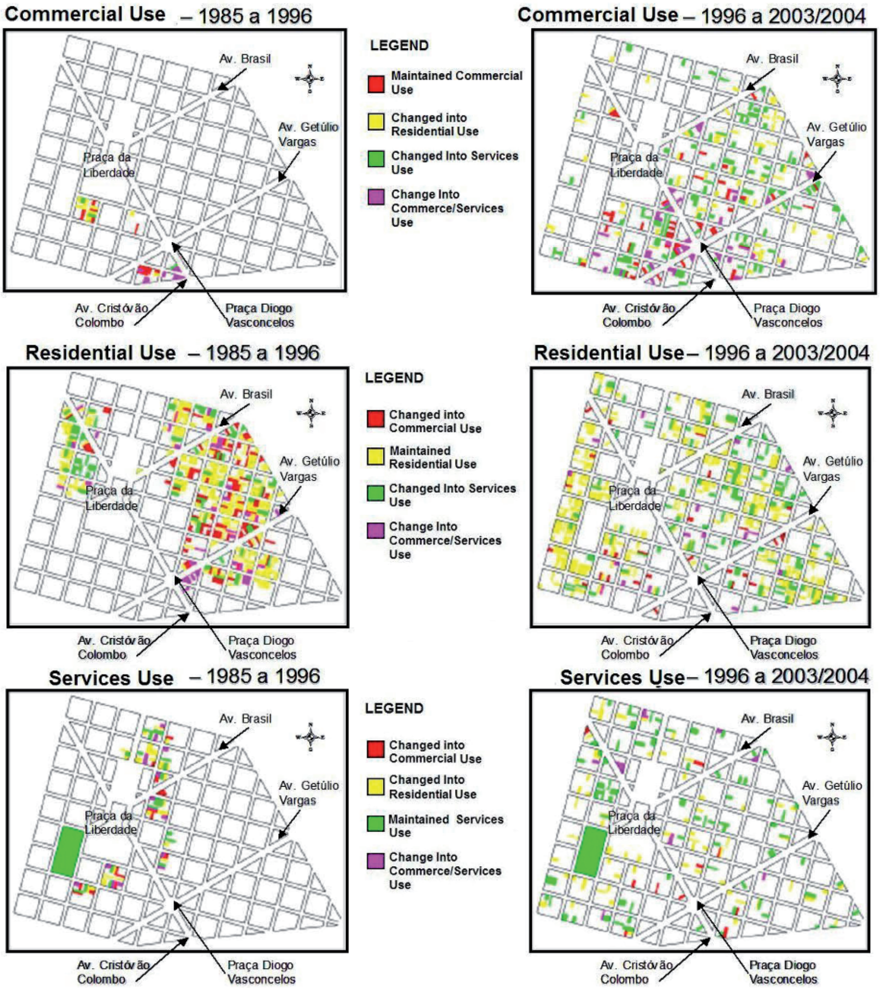

Fig. 12.7 Maps of changes for commercial, residential, and service uses

12.4.2 Land use change simulation model

The spatial simulation model was developed only for the period 1996-2004, because the data for the previous period presented larger uncertainties. As an input parameter, DINAMICA receives a transition matrix. Because this model operates at the raster cell level, it was necessary to transform the transition matrix obtained at the land lot level (generally about 400 m² in size) to the dimensions of the raster cells, in this study with the resolution of 10x10 meters – 100 m².

In this way, a new transition matrix was obtained by cross-tabulating the raster maps (Fig. 12.8). Despite the different spatial units, the matrices conformed in terms of the corresponding transition rates. Nevertheless, this new matrix does not represent the changes in terms of lot boundaries, but as the areal extent occupied by each land use.

Another important step in the development of the simulation model consisted of reducing its original complexity due to the large number of cell states and transitions. Notice that it is necessary to calibrate the model for each transition using the Weights of Evidence method. As a result, the model was reduced to 8 states, with the exclusion of the empty lot and the prevention of transitions between the large institutional areas, such as "Minas Tenis Clube" –a major sport centre and "Palácio da Liberdade"– the state of Minas Gerais government seat. Fig. 12.8 illustrates the transition matrix implemented in the simulation model, with 8 states and 45 transitions.

1996 \ 2004	commerce	residence	service	miscellaneous	institutional	com_serv	res_serv	com_res
commerce	0.166	0.224	0.380	0.025	0.031	0.148	0.010	0.018
residence	0.053	0.587	0.215	0.008	0.044	0.034	0.029	0.029
service	0.065	0.351	0.452	0.012	0.015	0.065	0.036	0.004
miscellaneous	0.079	0.243	0.257	0.020	0.000	0.250	0.072	0.079
institutional	0.000	0.000	0.017	0.000	0.983	0.000	0.000	0.000
com_serv	0.058	0.179	0.246	0.093	0.009	0.245	0.045	0.125
res_serv	0.000	0.249	0.549	0.075	0.000	0.070	0.056	0.000
com_res	0.139	0.227	0.233	0.047	0.000	0.346	0.000	0.008

Fig. 12.8 Transition Matrix for the simulation model

The next step consisted of obtaining the Weights of Evidence coefficients that define the influence of each one of the five territorial variables on the modelled 45 transitions (distance to Savassi square; distance to Liberdade square; distance to the main avenues, distance to residences and distance to commerce). The graphs in Fig. 12.9 illustrate the spatial relationship given by the Weights of Evidence with the variable "distance to Savassi square" and the main four land use transitions observed in the region. Positive Weight of Evidence values favour a transition whereas negative values repel it. These functions have been corrected to prevent the "block effect", that is the lack of information on land use over the street network. Observe the favourability of the commerce transition close to the Savassi Square (Fig. 12.9).

As a consequence of the large number of transitions, a total of 225 Weight of Evidences functions to be employed in the simulation model were obtained. This became possible thanks to DINAMICA modules that allow the categorization of continuous grey-tone variables and the calculation of their weights of evidence coefficients in an automatic fashion. Finally, a transition probability map was produced for each transition by summing the Weights of Evidence related to each of the five territorial variables (Soares-Filho et al. 2005). Notice that in the case of distances to residential and commercial areas, these variables can be recalculated as the model iterates, thus representing dynamic feedback from the model.

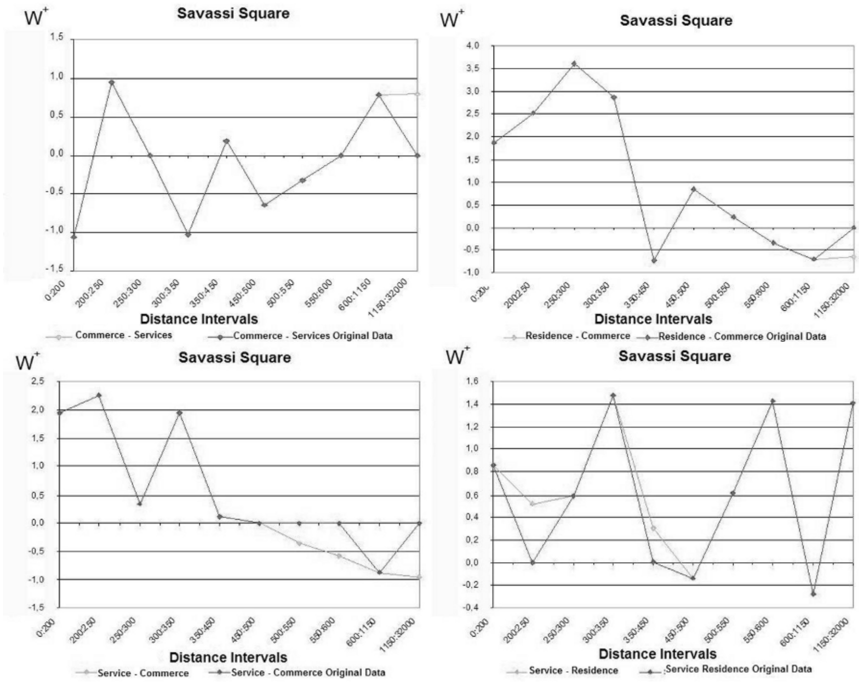

Fig. 12.9 Weights of Evidences coefficients for distances intervals to Savassi square with respect to the transitions: commerce-service, residence-commerce, service-commerce and service-residence

The transition probability maps determine the most probable locations for the quantity of cells to be changed as specified by the transition matrix (Fig. 12.8), both of which are input for Dinamica's CA transition functions. These special functions were designed to allocate the transitions throughout the land use map, with the aim of reproducing the patterns of changes. In order to do this, these functions permit the formation of a variety of sizes and shapes of patches of change, using the input parameters specified by the user. In this study, the *Patcher* function was set to produce patches with the size of four cells (each cell = 100 m²), aiming to approximate the size of urban lots - the original spatial unit of analysis – with in average of 400 m². Finally, the model was run for a single time step equivalent of 8 years, since its transition matrix could not be decomposed in a matrix of annual steps.

Fig. 12.10 presents the map output from the simulation for the period 1996-2004 in comparison with the real situation observed in 2004 and the spatial fitness map using the fuzzy method with an exponential decay function. The average adjustment of the simulation model achieved 54% in comparison with the score of 52% obtained when comparing the input map of 1996 and the reference map of 2004. According to Hagen (2003), one can consider a reasonable match when a simulation shows an increase in the fuzzy metrics from a reference situation that employs the initial and final observed maps. Therefore, the result of the model can be regarded as appropriate, especially taking into consideration its large number of states and transitions.

Using the same configuration of the 1996-2004 simulation model and input map of 2004, we performed a simulation with two time steps, each one with eight years, aiming to project the spatial configuration of Savassi neighbourhood by the year 2020. As a result, Fig. 12.10 (d) shows if the current trends persist into the near future, there will be a dominance of the service uses around the major commercial point of the Savassi neighbourhood –the Savassi square– and the formation of clusters for the remaining land uses.

12.5 Conclusion and outlook

Through this study, we showed that the Savassi neighbourhood passed through a profound transformation during the last two decades, resulting today in a region where street commerce mingles with a large number of offices amid islands of residential buildings. The co-occurrence of services and residences is a result of land speculation, which stimulated the concentration of high buildings with mixed use of commerce at the street level and residences in the upper stores.

The direct outcome of this land use intensification is the increase of traffic and people circulating through the region, which leads to the need of a new urban planning able to mitigate this situation. Also observed was the permanence of the institutional use and the reduction and agglutination of the commercial use in clusters, the latter phenomenon demonstrates the consolidation of "shopping malls" and commercial galleries to the detriment of street commerce. This trend has prevailed as a consequence of the lack of security on the streets, as well as the scarcity of infrastructure for public parking. The simulation model was useful to demonstrate that these changes do not occur randomly. In fact, they are influenced by the spatial arrangement of main urban land marks, such as squares and avenues.

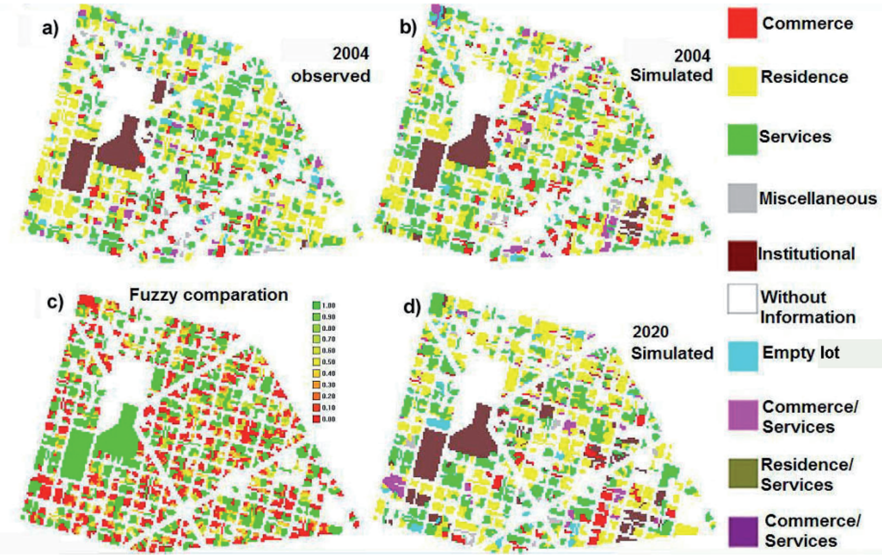

Fig. 12.10 a) Land use observed map compared with the simulation for 2004 (b) and the fuzzy validation map (c), and 2020 simulated land use map (d). Notice the tendency to form clusters of commerce in 2020 map

An important limitation to the spatial simulation model is its capacity to reproduce the observed patterns of change – a complicated process, especially in this study, considering the large number of parameters to be calibrated. However, the analyses, calibration and validation tools available in DINAMICA have facilitated the setup and operation of this complex model, showing that it is feasible to handle multiple states and transitions at a fine spatial resolution unit represented by the urban land lot. Moreover, the *Patcher* CA function can mimic this fine spatial unit using a raster representation.

