Chapter 8
Remote Sensing and Spatial Modelling of the Urban Environment

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8.1 The Urban Environment: A Remote Sensing and Land Use Modelling Perspective

With the beginning “urban millennium” (UNESA 2007), our interest in the societal, economic, and ecological functioning of urban systems is rapidly increasing (Pickett et al. 2001). Half of the world’s population inhabits cities, with an increasing share of megacity dwellers or people living in mega-urban regions (Kraas 2007). Urban agglomerations steer processes from the local to the global level and urban ecological science needs to develop a deeper understanding of how matter and energy flows driven by urban ecosystems function across scales (Grimm et al. 2008; Kaye et al. 2006). While a city’s physical footprint is limited, the ecological footprint of our increasingly urbanized world is rapidly expanding. Urban agglomerations are estimated to extend on an ecological footprint of up to 200–300 times their actual physical size (Folke et al. 1997). The sustainable provision of urban ecosystem services and maintaining urban biodiversity is hence closely connected to mitigating effects of imbalanced rapid urbanization (McGranahan and Satterthwaite 2003). Accordingly, urban ecology is becoming more prominent and will determine how sustainable future cities will develop from an environmental perspective. There is an urgent need for in-depth process understanding and a more profound knowledge of land use decisions that drive the urban structure and thereby heavily impact the urban environment and the provision of ecosystem services. Actually, urban regions offer the most intense interaction of humans with ecosystems and

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thereby a wealth of opportunities to gain a deeper understanding of related land use processes and impacts on urban ecosystem services. However, urban ecology is intrinsically complex; it exhibits many different research facets and an overarching theory is still to be developed. A methodologically sound basis is mandatory to lay the foundation of such theoretical frameworks and to provide input for model-based research to test hypotheses in urban ecology and land use change (LUC) impacts on urban ecosystem services (Alberti 2005; Pickett et al. 2008).

The importance of spatially explicit analysis and modelling in the context of urban ecology has been pronounced by numerous authors (Alberti 2005; Cadenasso et al. 2006a, 2007; Grimm et al. 2000; Pickett et al. 2008). Essentially, all consolidated findings in urban ecology are based on spatial observations and a conceptual understanding drawing to a large extent from spatially explicit research and models. Remote sensing techniques provide spatially explicit information on the urban environment at different spatial and temporal scales and in a consistent and reproducible manner. Spatial analysis and modelling of an integrated urban environmental dataset – including remote-sensing-derived and additional environmental and socio-economic data – allows the exploration of land use processes and likely impacts on the urban environment in urban areas from a human-environment system's perspective (Rutledge et al. 2008; Van Delden et al. 2007).

To assess the state of the urban environment, in recent years urban remote sensing has gained tremendous interest which may be due to two reasons: the advent of very high spatial resolution sensors and the increased interest in urban ecology. The latter is partly triggered by long-term ecological research (LTER) in the urban context (Hobbie et al. 2003; Wu 2010) and by the ever-increasing concern for urban ecosystems in a steadily urbanizing world. Related literature includes numerous special issues in remote sensing journals (Gamba et al. 2003; Gamba and Chanussot 2008; Weng and Quattrochi 2006b) and also a variety of book publications (Jürgerns and Rashed 2010; Netzband et al. 2007; Weng and Quattrochi 2006a). This wealth of new research is invaluable, as urban remote sensing covers a wide range of topics, including analyses of vegetation differentiation, urban climate, and energy fluxes (Gluch et al. 2006; Hung et al. 2006; Kaufmann et al. 2007), biodiversity (Cohen and Goward 2004; Seto et al. 2004), imperviousness (Phinn et al. 2002; Ridd 1995; Yang et al. 2003) or also the generic problems of urban growth (Griffiths et al. 2009; Herold et al. 2003; Schneider et al. 2005).