Therefore, the complexity of the observed dynamics, with 8 land uses and 45 transitions, of which several were concurrent, could be represented using the DINAMICA platform. Applications using this software involve studies from the local scale, such as the case of Savassi, with cell of

10x10 meters, up to continental level simulations, such as the example of the SimAmazonia model - an array of 140 million cells at 1 km² resolution developed to depict the Amazon basin dynamics (Soares-Filho et al. 2006). This shows the potential and flexibility of this software architecture for modelling various dynamic phenomena.

The projection for 2020 (Fig. 12.10d) provided the opportunity to explore the potential spatial configurations that may emerge from this recent intra-urban dynamics as well as its urban implications. In this context, it is important to mention that the model represents possible urban trajectories and not exactly what the future will present.

The availability of such tools for the representation of urban dynamics offers new possibilities for urban planning as they allow us to explore the impacts of a proposed intervention beforehand. Although this has not been a common approach to date, it is expected that the developed methodology will become an effective tool for supporting urban planning decisions, considering that the city is under a perpetual mutation. In this way, the model has also been designed to be used as a communication tool to warn decision-makers for future urban outcomes as well as to make the community aware about the need for investments for the development, preservation or recuperation of this important urban space.

Acknowledgments

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13 Creation and evaluation of development scenarios for metropolitan patterns

Valenzuela Montes LM, Aguilera Benavente F, Soria Lara JA and Molero Melgarejo E

Abstract
In this study, different forms of urban growth have been identified in the metropolitan area of Granada showing time-space distribution of the urban process over the last 30 years, territorial accessibility and the densification process in the types of occupancy. Once these different forms have been identified using a model based on cellular automata specifically developed for this field of study, several simulations were generated. In these simulations the growth patterns previously identified have been reproduced. Hence, the different resulting scenarios have been evaluated through spatial analysis metrics, which will be tested as an evaluating element for scenarios, through the criteria of the spatial mosaic structure formed by those scenarios.

Keywords: Simulation models, urban growth patterns, cellular automata, scenarios, landscape metrics, Granada metropolitan area

13.1 Introduction

The predictive models of land use change have experienced extraordinary development in the last few years (Batty 1997a, Benenson and Torrens 2004). Especially relevant are those that have modelled complex dynamic processes such as urban systems (Verburg et al. 2004) for which there are multiple bibliographic references. These change models are not a recent interest, as Batty (1997b) describes, dating back to the first attempts of building mathematical models for urban systems in 1950's. The introduction of computers in the model developing process resulted in an authentic revolution, boosting the existing analysis and computational capacity at that time (Berling-Wolff and Wu 2004).

One of the main characteristics of the predictive models developed in the last few years is the application of complex mathematical tools such as the cellular automata previously developed by John Von Neuman and

Stanislaw Ulam (Torrens 2000). These cellular automata became world-renowned due to the popular Game of Life published in 1970 by John Conway. Cellular automata are able to simulate spatial dynamics by reproducing the complex patterns shown in cities, as noted in White et al. (1997) and Frankhauser (1998). Moreover, cellular automata are able to specifically reproduce such patterns when composed of simple elements (Wolfram 1984). Therefore, cellular automata have been widely utilized in the creation of growth simulations in multiple cities such as Dublin and Cincinnati, in regions such as Holland (White and Engelen 2000), Santa Lucia Island (White 1996) or metropolitan areas in developing countries such as Lagos (Nigeria) (Barredo et al. 2003).

Nowadays, cellular automata are crucial in disciplines such as territorial planning and territorial distribution. Cellular automata are utilized to design future scenarios. Considering both actual trends and possible simulated alternatives, these future scenarios will contribute to the creation and evaluation of decision-making criteria. The simulation models which take into account current trends and processes have become significant tools in representing future scenarios. The creation of these future scenarios will aid in the discussion of sustainable growth, impacts of sectorial policies, effects of general municipal or supramunicipal planning, etc. In short, this process will be similar to a laboratory utilized to generate new arguments in favor of planning and evaluating the possible consequences of the proposals (Barredo et al. 2004, Aguilera 2006).

In this study, the growing interest in modeling urban processes (Benenson and Torrens 2004), coincides with the identification of new diffusely spreading urban growth. According to Font (2004), European Environment Agency (2006a), European Environment Agency (2006b), urban systems all over Europe are experiencing these patterns. In the case of Spain, these patterns result in a significant expansion of the main cities, and metropolitan areas. This process of urbanized land growth and construction of infrastructure impacts the natural landscapes (many of which bear important environmental and natural value), productive landscapes (agricultural areas on the periphery of the cities), traditional landscapes, etc. The expansion process, which takes place in these landscapes, results in landscape fragmentation and alteration (Forman 1995, Berling-Wolff and Wu 2004, Dramstad et al. 2005), and consequently in landscape homogeneity (Burel and Baudry 2002), regional diversity loss (Antrop 2000), the disappearance of productive agricultural areas (Fernández 2004), etc.

Considering the possibilities previously mentioned, the development of an urban growth simulation model has been proposed based on cellular automata for the metropolitan area of Granada (UAG). The model has been entirely integrated in the GIS IDRISI Andes Software. It is notable among the different characteristics of the model that the designed cellular automaton is much more complex than the classical automata utilized in the Game of Life (with 8 neighboring cells). It has been calibrated to reproduce the characteristics of the urban system, as noted in White et al. (1997). This higher complexity of the automata has resulted in a higher number of possible states, as well as in an extended neighborhood of 121 cells (11x11) with a 50x50 m dimension, representing a total neighborhood value greater than 1000 m surrounding each cell.

The final objective of the model will be to understand better the metropolitan complexity through the modelling of different urban growth patterns, which will be identified in the studied area. Future simulations for year 2020 will be generated in order to reproduce the above-mentioned growth patterns. Hence, the different scenarios based on the observed current trends will be taken into consideration. The evaluating comparison of these scenarios will be based on tools such as spatial analysis metrics linked to landscape ecology. For this reason, the results of these metrics will provide arguments for determining the behavior of the different patterns-scenarios and their possible relationship to certain dynamics and processes (Fig. 13.1), which originated from a more or less compact or spread growth model.

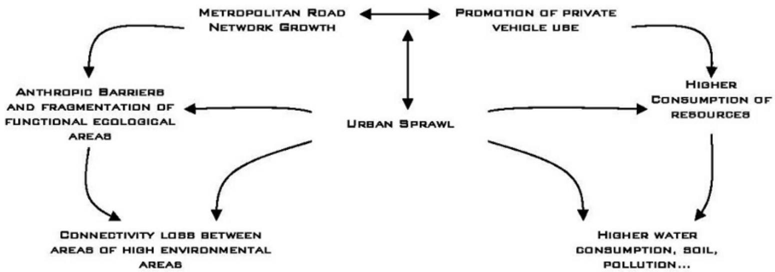

Fig. 13.1 Dynamics, Processes and Consequences of urban growth patterns

13.2 Text areas and data sets

13.2.1 Area of Study

The area of study selected includes the majority of the territory known as "Vega de Granada" (Fig. 13.2). It is located -in the depression created by the river Genil, located in the southeast of the Iberian Peninsula (Spain). The above-mentioned region has a significant agro-productive value (Menor 1998) and its spatial planning throughout history has reflected the financial importance of its agricultural exploitation. Traditionally, until the 1970’s, population, services, and activities were all concentrated in the city of Granada, while the means of support for the towns around Granada were mainly agricultural (Bosque 1962). However, since the late 1970’s and the beginning of the 1980’s, the area of study began to undergone significant urban transformations that continue today. These transformations originated from an intense growth in real estate, a lower land price in the neighboring towns of Granada, the improvements in infrastructure, the development of the private vehicle market, etc. In addition, they have also created a high and rapid growth of urban land, especially residential land, (Fernandez 2004) which has taken over the traditional region of “Vega de Granada” in the current metropolitan area.

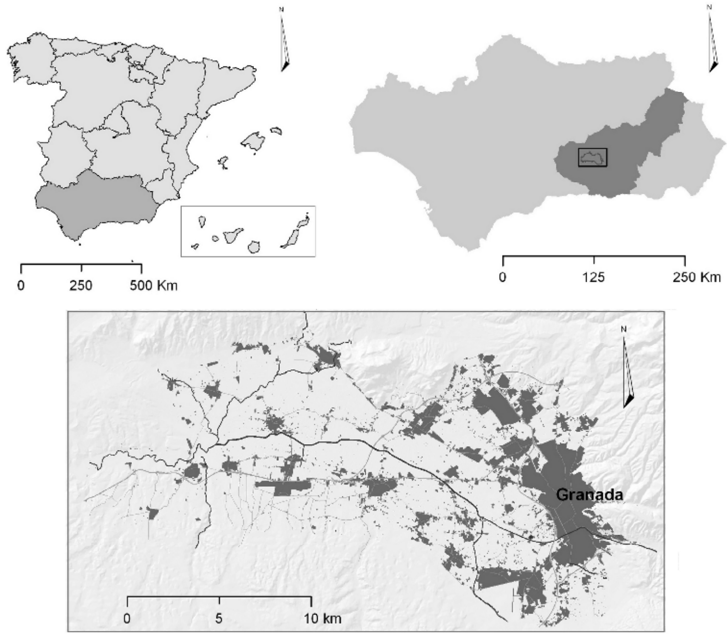

Fig. 13.2 Area of Study

13.2.2 Urban growth map

An urban growth evolution map has been created for the studied area for the period 1977-2003, by using the interpretation and digitalization process of aerial photography as well as the ortho-images available for the region of Andalusia. The result of this process is a map (Fig. 13.3), which illustrates the urban evolution of “Vega de Granada” towards a metropolitan area. It includes important processes of conurbation, both in the northern and southern areas, and the significant residential and industrial growth, especially those in the urban centres inside the area known as the "first crown" (Menor 1998, Fernández 2004, Aguilera 2006).

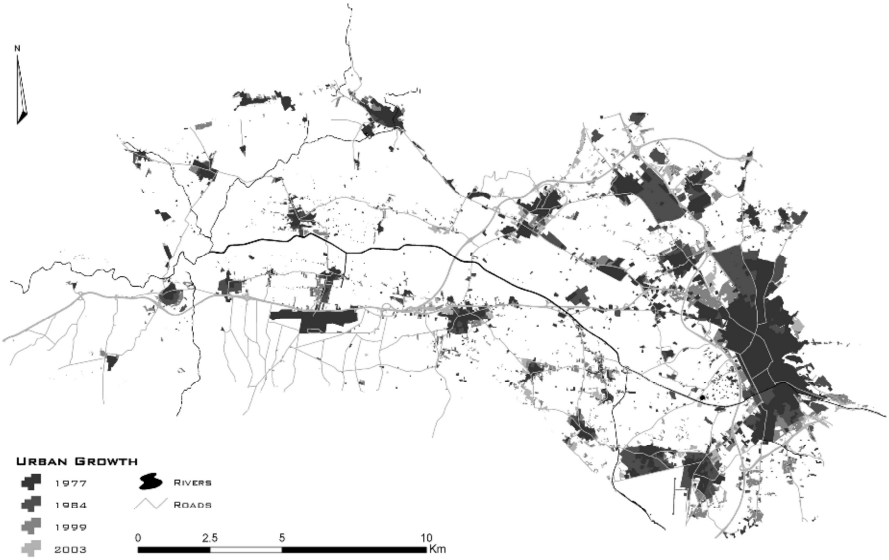

Fig. 13.3 Urban growth map of the metropolitan area in Granada (1977-2004)

Both in this map and in the different sources used for its creation, several categories of urban occupancy have been differentiated. They include those specifically formed by compact residential areas, spread residential areas, industrial areas, commercial areas, free spaces and green areas, and equipment needed for these categories. The generated model will work using these land occupancy categories. The map resulting from this interpreting process is shown in Figure 13.4.

13.3 Methodology and practical application to the data sets

The methodology applied in order to generate both future scenarios and evaluation scenarios is presented below. First, a map and a description of the urban growth patterns in the area of the study are presented. Then a description of the model built based on cellular automata has been carried out, as well as its operating mode and its implementation. This model will be used in order to generate simulations representing four future scenarios representing the different growth patterns detected.

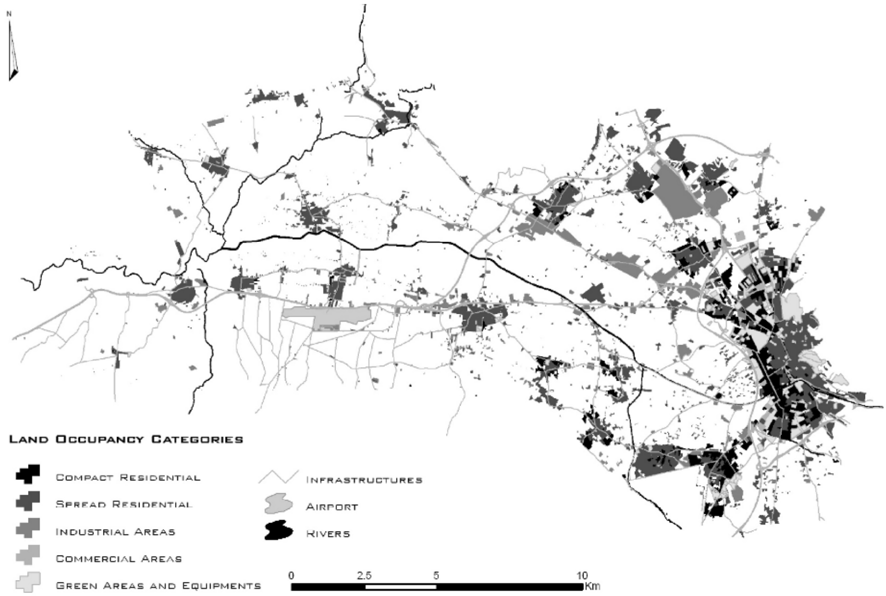

Fig. 13.4 Urban land use categories in the metropolitan area of Granada (2004)

13.3.1 Urban growth patterns

In order to identify different growth patterns in the studied area, the urban land growth over the last 30 years and the existing occupancy categories were analyzed. These patterns are considered as different growth morphologies, which are characterized by both their shape and their existing type of occupancy. In order to carry out the identification of the above-mentioned patterns according to their morphology, principles of accessibility, spatial contiguity and compactness have been followed. These principles are:

- Accessibility: Defined as the proximity to the road infrastructure network and communication junctions. According to this principle, those spaces nearest to major road infrastructures and important communication junctions will have a higher accessibility.
- Spatial Contiguity: Defined as the proximity to previously urbanized areas. According to this principle, those growths adjacent to previously urbanized areas will have higher spatial contiguity values, while those growths isolated from urbanized areas will have lower spatial contiguity values.

- Compactness: Related to the form in which urban growth develops. According to this principle, those growths, which are compacter denser and more circular will have higher values of compactness, while those types of urban growth, which are more linear will have lower values of compactness.

According to what has been previously stated, using the visual interpretation, four urban growth patterns have been identified in the studied area: (Fig. 13.5):

- Aggregated: Related to the forms of traditional urban growth in Mediterranean towns, with growth adjacent to the consolidated town (Monclús 1996). This growth is typical of the compact city model, favoring flows of social and cultural exchange, and at the same time improving the environmental efficiency of the urban growth (Rueda 2001). Usually, it is mainly integrated by compact residential areas mixed with free spaces and equipment needed for these areas. The urban land evolution in the northern area of the city of Granada between 1977 and 1988 shows this growth pattern.
- Linear Growth: This pattern identifies forms of urban growth, which preferentially tend to occupy the surrounding areas of the communication routes. The predominant typologies in these growth patterns are industrial lands or mixed activity lands (Font 2004), due to the logistic advantages present when occupying these routes. This linear growth pattern can be observed in the studied area along some of the most important communication infrastructures.
- Sparse Settlements: This pattern explains the appearance of urban forms with predominantly residential functions for spread residential typologies, in which the single-family house and a low urban density are the main characteristics. These patterns show growths with a strong dependency on private vehicle use, since in many cases the new growths are far from consolidated urban centers making the creation of a more efficient public transport system difficult. Some residential areas, located north of the studied area, are a clear example of this growth pattern.
- Junction growth: This pattern explains the urban growth which exists next to the main communication junctions such as crossroads, linear infrastructure junctions, etc. In the studied area, this growth pattern is characterized by both residential and industrial typologies. However, commercial typologies benefit the most. Some examples of this pattern are shown in the southern part of “Vega de Granada” region.

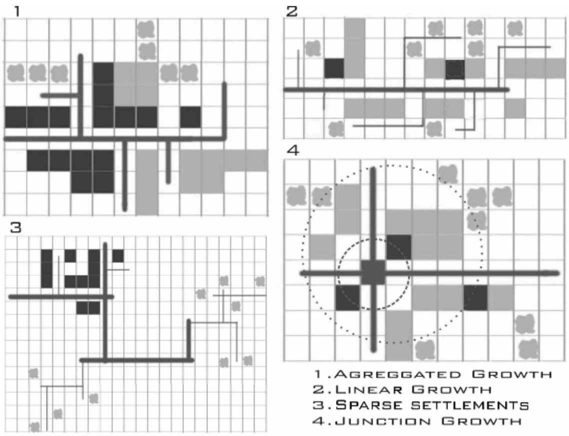

Fig. 13.5 Urban growth patterns schema

Table 13.1 summarizes the characteristics of each of the identified patterns, as well as the map of its distribution in the metropolitan area of Granada (Fig. 13.6).

Table 13.1 Charasteristics of Urban growth patterns

PRINCIPLES	URBAN PATTERN			
	AGREGGATED	LINEAR GROWTH	SPARSE SETTLEMENT	JUCTION GROWTH
ACCESIBILITY		(+++)	(+)	(++)
CONTIGUITY	(+++)	(+)		(+)
COMPACITY	(++)			(++)

[Influence level (+ Low ++ Medium +++ High)]

The simulation model based on cellular automata used to generate future growth scenarios has been developed and implemented through GIS Idrisi Andes Software based on the theoretical developments proposed in White et al. (1997) for the city of Cincinnati (USA). Previously, this has been utilized multiple times in the existing literature. The applicability of these methods has been revealed in several studies (White 1996, Batty 1997, Itami 1997, Torrens 2000) and therefore its application can be practical in this case. However, some modifications have been introduced regarding cell sizes, neighbourhood, and of course calibration values (Aguilera 2006, Aguilera et al. 2006). In particular, this model can be applied to simulate the growth of a metropolitan area, as shown in Barredo et al. (2003) for the metropolitan area of Dublin. However, the area of simulation in many other models includes only one city.

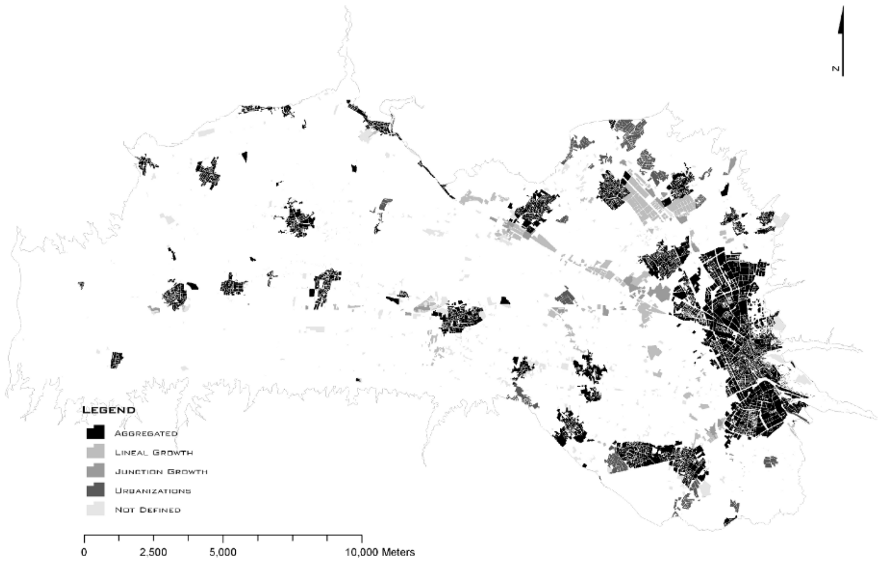

Fig. 13.6 Distribution of Urban Growth patterns in the Granada Metropolitan Area

13.3.2 Simulation model

The model employs the urban land use map as input data, which has been created in raster format and thus, will work at a cellular level. Among all the typologies or existing uses, the model defines a series of fixed states, which are not supposed to experience any changes, and which are utilized to represent stable elements (free spaces, equipment areas and road network); and dynamic states, which are subject to change, including compact residential land, spread residential land, industrial land and commercial land. Although the uses representing a fixed state do not change, their presence does influence the changes of the dynamic uses.

For each cell in the input layer, the model obtains a transition potential that represents the possibility of the appearance of a new dynamic typology (residential, commercial, industrial) in that specific cell. This transition potential will be obtained by combining four parameters:

Neighbourhood parameter: Composed of the cellular automata itself. This parameter estimates the probability of change for each of the cells in the raster input layer according to the existing neighbouring typologies. A neighbourhood formed by a regular grid with a 50x50 m cell size, composed of 121 cells has been defined. We have used 50x50 m cells, according the smallest fragment considered in the generation of the urban growth map. Thus the radius of the neighbourhood is more than 0.5 km. According to previous studies (White and Engelen 1997, Aguilera 2006), a longer diameter than 1km is considered sufficient to evaluate the neighborhood effect.

Certain uses will work as attracters for some other uses, while others will work as a repellent, whose degrees of intensity are determined according to the distance from the cell in question. For instance, industrial uses repel residential uses. The nearer they are to the cell in question, the more intense the repulsion is. This effect in attraction-repulsion is known in the literature as the "distance-decay effect" and as noted in White et al. (1997), it appears as a common characteristic in most cities. By adding all the attraction values for each of the neighbouring cells, a change potential value is obtained according to the neighbourhood parameter.

Territorial suitability parameter: Composed of two raster layers: slope map and urbanizable areas. The slope map is derived from the existing DEM for the area of study and the urbanizable areas map is obtained from the areas classified as urbanizable in the metropolitan planning.

Accessibility parameter: Defined as the Euclidian distance map for the different elements of a road network. These elements vary according to the use in question. Hence, commercial use areas are measured by the distances to the main network joints. However, for the remaining dynamic uses, the accessibility parameter has been obtained according to the Euclidean distance to the road network.

Stochastic Parameter: The objective of this parameter is to generate a "real" disorder degree that somehow characterizes distribution and the change in urban spatial processes. It is obtained according to the following equation:

$$v = 1 + \left(-\ln(rand)\right)^{\alpha} \tag{13.1}$$

Where rand is a random number between 0 and 1 and α is a parameter that permits an adjustment of the degree of perturbation. In this case, the value of α has been initially adjusted to the radial dimension (the slope of the relation between the size of the object and its diameter) calculated for the region of the metropolitan area in Granada, as Barredo et al. (2003) did in the case of Dublin (Ireland). Subsequently, as described in a previous study (Aguilera 2006) the parameter has been adjusted to the value of 0.3 which would permit a higher degree of similarity in the generated simulations.

The transition potential is finally obtained by combining these parameters according to the following equation:

$$P_j = v \times s_j \times a_j \left(\sum\nolimits_{k,i,d} m_{kd}\right) \tag{13.2}$$

Where:

P_j is the transition potential of each cell for the use j. It is the result of the combination of the neighbourhood, accessibility, randomness and suitability parameters.

v is the stochastic parameter, also referred to as the parameter of random perturbation.

s_j is the suitability parameter of the territory for the use j, according to the slopes and the land regime for the use in question.

a_j is the accessibility parameter, obtained as the Euclidean distance to the elements of a road network.

m_{kd} refers to the attraction/repulsion factor for the cells with state k in the area of distance d (neighbouring cells). These values of m_{kd} have been modified during the calibration process in order to generate the four different scenarios that will be shown afterwards.

The model has been designed to work through iterations. Each iteration corresponds to one year in the simulated period. For each iteration, the transition potential of all the cells is calculated for each of the dynamic states. Those with the highest potentials are selected to be transformed into a state in which the highest value is presented. These new cells are added to the input layer of typologies and then a new iteration is initiated. The number of cells selected in every iteration must be defined as a parameter of the model. For the ex post calibration simulations carried out in previous studies, the total number of pixels selected was determined by the annual urban growth rate for the period taken into consideration for the simulation. In other words, the number of cells that will experience a change in every iteration will be obtained only taking into account the growth rate corresponding to the date in question.

13.3.2.1 The implementation of the model

The simulation model has been implemented using the Idrisi Andes model builder, as previously mentioned, introducing all the tasks needed, without having to resort to connections between geographical input data, which are stored in a GIS and an external model. Programming will not be required, and extended software has been implemented making it easily reproducible and applicable to other cities.

The implementation has resulted in a group of more than 100 tasks, which can be divided into five groups.

The objective of the first four groups is to calculate the transition potential for each of the 4 dynamic uses. For each use, the neighbourhood effect is calculated, as well as the suitability, accessibility, and randomness effects, which are all combined in order to finally obtain the transition potential for each state. The objective of the fifth group is to select the highest transition potential for each pixel, and finally select those pixels which will turn into different states.

Fig. 13.7 shows schematically the group of operations needed to calculate the transition potential for a state, in this case, the compact residential state. The figure shows how the neighbourhood parameter is obtained from the effects of the attraction that bears on each of the states, both active and non-active. Afterwards, it describes the combination of this neighbourhood parameter with the accessibility, stochastic and territorial suitability parameters, in order to finally obtain the change potential towards a compact residential state.