To explore the processes and likely impacts of urban land use on the environment and the provision of urban ecosystem services, one powerful instrument is LUC modelling. It enables one to uncover the many relationships, driving factors, and underlying causes contributing to urban change (Batty 2007). LUC models are primarily used as learning tools to gain knowledge of changing mechanisms and causal relations within complex systems such as cities. Furthermore, LUC models can also be powerful to explore scenario-based future trends and to explore hotspots of likely LUC and the respective impacts on urban ecosystem services (Rutledge et al. 2008; Van Delden et al. 2007). LUC models contribute to the communication between researchers and decision makers (Verburg et al. 2006) and allow new insights to preserve and improve the existing urban environment and particularly its services in an urban context. In recent decades, a variety of LUC model applications have been carried out. They exhibit considerable differences in complexity, modelling techniques, drivers, spatial resolution and scale (local to global) and finally in regards to the investigation of land use type itself (Batty 2003; Haase and Schwarz 2009; Koomen and Stillwell 2007; Lakes et al. 2009; Pijanowski et al. 2006).

The aim of this paper is to illustrate the contributions of sophisticated and up-to-date technologies to an improved understanding of the urban environment, the provision of urban ecosystem services, and the underlying processes of LUC. We therefore begin with the need for information on the urban environment from a scientific and decision-maker point of view based on the already available information for our case study Berlin. We then present initial insights from two case studies on (a) very high resolution remote sensing techniques for assessing the urban environment and (b) land use modelling techniques to assess likely future LUC and its impact on the urban environment.

8.2 Availability of and Need for Information on the Urban Environment in Berlin

Land use change caused by human decisions as well as by climate and demographic changes affects the urban environment and the provision of ecosystem services in Berlin to a significant degree. It is particularly the case for Berlin that a mosaic of continuous growth, change, decline, and restructuring exists (White and Engelen 1993). Assessing and modelling these processes of land use change and modification is a major task to gain an improved understanding of the present and likely future city of Berlin. In addition to this focus on urban development under different scenarios of demography or climate change, a variety of environmental formal and informal planning and decision-support instruments exist to preserve and develop the environment within the urban area of Berlin, such as Preparatory Land-Use Planning, Zoning Ordinance, the Water Framework directive, the Fauna Flora Habitat directive, or the Environmental Impact Assessment Directive. The Strategic Environmental Assessment has developed to a key tool for sustainable development (Jones et al. 2005; Dalai-Clayton and Sadler 2005). This European guideline requires an environmental assessment of the effects of formal plans and programs which set a framework for subsequent planning levels.

To address these challenges of decision-making and urban ecosystem service preservation and development, the crucial prerequisite is the availability of reliable information on the present situation of the Berlin urban environment which is spatially explicit, sophisticated, and user-friendly. Also in Berlin there is an increasing interest in generating scenarios on likely future changes and potential impacts on the urban environment. In recent years, the amount and heterogeneity of available spatial information on the urban environment has rapidly increased. Different information technologies for assessing and analyzing environmental information are applied, including a growing variety of remote-sensing sensors and products (Hostert 2007; Schneider et al. 2007). Remote sensing techniques have augmented additional acquisition methods and have been a fundamental information source, including the assessment of the sealing degree (Haag et al. 2008) and the vitality of tree species (Damm 2009). They have been particularly valuable for the field of nature conservation, where a significant demand for area-wide and up-to-date data exists, for example with biotoptype and NATURA 2000 mapping.

As well as the increase in data acquisition techniques of the urban environment, the number of users and data providers is steadily growing so providing a sophisticated management system environmental information and spatial data in general is now one of the major challenges. The concept of the spatial data infrastructure is to explicitly address this issue of data provision in a transparent and user-friendly way (De Man 2006). In Berlin, the Spatial Data Infrastructure (SDI) is brought forward by a joint committee of Berlin and Brandenburg stakeholders (http://gdi.berlin-brandenburg.de). An online geo-portal provides information on the available data in the two federal states with state-of-the-art standards and technologies. These include a Web-Map-Service, a Web-Feature-Service, and a Web-Catalogue-Service all of which allow user-friendly access to available information, and even more importantly, allow access to relevant metadata on available geodata, and data on the urban environment, respectively. Access to a large number of environmental datasets exists with the Environmental Atlas as one of the most important, maps of land use planning or a soil pollution register (please see http://gdi.berlin-brandenburg.de). Berlin was actually one of the first cities in Germany to implement such an environmental information system which since then has been further developed and migrated into a broker that allows access to a large amount of Berlin data for several application fields. With this new generation of Environmental Information Systems, the aim is to allow information, communication, and transaction of environmental data (Schneider et al. 2007).