These five groups are identified in Fig. 13.7, illustrating the group of operations implemented in the Idrisi model builder, in which the first four groups are allocated to the calculation of the transition potentials and the last group of the selection has been pointed out.

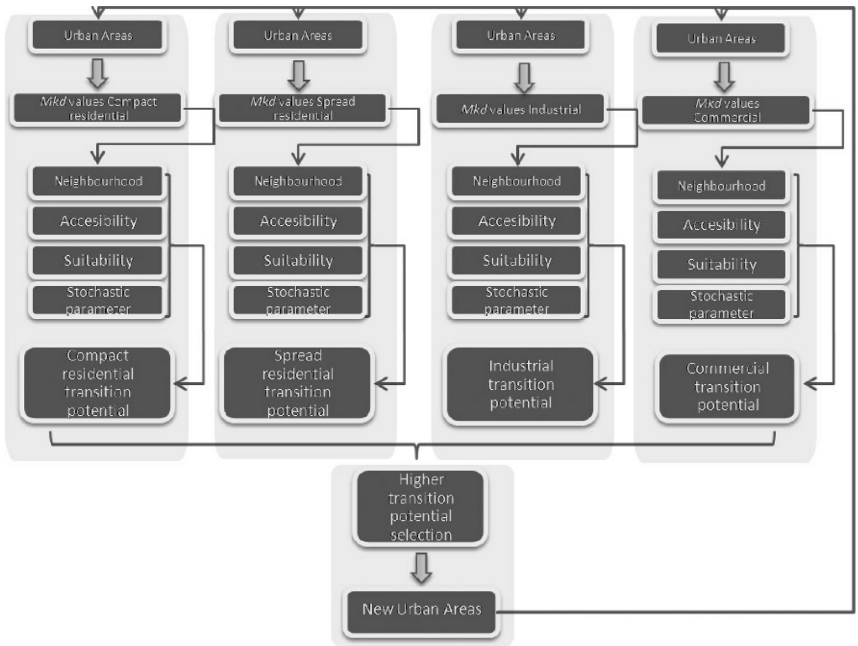

Fig. 13.7 Schema of the Implemented Simulation Model. The first four groups calculate the potential of each of the dynamic uses. The last group selects pixels with higher transition potential and adds them to existing urban areas

13.3.2.2 Model calibration and future scenarios

After the model has been implemented, a model calibration must be carried out in order to enable the model to produce future scenarios.

This model has been calibrated for the studied area in different previously researched areas, with acceptable results. Using the CA-based-model, a simulation for 1999 was generated from available data for 1984. The simulation obtained for 1999 was compared with reality through a coincidence matrix. Results for the kappa index are shown in Table 13.2.

Table 13.2 Kappa index for each use obtained in previous research

Use	Kappa Index
Compact Residential	0.7492
Spread Residential	0.7162
Industrial	0.6713
Commercial	0.5747

In this work, we present 4 future scenarios representing the urban land use patterns described above. According to this we will have one scenario for each one of the urban land use patterns. No mixed scenarios have been developed because our main intention is to generate and evaluate simple scenarios. Future research should be able to generate these mixed scenarios in order to show more realistic simulations.

This calibration process has been carried out using the trial and error method and through the modification of the weights m_{kd} for each use and for each distance to the central cell, which will create the attraction-repulsion effects of some uses in respect to others. Thus by changing only mkd values, the CA-model reproduces different urban land use patterns.

Table 13.3 shows the spread of residential calibration values of m_{kd} in four scenarios according to the distances. These distances are composed of 18 levels. Each level represents a distance value (1, $\sqrt{2}$, 2, $\sqrt{5}$, $2\sqrt{2}$, etc.) showing the previously described distance-decay effect. Note that many mkd values change in order to reproduce each scenario pattern.

This calibration process has been carried out for each active land use (spread residential, compact residential, industrial and commercial). Then four future scenarios for year 2020 have been generated, showing the patterns previously described.

13.3.3 Evaluation of the future scenarios

This third section will present the methodology for evaluation of four future scenarios that will be based on the application of spatial analysis metrics. These metrics have been widely applied in studies of landscape ecology (Forman 1995, McGarigal and Marks 1995, Botequilha and Ahern 2002). However, since the metrics are utilized to measure spatial characteristics, they can be utilized to identify and characterize spatial properties of other uses, especially the urban uses (Herold et al. 2005). These metrics are not as widely utilized in these cases as in the already "classical" studies of landscape ecology. However, in this case they can add new possibilities to the analysis of the spatial pattern in the frame of a increasing interest in the evaluation of urban dispersion processes in Spanish cities (Dalda et al. 2005) and European cities (Kasanko et al. 2004)

Table 13.3 m_{kd} values for the spread residential use in the four different scenarios

Spread Residential Use Calibration	**Distance Zones**																	
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
Lineal Growth																		
Commercial	6	6	3	3	3	3	0	0	0	0	0	0	0	0	0	0	0	0
Industrial	0	0	0	0	0	7	6	7	6	7	6	7	6	7	6	7	6	7
Spread Residential	90	90	90	90	90	90	70	70	70	5	5	5	5	5	5	5	5	5
Compact Residential	60	25	20	16	12	6	6	6	6	6	6	6	6	6	6	6	6	6
Free Space	40	25	15	10	7	7	7	7	7	7	7	7	7	7	7	7	7	7
Equipament	50	35	25	20	14	10	9	8	7	6	5	5	5	5	5	5	5	5
Road Network	100	100	100	100	100	100	100	95	95	95	95	95	95	95	95	95	95	95
Junction Growth																		
Commercial	6	6	3	3	3	3	0	0	0	0	0	0	0	0	0	0	0	0
Industrial	60	60	60	60	5	5	5	5	5	5	5	5	5	5	5	5	5	5
Spread Residential	90	90	90	90	90	90	70	70	70	5	5	5	5	5	5	5	5	5
Compact Residential	50	50	50	50	50	0	0	0	0	0	0	0	0	0	0	0	0	0
Free Space	40	25	15	10	7	7	7	7	7	7	7	7	7	7	7	7	7	7
Equipament	50	35	25	20	14	10	9	8	7	6	5	5	5	5	5	5	5	5
Road Network	70	60	47	35	21	17	14	12	10	11	11	10	11	10	11	10	11	10
Aggregated Growth																		
Commercial	-30	-10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Industrial	0	0	2	5	6	7	6	7	6	7	6	7	6	7	6	7	6	7
Spread Residential	95	95	95	95	80	80	80	80	80	80	80	80	80	80	80	80	80	80
Compact Residential	49	25	25	16	12	9	6	6	6	6	6	6	6	6	6	6	6	6
Free Space	40	25	15	10	7	7	7	7	7	7	7	7	7	7	7	7	7	7
Equipament	50	35	25	20	14	10	9	8	7	6	5	5	5	5	5	5	5	5
Road Network	3	3	3	7	7	7	9	7	9	7	9	7	9	7	9	7	9	7
Sparse settlement																		
Commercial	-30	-10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Industrial	0	0	2	5	6	7	6	7	6	7	6	7	6	7	6	7	6	7
Spread Residential	70	70	70	70	70	70	70	70	70	70	70	70	70	70	70	-9	-9	-9
Compact Residential	50	50	50	50	50	0	0	0	0	0	0	0	0	0	0	0	0	0
Free Space	40	25	15	10	7	7	7	7	7	7	7	7	7	7	7	7	7	7
Equipament	50	35	25	20	14	10	9	8	7	6	5	5	5	5	5	5	5	5
Road Network	70	60	47	35	21	17	14	12	10	11	11	10	11	10	11	10	11	10

When using those metrics in urban system analysis, a selection of the metrics must be previously carried out. Some of the metrics have been proposed in the existing bibliography. In any case, as noted in Parker et al. (2001), a group of metrics commonly accepted for its use in the studies of urban processes does not exist since the meaning of each metric can change according to the characteristics of the urban landscape.

Groups of spatial metrics have been proposed by authors such as Torrens and Alberti (2000) or Botequilha and Ahern (2002), as well as Herold et al. (2005) who use similar tools in their analysis. In this study, the metrics have been selected according to those proposed by the mentioned authors. The group of metrics utilized is described below. FRAGSTATS 3.3 Software has been utilized in order to carry out the calculations (McGarigal and Marks 1995).

Patch Number (PN): Is the simplest metric in the landscape ecology and can hint an idea of how divided or fragmented a certain use is by only identifying the number of individual patches existing in each of the identified uses.

Medium patch size (MPS): Is the average surface of individual patches for a certain use (McGarigal and Marks 1995). In this study, it will be applied for the urban uses.

Medium patch compactness (MRGYR): This metric is also known as the radius of gyration and it determines the compactness of the different patches. It is the average of all the patches for a given use of the radius of gyration parameter (RGYR or GYRATION), which is calculated for every patch as the distance of each pixel to the centroid of each patch.

Perimeter-Area Fractal Dimension (FRACTAL): This index shows the complexity in shape, of the different patches through the relationship between the perimeter and the area of each patch. The closer the value is to 1, the simpler the shape. On the contrary, the closer the value is to 2, the more complex the shape.

Mean Proximity Index (MPI): This parameter, developed by Gustafson and Parker (1994), is determined by the average value for each type of occupancy category or use of the proximity index (PI). The PI is equivalent to the summation of the areas in m^2 for the patches of an existing use in a given distance from the initial patch, divided by the summation of the minimum distances between those patches and the initial patch, squared.

13.4 Results

The results generated by the model are obtained from four simulations of future scenarios. Each of the simulations represents one of the growth patterns described in the second epigraph. These results were obtained through consecutive calibrations of the model for each of the scenarios, until the desired results were achieved considering the spatial structure of each of the patterns. Subsequently, a group of metrics previously described will be applied to each of the scenarios in order to carry out the evaluation of the scenarios.

Fig. 13.8 shows the results of the four generated scenarios. For each scenario, different categories of urban occupancy are presented in grey. The differences between the four scenarios are evident at first glance. Before evaluating the scenarios through spatial analysis metrics, the results were interpreted from a visual point of view.

Fig. 13.8 Simulated Scenarios for urban growth patterns. Year 2020

Firstly, the linear growth scenario is characterized by an intense growth in industrial lands, as well as a spread residential growth, around the main metropolitan communication networks and in the networks nearest to the urban centre. The nodal growth scenario around the main metropolitan nodes is characterized by an urban densification around each node, especially in the residential areas, both spread and compact. It also includes the industrial and commercial areas around certain nodes. This fact gives them a mixed character.

The aggregated growth scenario is perhaps the easiest to identify. It is characterized by an occupation around the consolidated areas; through growths in land, mainly spread residential and industrial. These growths are very compact, showing growths that morphologically tend to fill in the existing gaps and to produce occupations around the most consolidated and important industrial cores and areas.

Finally, the sparse settlement scenario consists of the aggregation of the small isolated existing edifications in groups of residential areas, both spread (majority) and compact, which grow separate from the main cores.

13.5 Validation and discussion of results

A group of spatial analysis metrics previously described were obtained for each of the four scenarios through the software FRAGSTATS (McGarigal and Marks 1995). The results of each of these metrics were generated for the different dynamic uses of each scenario, so that the differences between the scenarios for each metric can be clearly observed. The values of the metrics were also included for the existing situation in 2003, in order to better identify the changes experienced in each of the future scenarios. Fig. 13.9 graphically illustrates the results of the proposed metrics, as well as the table containing the results of the metrics.

The results of each of the metrics for the different scenarios are individually discussed below:

PN: The Patch Number metric defines the number of patches existing in each of the dynamic uses contemplated by the model. These patches range from only one pixel to any number of adjacent pixels. In regards to this metric, the values of the different scenarios are higher than those in the existing simulation in 2003; all except for the aggregated growth scenario which yields lower values in all the dynamic uses, except in the industrial case. Therefore, the aggregated scenario results in the lowering of the number of existing patches, through the aggregation of spread patches, while the other scenarios generally result in their increase. It is worth noting that the linear growth scenario shows a higher number of patches existing in areas near the communication networks, especially in the industrial and spread residential uses, as previously noted when commenting on the cartography of the scenarios. Another point worth noting is the lower number of patches existing in the commercial use as in the case of the nodal scenario. The nodal scenario strengthens the growth in the commercial areas, near the communication joints. However, these commercial areas already exist in those nodes, resulting in a growth of those patches but not in the appearance of new ones.

On the contrary, in the case of the aggregated scenario, the new residential growths generate the appearance of new commercial patches.

In the case of the nodal scenario, it is worth mentioning the elevated number of existing patches in the compact residential areas that appear as new independent and isolated groups, following their own identified pattern.