Studying the urban environment with regard to LUC and ecosystem service provision requires the integrated analysis of different environmental data as well as socio-economic data independent from the method of data acquisition. New technologies open up new application fields on the one hand, such as the growing spatial and temporal resolutions of remote-sensing data (van der Linden and Hostert 2009), the increasing capacities of internet-based access (Schneider et al. 2007), or the spatial analysis and modelling techniques. The use of these newly available techniques for a specific aim requires a profound knowledge on the user needs and on the benefits as well as challenges of available data such as shown for the example of urban habitat networks in Berlin (Lakes and Pobloth 2005). On the other hand, it is the actual question arising in science and decision-making such as assessing ecosystem services from very high resolution remote sensing or local impact analysis of LUC on ecosystem services driven by demographic change which requires new approaches, selecting the most appropriate available data, and spatial modelling techniques.

8.3 Very High Resolution Remote Sensing for Urban Ecosystem Service Analysis

8.3.1 State of the Art

The urban space has increased in significance as a field of concentration and spatial attraction of human capital (Seto 2009). Its dynamics, either waxing or waning, is driven by a variety of social, economical, and ecological factors causing disparities within the urban environment. Consequently urban space is categorised into different spatial units such as those with social disparities, economic centres, and areas providing large shares of ecosystem services. Science will not address challenges of ecosystem services in urban areas if the urban space is taken as a single unit while intra-urban analysis still lacks detailed studies (Troy et al. 2007). As today's significance of the urban space increases, the field of urban ecosystem services becomes more important (Cadenasso et al. 2006a). Up to now, services such as air filtration, micro climate regulation, carbon storage, noise reduction, rainwater drainage, sewage treatment, provision of food, recreational, and other aspects have been barely addressed in the urban context (Bolund and Hunhammar 1999; Oberndorfer et al. 2007). In contrast to earlier approaches, the urban environment, and in particular vegetation analysis, is now – from an anthropocentric point of view – one important indicator to assess and approximate the state of urban ecosystem services. The major question will be what are interactions between the urban structure and the vegetation derived ecosystem services? (Cadenasso et al. 2006a; Pickett and Cadenasso 2008) This then allows the identification of the range and ecosystem services and the identification of those groups that benefit and those that do not. As Phoenix (Arizona, USA) and Baltimore (Maryland, USA) serve as case studies on urban ecosystem services, they address fluxes, relationships, and linking of ecology and socio-economy over time in particular (Benton-Short and Rennie-Short 2008; Cadenasso et al. 2006b).

Major challenges for urban ecosystem service analysis are access to appropriate data, a patchwork of multisource datasets, different levels of aggregation of vegetation, limited spatial coverage of data, differences in data acquisition time, a lack of updates, as well as missing volume data on vegetation. Multi-spectral remote sensing can be used to derive features of physical parameters such as vegetation coverage, multi-temporal datasets offer change detection and updates of the earth's surface. Remote-sensing-derived classification of urban vegetation has been addressed in many ways, but, up to now, has most often been limited to only few classes such as grass and trees. In-depth analysis of one vegetation class was limited by the availability of appropriate sensors and the heterogeneity of the urban surface. Analysis of ecosystem services which may be linked to a specific vegetation species have hence also been restricted. This remotely derived vegetation information however may serve as an objective, statistical measure and as an additional parameter for multi-variate analysis of ecosystem services by linking physical features of remote sensing and spatial information on socio-economics.