MPS: The Medium Patch Size shows the average size of the patches identified through the use of the PN. It is evident when first analysing the values of the PN, that the highest values of the MPS all correspond to the aggregated scenario, except in the case of commercial use. The aggregated growth results in a growth of patches and a lowering of their number, due to their aggregation. The lowest values of the MPS are found in the sparse settlement scenario, in the case of the compact residential use, due to the more disperse new residential patches generated by this scenario. Low values can be also found in the linear scenario, in the case of commercial use, due to the appearance of new incipient commercial areas near the surroundings of the motorways, The values of industrial use are lower than those in the situation existing in 2003, with a lower number of industrial patches. In scenarios such as the linear, the patches aggregate in new industrial areas in the borders of the infrastructures.

FRACTAL and *MRGYR*: Both metrics present an idea of the shape and compactness of the existing patches for each use. In this sense, the results reveal values according to the patterns presented in each of the scenarios. For instance, the linear scenario, with an intense industrial growth in areas bordering infrastructures, reveals low values of compactness and high values of the perimeter-area relationship, which results in patches in a linear arrangement that are barely compact in shape. The opposite occurs in the aggregated scenario, in the case of residential areas, which shows more compact patches resembling a circle. It is also worth noting the high compactness of the commercial areas in the nodal scenario, due to an intense growth in the existing commercial areas in one of the main communication joints, which generates a compact and aggregated commercial area. The high values of the perimeter-area relationship, in the case of industrial use, for the existing situation in 2003 are also worth mentioning. These high values are caused by the elevated number of small patches with elongated shapes, as previously mentioned. The growths in the industrial use in any of the scenarios results in the aggregation of many of these patches and in their not so elongated shapes, which means a lowering in the FRACTAL index.

MPI: The Mean Proximity Index presents an idea of how connected the patches are in a determined use for a certain radius. In this study the radius selected is small, 100 metres. The results show the highest values for the aggregated scenario. The RESIDENTIAL scenario has the lowest values, especially regarding the compact residential use, where the differences are more obvious. It is also worth mentioning the highest values in the linear scenario, in the case of industrial use, due to a more continuous arrangement of the industrial patches around the different axis.

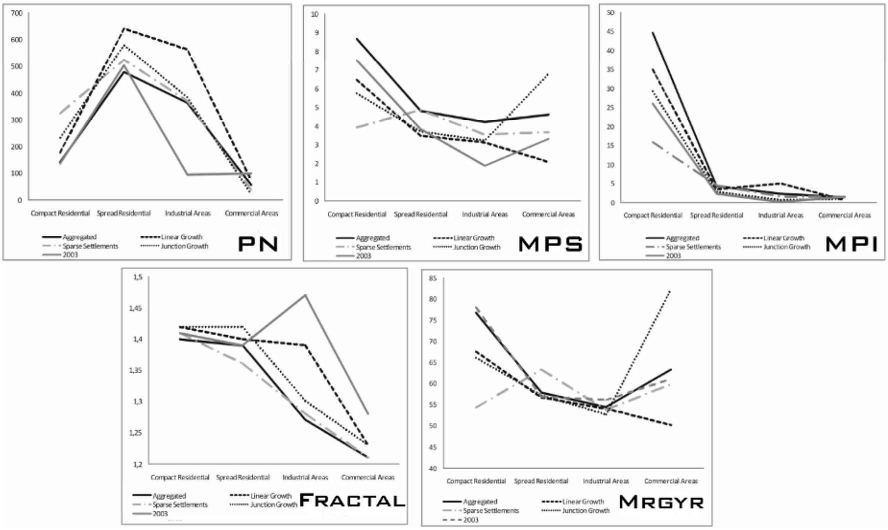

Fig. 13.9 Spatial analysis metrics results

In order to conclude the discussion of the results of the metrics applied in the different scenarios, a distribution of the values of the metrics has been created relating land uses and scenarios representing the trends of the different simulated patterns, taking as a reference the starting scenario, which is the scenario in 2003 (Table 13.4). It is worth noting the metric values (for scenarios and uses) which are more or less close to those in 2003, as well as those uses and scenarios that present the highest values, and those that present the lowest ones, always regarding the 2003 scenario. On the one hand, the idea of stability or the dynamic of the spatial configuration is obtained according to the scenarios, and on the other hand the morphometrical aspects are found to be more or less sensitive to the relational dynamic of uses and patterns, according to the field of application of the simulations.

Above all, it is worth noting that the use which changed the most, from the 2003 scenario in the group of metrics is the Compact Residential use in combination with the RESIDENTIAL scenario (MPS and MRGYR) and the aggregated scenario (MPI). The use which showed the least change, from the 2003 scenario, is the Spread Residential use in combination with the Nodal scenario (MPS), the linear scenario (MRGYR), and the Aggregated scenario (Fractal).

Table 13.4 Metrics summary: distribution of the values of the metrics by land uses and scenarios

METRICS	LAND USE (BY SCENARIO) with the further value related to values of scenario 2003	LAND USE (BY SCENARIO) with the closer value related to values of scenario 2003	Land use with the highest values	Scenario with the highest values	Land use with the lowest values	Scenario with the lowest values
PN	Industrial (Linear)	Compact Residential (aggregated)	Spread Residential	Linear	Commercial	junction
MPS	COMPACT Residential (Sparse Settlement)	Spread Residential (junction)	Compact Residential	Junction	Industrial	2003
MRGYR	Compact Residential (Sparse Settlement)	Spread Residential (Linear)	Commercial	Junction	Commercial	Linear
FRACTAL	Industrial (Sparse Settlement)	Spread Residential (Aggregated) and compact residential (Sparse Settlement)	industrial	2003	Commercial	Aggregated/ Sparse Settlement
MPI	compact Residential (Aggregated)	Commercial (Sparse Settlement)	Compact sidential	Aggregated	Commercial	Linear

In regards to the sensitivity of the metrics, it is worth mentioning that the Commercial use is predominantly the use with the lowest values, almost in all the metrics, except in the MPS, which is clearly related to the lower surface presence of this use in the metropolitan area. It is also important to note that the use with the lowest number of high values and/or low values is the Industrial use, which presents an idea of the lack of attraction in this use, even more, the intense repulsion. Regarding the scenarios, it draws the attention to the fact that the RESIDENTIAL scenario is the one with the lowest number of extreme values, as opposed to those which show the highest number of extreme values (highs or lows) such as the Linear and the Nodal scenario.

13.6 Conclusion and outlook

Firstly, it worth pointing out how spatial analysis metrics significantly differentiate between the diverse growth scenarios, resulting in the understanding and detection of the different patterns that serve as examples of each scenario. These metrics have been utilized in multiple studies about landscape ecology (Franco et al. 2005, Botequilha et al. 2006). In the last decade these metrics have been utilized more often, as an instrument applied to the interpretation of structure, shape, and function of the urban development's landscape (Alberti 1999, Lausch and Herzog 1999, Herzog and Lausch 2001, Herold et al. 2005).

These metric tools can be applied in analyzing, evaluating, and planning, making the orientation of socioeconomic processes and metropolitan growth patterns more integrated and sustainable (Carsjens and Ligtenberg 2007, Azócar et al. 2007). Therefore, the extrapolation ranging from different ecological approaches, connectivity analysis (Tishendorf and Fharing 2000), its fragmentation or change pattern, to planning approaches of the "urban sprawl" or in the metropolitan areas (Nuissl et al. 2005) results in an interdisciplinary enrichment, and in conclusion, an enrichment of the decision making process.

This perspective has been applied in the study in an attempt to understand the urban growth patterns according to land uses. The attraction and repulsion are simulated through the transition potential of each cell, whose main goal is the search for the relationships between uses, according to the proposed scenarios-patterns. The relational interpretation of the transition potential has become a useful tool in interpreting trends, dynamics, and stabilities of the different uses according to the chosen scenario.

Moreover, the results from the variation of the metrics have reinforced the understanding of where, how, and why certain uses grow more or less in respect to the joints, the road infrastructures and the pre-existing residential areas. In this respect, the metrics open new horizons to manage the metropolitan dynamic, through considering the compactness (MRGYR), the cohesion (MPI), the axiality (MRGYR, Fractal), the fragmentation (PN,PD,MPS), and in conclusion, the urban complexity (Fractal).

Logically, the information obtained from these scenario metrics in respect to the previous planning criteria, is not rich enough to discard the uncertainty when simulating and interpreting the different scenarios. In this sense, it would be useful for the progress of the methodology and its final applicability, to proceed in three crucial directions: the distinction of more land uses (typologies, activities and densities); the application of other metrics, resulting in a better understanding of the environmental and socioeconomic consequences of the scenarios (diversity indexes); and the design of mixed scenarios (in consequence to what has previously been stated) resulting in an identification and evaluation of the most sustainable growth patterns.

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14 Towards a set of IPCC SRES urban land use scenarios: modelling urban land use in the Madrid region

Barredo JI and Gómez Delgado M

Abstract

The objectives of this study are to test the applicability of urban land use change models for the simulation of climate change scenarios for large regions and to define the future research needs in this topic. Specifically, the scenarios A1, A2 and B2 produced by the Intergovernmental Panel on Climate Change (IPCC) in the Special Report on Emissions Scenarios (SRES) have been used for the implementation of three urban land use scenarios in the Madrid region. A cellular automata-based model has been used for the modelling component of the experiment. The land use scenarios were developed for an area of about 10,000 km². This area includes about 340 municipalities of the Madrid Autonomous Community and other municipalities beyond it representing the functional region of Madrid. The IPCC SRES emissions scenarios were used to produce the storylines describing the narrative socio-economic and political conditions that will drive future land use change. The scenarios produced cover the period 2000-2040. CORINE land use datasets were used as input data into the model. This European-wide dataset creates the possibility of modelling large European areas using a single implementation of the model. This approach opens new possibilities for the assessment of the impacts of urban land use development (e.g., transport needs, increasing exposure to natural hazards, impacts from climate change, urban sprawl).

The results of the experiment were useful for studying aspects such as urban sprawl and sub-urbanisation. These two effects of urban growth have become a serious concern in Europe. Simulating sprawl and sub-urbanisation by using land use change models provides planners with a powerful tool for territorial decision-making. Indeed, the inclusion of SRES scenarios in an urban land use modelling approach enables the exploration of potential environmental impacts arising from several paths of socio-economic evolution and climate change. The proposed methodology

also provides the possibility to discern the effects of urban and regional planning instruments and policies at local and regional level.

Keywords: Land use change, land use modelling, cellular automata, Madrid, SRES, scenarios

14.1 Introduction

The objectives of this study are to test the applicability of urban land use change models for the simulation of climate change scenarios for large regions and to define future research needs in this topic. Specifically, the scenarios A1, A2 and B2 produced by the Intergovernmental Panel on Climate Change (IPCC) in the Special Report on Emissions Scenarios (SRES) (Nakicenovic and Swart 2000) have been used for the implementation of three urban land use scenarios in the Madrid region. A cellular automata (CA)-based model (White et al. 1999, Barredo et al. 2003, Barredo et al. 2004) was used for the modelling component of the experiment. The land use scenarios were developed for an area of about 10,000 km². This area includes about 340 municipalities of the Madrid Autonomous Community and beyond, thus representing the functional region of Madrid. The IPCC SRES emissions scenarios were used to produce the storylines describing the narrative socio-economic and political conditions that drive future land use change. The scenarios produced cover the period 2000-2040. Thus three land use scenario datasets were produced for this particular timeline. We used CORINE datasets (EEA 1993) as input data into the model, thus the resulting scenarios have the same spatial and thematic properties of CORINE. Using this European-wide dataset creates the possibility of modelling large European areas in a single implementation of the model with high spatial resolution, up to 100 m, and with a detailed number of land use classes. This approach opens new possibilities for assessing the potential impacts related to urban land use dynamics on several sectors such as transport needs, exposure to natural hazards, impacts from climate change, urban sprawl, etc.

Several approaches have been developed for the simulation of urban land use using climate change scenarios as drivers for socio-economic and political conditions. Solecki et al. (2004) downscaled two climate change scenarios, A2 and B2, into the SLEUTH model (Clarke et al. 1997, Clarke and Gaydos 1998) for the production of two future urban growth land use scenarios in the New York Metropolitan Region for 2020 and 2050. Solecki et al. (2004) used the SRES to define the potential conditions of future land use change. The SRES A2 and B2 were used as the meta-narrative to define future regional development patterns and associated land use change. Thus, from two meta-narrative stories the SLEUTH model was calibrated and specific urban growth parameters were defined for the production of both land use scenarios. In a study for the Netherlands, De Nijs et al. (2004) produced a set of land use maps for 2030 using a set of SRES-like scenario meta-stories. A total of four scenarios were implemented and translated it into spatially-detailed land use maps. This study was developed at a country scale and for a simulation period of about 30 years. The Environment Explorer model (Engelen et al. 2003) was used in this work for the implementation of the future land use maps.

The studies of Solecki et al. (2004) and De Nijs et al. (2004) share several commonalities. In both cases a dynamic spatial model, which was originally developed for the assessment of urban land use growth, is used. And in both cases a similar extension is considered for modelling, about 40,000 km² in the Netherlands and some 36,000 km² in the New York Metropolitan Region. Indeed the spatial limitation posed by this type of models is one of the topics to be addressed for the development of the next generation of urban land use growth models for the simulation of climate change scenarios. However, it is worthwhile to mention that because of the fine resolution of the SLEUTH and the Environment Explorer, they produce detailed scenarios that are useful for many applications and in different contexts. Another common aspect in both studies is the fact that the land demands for urban land use classes were produced externally to the modelling environment. The external definition of land demands is the main characteristic of constrained land use models (Barredo et al. 2003). The method for the production of land demands is in our view one of the issues to be addressed for a more comprehensive approach for climate change scenario simulation through land use models. The modelling tools used by Solecki et al. (2004) and De Nijs et al. (2004) can be included in the family of spatial dynamic models for urban land use simulation. For a review of this type of model see Batty (2005).

The continental-scale modelling approach of Reginster et al. (2006) is a different conception of land use modelling. This approach is implemented for a long period from 2000 to 2080. Several initiatives for continental to global scale land use modelling have emerged in the last few years, for a review see Heistermann et al. (2006). This family of global to continental models follows a rather different approach if compared with the above-mentioned dynamic spatial modelling approaches. The modelling approach of Reginster et al. (2006) is structured in three steps. The first step is similar to the previous applications of de Nijs at al. (2004) and Solecki et al. (2004), and consists of the interpretation of global-scale storylines from climate change scenarios, usually SRES. Secondly, the estimation of land demands through a statistical method. And the last step is the land use allocation by using a set of spatial rules. This approach has the advantage of being able to simulate large geographic areas such as the European Union in a single implementation of the model. Nevertheless, the continental scope of the model produces a number of disadvantages, including coarse spatial and thematic resolution (number of land use classes). A relevant difference between the continental approach of Reginster et al. (2006) with the two previous studies is the process of allocation of new urban land use areas. In the approaches of Solecki et al. (2004) and De Nijs et al. (2004), the urban growth is defined from a bottom-up approach, as it is the basis of the CA-based modelling approach (Barredo et al. 2003). CA-based models are implemented as emergent systems (Batty 2005), thus the land use patterns emerge from a myriad of local level interactions between cells having different land use configurations. In the approach of Reginster et al. (2006) the allocation of new urban land use areas is the consequence of a series of rules at a more general level. We find that the allocation method of this approach, in many respects, follows a top-down set-up.

It is reasonable to say that both model approaches under consideration have both advantages and disadvantages for the simulation of land use climate change scenarios. These aspects must be considered for the implementation of future modelling approaches for climate change scenarios at continental level with relatively high spatial and thematic resolution.

14.2 Test area: current land use trends and facts

Madrid is the capital and largest city of Spain. It is also the capital of the Autonomous Community of Madrid. The metropolitan area of Madrid, originally defined in 1963 by 27 municipalities, today even encompasses towns and cities outside the Madrid Community. Territorial change was particularly intense during the late eighties and throughout the nineties. Today all 179 municipalities of the Madrid Community can be considered part of the Madrid region (López de Lucio 2003). Furthermore cities such as Guadalajara and Toledo, outside the Madrid Community, at a distance of 60 and 74 km respectively can be considered dynamically integrated within the Madrid region. Currently, the core city has an area close to 600 km² and 3.1 million inhabitants. The Community of Madrid covers approximately 8,000 km², of which 1,000 km² was developed land in the year 2000.

The Madrid region is considered to be one of the hot-spots in urban development in the EU (EEA 2005, Ludlow et al. 2006). The other two areas in Spain showing extraordinary urban growth rates are the Mediterranean coastal areas of the Valencia and Murcia Autonomous Communities (OSE

2006). The coastal areas of these two communities experienced a 21% increase of artificial areas between 1975 and 1990 (Perdigão and Christensen 2000). More recently, during the nineties, the increase reached a worrying 50% level. This situation is comparable with the development in the Madrid region. Urbanised land in Madrid has grown by 50% in the nineties (Fernández-Galiano 2006). This rate can be considered very high if compared with the national rate of 25%, and even higher if compared with the EU's figure of 5.4% for the same period (EEA 2005). The extraordinary artificial land development in the Madrid region is the result of a number of drivers other than population growth. The population of the Madrid Autonomous Community showed a growth rate of 5.16% during the nineties. In the same period the growth rate in Spain was only 3.15%.

In the 60s, 87% of the population and the most important economic activities of the Madrid region were concentrated in the core city. During that decade, concentration of people and activities was considered a problem. To resolve this problem several industrial nuclei were planned and then allocated in Toledo and Guadalajara. The result of those planning measures was the beginning of a de-centralisation process regarding people and economic activities, which afterwards led to an uncontrolled process. During the last decades of the 20th century, the core city of Madrid has already shown a spatial pattern in which 'leaps' in the spatial continuity of the city produced clusters of vacant land inside the urban fabric of the city (dal Cin et al. 1994). By 1985, such a pattern was clearly noticeable in the maps of Madrid. Today, the influence of the city's large buffer has aggravated this situation, and the region of Madrid shows a rather scattered development pattern (Fig. 14.1). The problems related with scattered development for the core city were already pointed out in 1994 (dal Cin et al. 1994). One being the difficulties encountered for the provision of urban facilities and services.

There is not a single causal factor for the intense urban growth registered in Madrid in the last few years. A number of interlinked socio-economic factors have produced an enormous pressure on this area. The first factor to be considered is a social demand for first and second residences. 513,000 new residential units have been created in the region in the nineties (López de Lucio 2003). However, the population increase for the same period was only 240,000 inhabitants. This produces a surprising and hardly explainable ratio of 2.14 new residential units for each new inhabitant. Obviously, economic interests of both citizens and private firms are heavily re-shaping the real state market in the region. In 2001, there were 2.44 millions of residential units in the Madrid region for a total population of 5.4 million inhabitants, which produces a ratio of one residential unit for each 2.22 inhabitants. The current favourable economic situation in Spain together with the competitive interest rates for the mortgages in the Euro-zone and the high social demand for housing has produced the impressive above-cited figures. Another factor which is markedly driving the de-centralisation process occurring in the Madrid region is the increased mobility. A substantially improved transport network, i.e., new toll motorways, three motorway rings around the city, new and improved metropolitan and train connections, etc. are increasing accessibility in a number of areas that today can be considered integrated with the Madrid region, e.g., Guadalajara, Toledo (Fig. 14.1). Indeed the largest land transitions are taking place around the areas with improved accessibility. Conversely, the new low-density residential areas at the outskirts and periphery of the city are generating new mobility needs and hence producing a vicious circle, in which new settlements name the improvement of the transport connections as one of their most important priorities. The overall effect of the above-mentioned factors is a tremendous increase of prices for residence within the Madrid region. The prices decrease proportionally with the distance from the city centre. This forces an ever-growing number of people to become involuntary commuters relying largely (more than 50%) on the use of private car. These socio-economic drivers have lead to an intense de-centralisation process of both population and economic activity in the Madrid territory (López de Lucio 2003). In Fig. 14.1, this process can be clearly seen in the newly developed areas between 1990 and 2000.

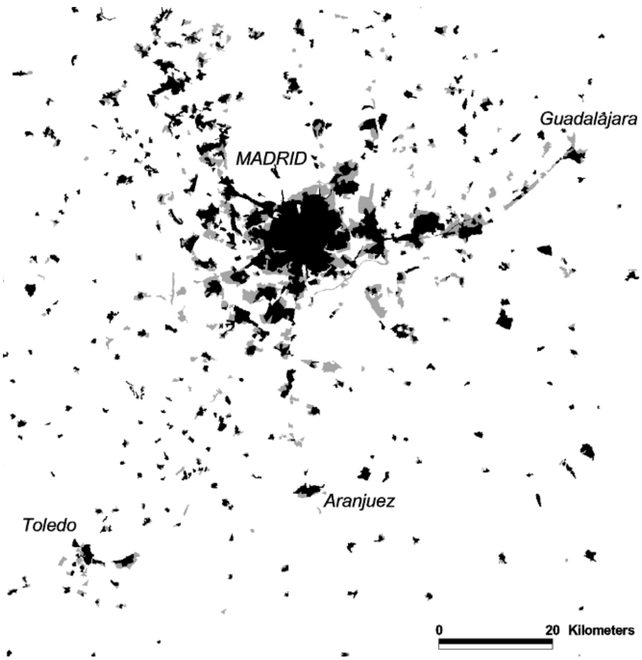

Fig. 14.1 Built-up areas in the Madrid region in 1990 (black) and 2000 (grey) from CORINE

In the Madrid functional region the urban land use class with the largest share in 2000 is the discontinuous urban fabric (Fig. 14.2b). This land use class accounts for 49,000 hectares, and it is where the new low-residential clusters were allocated. This land use class increased by 41% in only ten years between 1990 and 2000 (Figure 14.2a and b). Conversely, continuous urban fabric grew by only 13% in the same period. Construction sites and industrial or commercial areas also had an impressive growth of 200% and 107%, respectively. However they represent less than a half of the land covered by discontinuous urban fabric in 2000.

A number of territorial effects have been identified as consequence of the size increase of the Madrid functional region. López de Lucio (2003) gives an assessment of those effects: population and employment redistribution, new dynamics of housing with very high rates of growth, and the appearance of new territorial hubs served by large, decentralised shopping and entertainment malls. These effects are also occurring well beyond the Madrid community. Interestingly, a great number of municipalities at a distance of about 50 km from the core city registered a population increase of more that 100% in the period from 2001-2006 (INE 2006). Today the territory of Madrid is moving towards a sprawled-like region (Munoz 2003). This process is taking place within a weak spatial planning framework (López de Lucio 2003, Fernández-Galiano 2006), which is common to a large number of other European urban regions, in which the regulatory capacity of municipalities is not always able to deal with the enormous forces that are reshaping the territory (Fernández-Galiano 2006).

The region of Madrid is moving towards a dichotomy that has to be addressed soon. On the one hand there is an urban region based on the idea of competitiveness and free market forces, on the other hand a city region where competitiveness is sought in both a more environmentally and socially sustainable way through proper spatial planning and involvement of stakeholders. The first choice offers a number of possibilities. It creates a competitive region in terms of economy and image, favouring new activities and investments in the region. But the disadvantages of such a choice have to be considered in a broad holistic context within a long-term planning perspective (López de Lucio 2003). This development style with a dispersed spatial form is resulting in a very high consumption of territory, water, energy and other resources (Munoz 2003). Increasing mobility and mobility needs are producing emissions, which play a role in failing to reach the targets of the Kyoto protocol for Spain. And moreover, the sprawl-like development is profoundly modifying the territory in an unsustainable way.

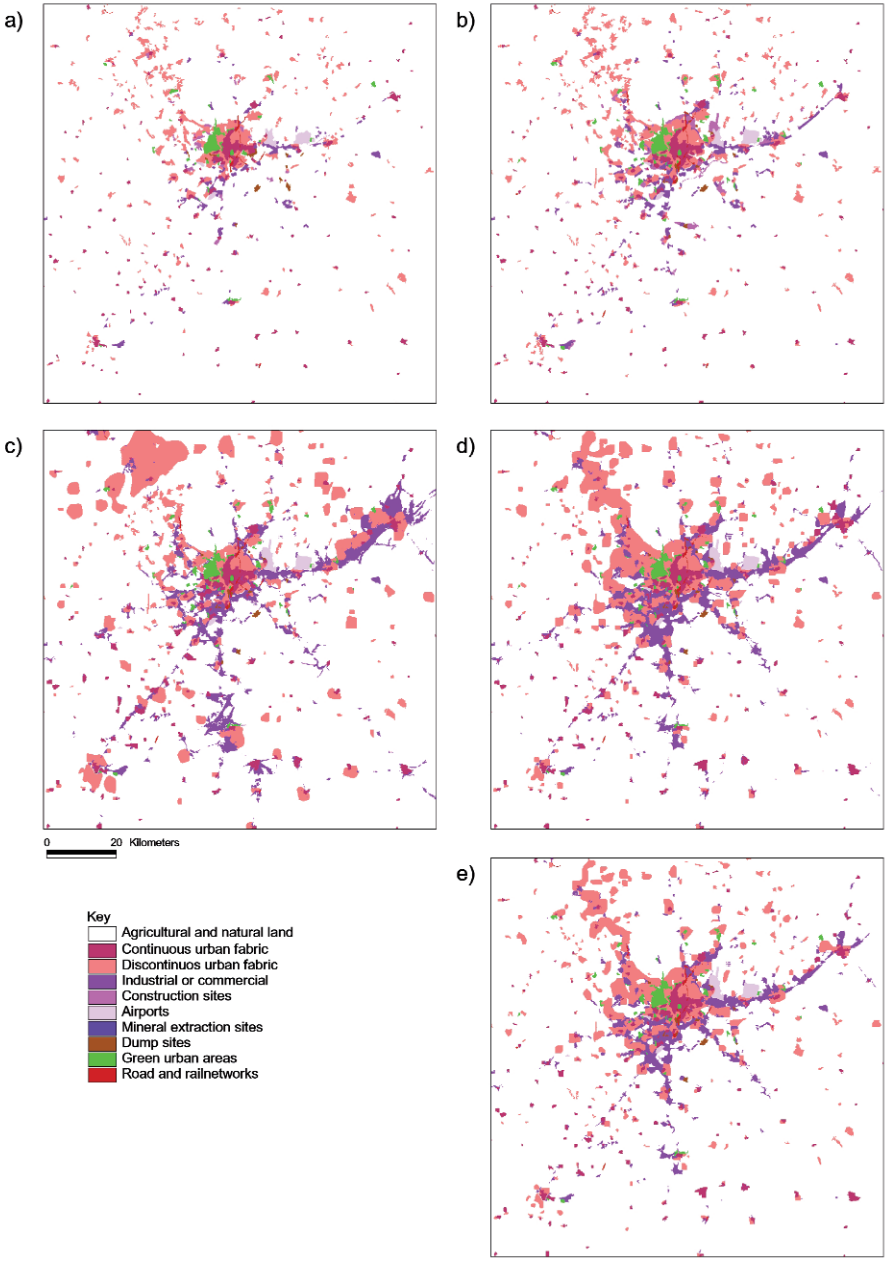

Fig. 14.2 Urban land use in the Madrid region: (a) CORINE 1990, (b) CORINE 2000; scenarios for 2040: (c) A1 - Scattered growth, (d) A2 - Rapid urban growth, (e) B2 - Compact development

14.3 Methods

14.3.1 Cellular Automata-based model structure

The CA-based model used for the implementation of the land use scenarios comprises several factors that drive land use dynamics in a probabilistic approach. Previous studies in the urban land use modelling arena have shown a number of factors that drive land use dynamics i.e., accessibility, land use zoning regulations, suitability and the effect of the existing land use patterns in a given neighbourhood (see: Batty 2005). Barredo et al. (2003, 2004) defined the process of urban land use dynamics as a probabilistic system, in which the probability that a place in a city is occupied by a given urban land use type at a given time step is a function of accessibility, suitability, zoning status, and the neighbourhood effect measured for that specific land use type at that specific time step. In addition, a stochastic parameter is included for simulating the degree of stochasticity that is characteristic in most social and economic processes. All these factors have been included in the MOLAND model (White et al. 1999, Barredo et al. 2003, Barredo et al. 2004).

The MOLAND model is implemented with a probabilistic approach. Thus the model assesses several factors for the calculation of transition probabilities for each cell and for each land use class at each time step (usually one year). The factors are:

- *Accessibility*: The accessibility factor represents the importance of access to transportation networks for various land uses for each cell. Thus, one accessibility layer is produced for each land use type. This is because one activity might require better accessibility than another. Accessibilities are calculated as a function of distance from the cell to the nearest point in the transport network. Accessibility is a dynamic factor within the model, thus it is updated on each time step (year).
- *Suitability*: Suitability can be defined as a weighted sum or product of a series of physical, environmental, infrastructural, historical, and institutional factors. Nevertheless, suitabilities are usually defined by a slope layer (Clarke and Gaydos 1998). The steeper the slope, the lower the suitability for urban land use. In this study we used a slope layer for setting-up the suitability layers. For computational purposes, it is normalized to values in the range 0–1 and represents the inherent capacity of a cell to allocate a particular land use class. The suitability layers are usually generated in a GIS and then imported into the model. Suitabilities remain constant during the simulation.

– *Zoning status:* This factor influences the land use allocation establishing the legal restrictions for land use allocation. This factor remains constant during the simulation unless the user chooses to set different layers for many time periods.
– *Neighbourhood effect:* The neighbourhood space is defined as a circular region around the cell with a radius of eight cells. The neighbourhood thus contains 196 cells that are arranged in thirty discrete distance zones. The neighbourhood radius is 0.8 km; this distance delimits an area that can be defined as the influence area for urban land use classes. This distance is similar to what city dwellers commonly perceive to be their neighbourhood, and thus should be sufficient to allow local-scale spatial processes to be captured in the model transition rules.
– *Stochastic parameter:* This parameter determines the level of stochasticity of the simulation. A value close to 0 produces a rather deterministic simulation, and a value greater than 3 or 4 creates a rather random distribution of new land use classes and patterns.

In standard CA the fundamental idea is that the state of a cell at any given time depends on the state of the cells within its neighbourhood in the previous time step, based on a set of transition rules. In the MOLAND model a vector of transition potentials is calculated for each cell from the suitabilities, accessibilities, zoning status and neighbourhood effect. Then the obtained deterministic value is modified by the stochastic parameter using a modified extreme value distribution. The effect of the stochastic parameter is that the resulting transition potential of a few cells is slightly modified, while a few others are changed significantly. The transition rule works by changing each cell to the state with the highest potential. However, the transition rule is constrained by the fact that the number of cells in each land use class must be equal to the number of cells demanded in that iteration. Cell demands are generated outside the model. During each iteration all cells are ranked by their highest potential, and cell transitions begin with the highest-ranked cell and proceed downwards until a sufficient number of cells of a particular land use class have been achieved. Each cell is subject to this transition algorithm during each iteration, although logically most of the resulting transitions are unaltered, that is to say the cell remains in its current state.

Fig. 14.3 shows the conceptual structure of the model. Initially a set of transition rules is implemented during the calibration and then incorporated into the model. Also a set of land demands for the urban land use classes for the whole simulation period is defined and implemented in the model. Zoning and suitability layers are usually included in the model as constant factors. Nevertheless, they can be updated in specific time steps. Then the accessibility layer is calculated in the model for the initial time step on the basis of the transport network layer. Then the model produces in several iterations, or time steps, many land use and accessibility layers until reaching the target year of the simulation. The land use and accessibility layers created were retrofitted to the model until the last time step of the simulation is reached. Then the final land use map is produced. A detailed description of the model can be seen in Barredo et al. (2003, 2004).

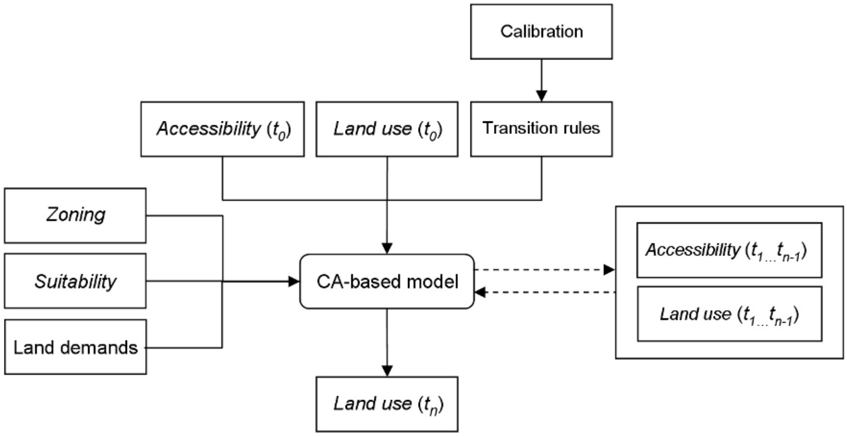

Fig. 14.3 Implementation of the Cellular Automata-based model (in italics: spatial datasets)

In this experiment we use the intuitive calibration method of White et al. (1997) and previous calibration experience of other cities such as Dublin (Barredo et al. 2003) and Lagos (Barredo et al. 2004). The model is calibrated by running a simulation initiated from a historical land use layer. Thus a simulated reference land use layer is produced and compared with the reference land use layer. When the result of the accuracy assessment is satisfactory, future scenarios are produced. For a description of the calibration procedure of the model see Barredo et al. (2004). The testing of simulation results has often been considered a weakness in urban land use modelling. A practical way of testing the calibration of the model is to run a simulation using historical datasets. The increase in the number of cells for each land use class during the simulated period is usually calculated from historical land use trends. Thus the calibrated simulation accounts for an exact evolution of each land use class. In the case of simulations for future scenarios, the land use area demands are usually defined on the basis of the meta-narrative descriptions and the historical evolution of land use, population, GDP, and other socio-economic indicators.

Land use models create ways of thinking about cities and urban regions, thus providing an informed basis for discussion about the best management options and planning. These types of models are not implemented for prediction, nevertheless they are usually calibrated and tested based on the observation and comparison of real and simulated maps. When implementing scenarios, the assumptions defined in the calibration phase are modified accordingly with the meta-narrative descriptions of each scenario. Thus a set of transition rules and land demands is implemented for each scenario within the model. The resulting scenarios are by no means predictions that could form the basis of policymaking. In spite of this, the scenarios are useful tools that offer insights that can aid policy-making (Batty 2005).

Complex systems are characterised by collective properties, which define the behaviour of the system as a whole. However, much of the behaviour of the constituent parts can be different from the whole and sometimes partially unknown (Barredo et al. 2003). This strengthens the argument that these types of models are informative but can not be considered for prediction. Indeed it is assumed that the overall pattern of urban systems emerges from a myriad of interactions at the local level giving way to the process of "urban" emergence in the cellular landscape of the model. This type of model enables us to think about interventions in cities at the level of processes but we can not exactly predict what the outcomes of such an intervention might be (Batty 2005). Instead we have to work at the level of the land use patterns, which emerge from the different configurations of the system as consequence of different scenario setting.

14.3.2 Climate change scenarios and storylines for urban land use development

The first step towards the implementation of a set of climate change land use scenarios is to define a set of meta-narrative descriptions or storylines corresponding to each scenario. In this study, the scenario development is based on the SRES (Nakicenovic and Swart 2000) of the IPCC. The four marker scenarios, i.e., A1, A2, B1 and B2 of the SRES provide the insights for the implementation of the meta-narrative description of each land use scenario. Each meta-narrative description should represent a set of drivers for urban land use development during the simulated period. Thus each scenario is described through different socio-economic development pathways (Schröter et al. 2004). For this purpose we made several assumptions concerning development styles, land use demands, socio-economic conditions and other factors such as spatial planning policy options and economic evolution. One storyline was produced for each scenario describing the drivers that they represent. The set up of the meta-narrative descriptions is considered to be the first step in climate change land use modelling studies (see: de Nijs et al. 2004, Solecki and Oliveri 2004, Reginster and Rounsevell 2006). Table 14.1 shows a qualitative description of meta-narratives in a number of studies regarding urban land use simulation of climate change scenarios. Previous studies on this topic were useful for the implementation of the meta-narratives in this work.

In the following paragraphs we describe the meta-narratives implemented for the Madrid region. These meta-narratives represent three future development paths and are based on an interpretation of the SRES storylines and previous work in this field.

A1 - Scattered growth: This could be considered a pessimistic scenario with very rapid urban growth. It shows a significant increase in the extension of built-up areas in the Madrid region. This is a market-led development scenario, having very rapid economic growth and slight population increase. Urban growth is mainly taking place in peripheral areas. Within this scenario the city moves towards a sprawled development style. There is an increasing clustering and scatteredness of new urban areas and diffuse suburbanisation and peri-urbanisation. There is high influence of road transport and private car use. There is lack of spatial planning restrictions either at the local or regional level.

A2 - Rapid urban growth: This scenario represents a moderate economic growth with a steady increase in the population. It has rapid urban growth with an increasing share of low density areas, low infilling and patterns of diffuse suburbanisation. The influence of road transport and private car use is high. However there is also a shift towards a higher share in public transport (metropolitan, train). There are no relevant spatial planning restrictions.

B2 - Compact development: This is considered an optimistic scenario. The population is relatively stable with low to moderate economic growth. In this case a more compact urban development style prevails. It represents a rupture with the current trends in the Madrid region. There is a slight increase of urban areas with increased infilling. The relevance of road transport is medium to low. Spatial planning relies in a sustainable development policy towards compact development. Preservation of natural areas and green urban areas becomes a priority.

The second step for the implementation of the land use scenarios is to quantify the demand for urban land use for each meta-narrative. This is a critical aspect for the implementation of the land use scenarios, since it will drive the shift in the absolute amount of land conversion. This could be the result of using macro-economic models such as in Reginster et al. (2006), the result of literature revision and development impact studies assessment as in Solecki et al. (2004) or can be produced by trend scenario assessment as in de Nijs et al. (2004). Macro-economic modelling creates a number of advantages for the production of land demands. Nevertheless their use could be limited by the availability of such type of models or assessments for the modelled area. In this study we followed a similar approach to that of Solecki et al. (2004). Thus by assessing trends of urban land use conversion in the decade 1990-2000, we produced three land demand datasets for each of the meta-narratives implemented.

Scenario A1, which represents a very rapid urban growth, will be defined as having 10% more conversion than the reference trend projection (1990-2000). We have to keep in mind that the urban growth registered in the Madrid region in the reference period is considered to be extraordinarily high. Thus a further increase of 10% in the rate of urban growth would produce a relevant impact in the region. Scenario A2 will be defined as having the same conversion as registered in the reference period, thus it will represent a continuation of the rapid urban growth of the region. And scenario B2 will represent a decrease of 40% of conversion in relation to the trend conversion observed in reference period.

The final step for the implementation of the scenarios was to translate both the meta-narratives and the land demands into the model. Furthermore a number of changes in the calibration parameters were introduced for the simulation of the three scenarios. Among them the stochastic parameter was calibrated in order to represent different scatteredness/compactness patterns and the allocation of new urban clusters in areas originally defined as vacant land in the initial year of each implementation. The accessibility parameters also play an important role, its relevance is higher in the A family scenarios and lower for B2. Thus three different model settings were produced for the simulation of the scenarios.

14.4 Results: IPCC SRES urban land use scenarios

Before the implementation of the scenarios, the model was calibrated by using datasets from 1990 and 2000. CORINE datasets were selected for the study area and transport network layers were collected from the TELEATLAS database for Europe. Results of the accuracy assessment for the calibration period are shown in Table 14.2 We use the accuracy assessment approach of Hagen (2003) and Hagen-Zanker et al. (2005) for the calibration of the model. Results in Table 14.2 show a reasonably good agreement between the observed and simulated map for 2000. The results are comparable with other studies using a similar model platform (i.e. de Nijs et al. 2004) and those of previous MOLAND model applications (Barredo et al. 2003, Barredo et al. 2004).

Table 14.1 Qualitative description of meta-narratives used in studies of urban land use simulation of climate change scenarios

SRES scenarios	Madrid region (this study)	Europe (Reginster and Rounsevell 2006)	New York Metropolitan Region (Solecki and Oliveri 2004)
A1	- Significant increase in the extension of built-up areas (higher than A2) - Increasing clustering and scatterness of new urban areas - Diffuse suburbanisation and peri-urbanisation - High influence of motorways in road corridor growth - New centres often will be located in natural and agricultural areas - Increasing share of vacant land between urban clusters - Lack of planning restrictions - Population is relatively stable	(A1F1) - Rapid economic growth - Increasing urban land use around large cities - Lack of planning restrictions - Diffuse suburbanisation - Urban sprawl - Population is relatively stable	Not implemented
A2	- Rapid urban growth - Increasing share of low density areas - Low infilling - Diffuse suburbanisation - Loose spatial planning policy - Increasing population	- Significant increase in the extension of built-up areas - Small/medium size cities expand most rapidly - Suburbanisation and counterurbanisation - Increasing population	- Rise in the per capita land use conversion - Road corridor growth - Growth in new suburban and peri-urban areas - New centres often will be located in agricultural and forested areas - New loop motorway will be built 75 km from the regions centre - Minimal infilling
B1	- Not implemented	- Priority for a sustainable environment - Compact form of cities - Planning: preservation of green urban areas, regeneration of old city centres - Slow population growth	- Not implemented
B2	- Slight increase of urban areas - Sustainable development policy - Spatial planning policy: compact development - Preservation of natural areas and green urban areas - Increased infilling - Medium/low relevance of motorways accessibility - Population is relatively stable	- Urban areas increase only slightly - Sustainable development policy - More flexibility in the density of cities, compared with B1 - Planning: preservation of green spaces around cities and regeneration of old city centres - Stability of European population	- Decrease in the per capita land use conversion - Road influenced growth will continue to be important - No new roads will be built - Growth along railroad corridors because of the increase in the use of public transport - Minimal spontaneous growth, as well as fewer new spreading centres - Increased rates of infilling, compact growth and edge growth will take place in existing urban and/or suburban areas - Conservation buffers and areas will be created

The existence of land use patterns might be understood holistically at the level of the whole simulated area. Modelling scenarios of urban systems should account for the overall appearance of the system in regards to the distribution and configuration of land use patterns. The more intuitive comparison method between land use maps is a visual comparison. The main feature of the visual analysis is the resemblance between the observed and the simulated map for 2000. The visual comparison produces a first impression about the accuracy of the model. However, statistical tests like those in Table 14.2 are needed in order to obtain accuracy values. It has been shown that procedures using coincidence matrices are not well suited for testing urban land use simulation models (White et al. 1997, Torrens and O'Sullivan 2001). The main problem is related to the incapacity of quantifying patterns as such, because coincidence matrix and Kappa statistic are based on independent comparisons between pairs of cells. The Fuzzy Kappa measure is considered to be an improvement in this respect. This statistic yields results that are more gradual than those from other methods such as Kappa statistic or cell-by-cell comparison. Thus it is more likely to give an adequate indication of small differences (Hagen 2003). A rather different avenue is to test the accuracy of the future scenarios developed. In that case we have no observed map, thus other methods such as sensibility analysis can be implemented.

Table 14.2 Results of the calibration of the MOLAND model for 1990-2000

Land use map 1:	Observed 2000
Land use map 2:	Simulated 2000
Kappa	0.925
K-location	0.945
K-histo	0.979
Fuzzy Kappa	0.914
Fraction correct	0.943

It seems necessary to make a distinction between model calibration and model validation. Calibration refers to the process of creating a model such that it is consistent with the data used to create the model (Verburg et al. 2006a). The aim of the model validation is to improve the robustness and acceptability of the model. For example, exploring the effects in the results of errors and uncertainties in the input data or ascertaining the degree of influence of any parameter on the performance of the model. In the last few years, we have seen a growing interest in exploring new methods for uncertainty analysis as an alternative to error analysis. The aim is to assess the risk that we assume when using the outputs from a given modelling approach in a decision making process (Gómez Delgado and Barredo 2005). This type of analysis is necessary for scenario approaches trying to explore future paths, which are impossible to validate completely for an obvious lack of real data (Verburg et al. 2006a). A sensitivity analysis should be part of the validation process in order to test the stability of the model. Several indices have been developed in the field of computational modelling for measuring the change in the model results relative to a change in one or more of the input parameters. Several studies have corroborated that the indices could be successfully used in spatial models (Gómez Delgado and Tarantola 2006).

The A1, A2 and B2 land use scenarios for 2040 were successfully implemented. The three scenarios produced show divergent patterns of land use (Fig. 14.2c, d and e). The potential impacts of A1 scenario, in terms of land consumption and the number of new commuters relying on private car, have to be carefully assessed in the context of a sustainable development policy for the Madrid region. A1 scenario shows a dramatic decrease in the amount of natural and agricultural land during the modelling period. This scenario shows the more scattered and diffuse urban land use pattern. Urban nuclei in peripheral areas have grown more than the urban areas closer to the core city. The effect of radial and concentric motorways is clear in the distribution of new urban areas in this scenario. This is considered a sprawled-like scenario, the city moves toward the outskirts with a very low proportion of infilling and large clusters of vacant land between the urban nuclei. The proportion of low density residential areas increases as well.

For the A2 scenario diffuse and periurban developments have appeared around the core city. The overall urban land use pattern is not as scattered as it is in the A1 scenario. There is a relevant influence of the road transport network in the distribution of new urban nuclei and growth of urban areas (Fig. 14.2d). There is a rapid urban growth in this scenario. Nevertheless a moderate economic growth influenced the development of new urban areas. Thus the urban areas increase slightly less than in scenario A1.

The B2 scenario shows a much slower process of urban growth. This scenario could be the result of a series of spatial planning regulatory measures and policies. Fig. 14.2e shows a more compact urban land use pattern with a higher proportion of infilling. Still a relevant proportion of vacant land can be seen in the map as consequence of the pattern existing in the initial year of the modelling period.

14.5 Discussion and concluding remarks

The results of this work confirm the applicability of dynamic spatial models for the simulation of climate change scenarios. The experiment was specifically useful for studying aspects such as urban sprawl and sub-urbanisation. These two effects of urban growth have become a serious concern in Europe (Ludlow et al. 2006). Simulating urban sprawl and sub-urbanisation by using land use change models provides urban planners with a powerful tool for territorial decision making. Indeed, the inclusion of IPCC SRES scenarios in an urban land use modelling approach enables the exploration of environmental impacts arising from several paths of socio-economic evolution and climate change. The proposed methodology also provides the possibility to discern the effects of urban and regional planning instruments and policies at the local, regional and national level. A scenario-based approach supports the understanding of future consequence of current actions and drivers in future land use dynamics. Thus, alternative development paths give an overview of the potential impacts of current spatial planning measures and policies. The scenarios produced show a high level of realism in a reasonable long time period of 40 years. Nevertheless the size of the area modelled could be considered a limitation for small scale studies, as those related with climate change. This type of study is focused on either continental scale or large tiles such as the whole Iberian Peninsula.

We agree with the fact that "models developed for applications at large scales (for small areas) are not necessarily applicable at small scales (e.g. Europe-wide)" (Reginster and Rounsevell 2006: 634). But it is also true that models developed for applications at small scales do not have the spatial and thematic (number of land use classes) accuracy necessary for a number of purposes such as transport-emission impacts, exposure to natural hazards, urban sprawl, fragmentation of natural areas, sustainable spatial planning, etc. In Table 14.3 we present a comparative assessment of the two approaches for urban land use simulation of climate change scenarios. As can be seen in the table, the two families of models show a series of advantages and limitations.

The comparative assessment of Table 14.3 gives an overview of the potentialities and limitation of both approaches. It is obvious that currently there is no one single approach satisfying all requirements needed in studies of urban land use simulation of climate change scenarios. It is very likely that a new generation of land use simulation models will be the result of a merging of the more powerful features of both approaches. To this end a number of caveats are still to be addressed.

Among the issues that should be considered, the relationship between spatial resolution and size of the study area is one of the main concerns. From Table 14.3 it is evident that high resolution implementations can be developed only for relatively small areas of about 10,000 to 40,000 km^2. And that small scale applications at the continental level lack spatial and thematic resolution. How to deal with this issue is one of the research topics to be addressed. A mid-term solution could be to provide scenarios with a spatial resolution of about 500 m. and for large regions on the order of the Iberian Peninsula for example. How to deal with regional differences in urban land use growth is the second aspect to be addressed. The dynamic spatial modelling approach gives a solution for this, nevertheless how to implement it at continental level remains a challenge. Interestingly a merging of the methods for land allocation from the two approaches might result in a new way of understanding urban land use modelling at the continental scale.

Table 14.3 Comparison of two families of models for urban land use simulation of climate change scenarios

Properties	Dynamic spatial modelling approaches: This study, Solecki et al. (2004), de Nijs et al. (2004).	Continental scale land use modelling approaches: Reginster et al. (2006), Schröter et al. (2004).
Spatial resolution (grid size)	100 to 500 m	10' x 10' grid cell (ca. 15 x 15 km).
Thematic resolution (number of land use classes)	18 in this study, 4 of which are urban land use categories.	Just a few classes, only one in the case of urban land use.
Time scale (modelling period)	Until 2030, 2040, 2050.	Up to 2080.
Size of the study area	10,000 to 40,000 km².	Continental-wide.
Scenario land demands	Through literature revision and development impact studies; trend scenario assessment.	Through a statistical model using as input population and GDP scenarios.
Ability for modelling regional differences in urban land use growth	Within this approach it is possible to produce different spatial configurations in a single implementation (e.g. radial/sprawled; road influenced/diffuse).	This approach is able to produce different spatial configurations and consumption rates for different European countries.
Model calibration	The calibration is usually based on observed land use maps i.e., from past to present. Sensibility assessment is feasible for future scenarios.	A validation of the statistical model for land demands is produced based on observed statistics.
Requirements for the implementation of the model platform	Relevant skills (calibration, set-up, etc) are needed to use the model platform.	More open structure by using explicit spatial allocation rules.
Urban land use modelling approach	Dynamic bottom-up approach: the land use layer retrofits the model for each iteration. Patterns emerge from local rules applied in a dynamic fashion.	Top-down approach: a set of general spatial rules governs the allocation/transition of land use units.

The issue of how land demands should be produced is a critical aspect of the model implementation. The approach of Reginster et al. (2006) is more robust because of the use of a statistical model. Nevertheless only two variables are available so far for its implementation for long periods i.e., population and GDP (Arnell et al. 2004). Using macroeconomic modelling produces a more comprehensive approach for estimating land use demands, including non-urban land use classes. The works of Verburg et al. (2006b) and Rounsevell et al. (2006) give light in the use of macroeconomic models such as GTAP and Image for land demands estimation under several scenarios. Nevertheless the estimation of urban land use demands remains a complex matter with a high degree of uncertainty.

Long term simulations are subject to a relevant amount of uncertainty. The larger the simulation period is, the bigger the uncertainty. In addition there are several sources of uncertainty that must be addressed e.g., the meta-narratives, land demands, spatial information used in the implementation of the model, model calibration, transition rules, etc. How to assess the uncertainty in these types of models is another challenge to be considered in this field. The modelling science should go hand in hand with the advances in the uncertainty field; otherwise the risk is to produce land use scenarios with poor significance.

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