Conventional remote sensing analysis has used space-borne systems such as Landsat which offers high coverage (swath width of 185 km), but low spatial resolution of 30 m within the spectral range for vegetation analysis (Eurimage 2007). Other systems with very high spatial resolution (<1 m) as spaceborne systems such as Quickbird have very limited coverage (swath width of 15 km) (Eurimage 2009). New sensors such as RapidEye proceed in between and offer high spatial resolution data (6.5 m) as well as a swath width of 77 km with continuous observation coverage up to 1,500 km. Hence, the benefits of high spatial resolution remote sensing and comparability of data for area-wide vegetation analyses can be explored (Hostert et al. 2010). High temporal resolution with the additional inter-annual vegetation information of remote sensor systems such as RapidEye may provide important information for vegetation differentiation on the one hand as well as add new insights into changes within ecosystem service provision throughout the year on the other hand. For example, intra-annual dynamics of leaf unfolding or leaf fall will cause recurrent variations in physical parameters over time and will differ between vegetation types (Morin et al. 2009; Nilsson and Källander 2006; Wesolowski and Rowinski 2006). In result, ecosystem services such as retention of rainwater and air filtration will be affected. Further benefits for ecosystem services may be derived from additional height information such as shown for a vegetation classification based on spectral mixture analysis of a Quickbird image and additional LIDAR height information (Tooke et al. 2009). Fusion of multi-temporal and multi-spectral data analysis with large coverage and high spatial resolution on the one hand and height and volume data on the other hand indicates a successful approach in assessing the urban environment for ecosystem service analysis.

8.3.2 *Case Study*

In Berlin, a huge variety of environmental information is available already, such as information on vegetation in the Environmental Atlas or a LIDAR-derived 3D model of buildings (Berlin Department of Urban Development 2009). However, for sophisticated ecosystem service analysis, these datasets are missing important information on current changes; since area-wide updates are rare. Furthermore, the location and specification of vegetation is based on combinations of different methods of assessment which limits the comparability across Berlin (Berlin Department of Urban Development 2009). Furthermore, vegetation has been excluded from remote sensing based urban 3D and seasonality analyses up to now (Fig. 8.1).

For the stated challenges of urban ecosystem services, our remote-sensing approach aims to tackle the challenges of up-to-datedness, comparability, and urban vegetation volume information in the city of Berlin, Germany, (Fig. 8.1):

1. Vegetation differentiation for urban ecosystem services: it is necessary to create up-to-date information on the urban environment city-wide. In-depth analysis can then identify and compare differences within urban vegetation beyond the

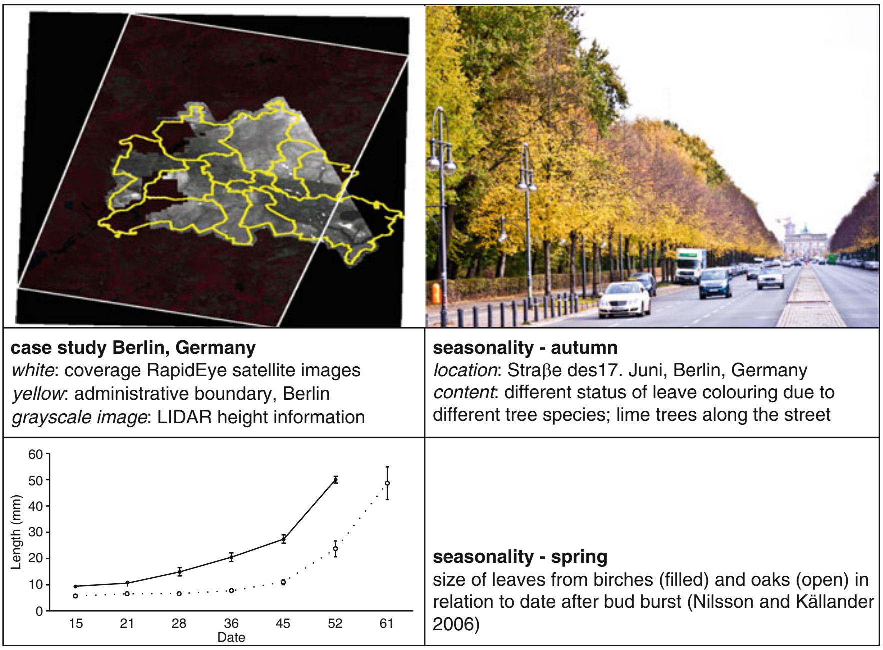

Fig. 8.1 Case study Berlin – seasonality

most frequently assessed classes of grass and trees are needed. Hypothesizing that different vegetation offers different types and/or values of ecosystem services, the results can then be used to calculate ecosystem service provision.

2. Quantification and interaction between urban ecosystem services and socio-economics: 2D outputs do not offer a realistic quantitative measure on ecosystem services, because many ecosystem functions correlate to vegetation volume and connectivity in a 3D space. Linking those environmental and socio-economic data will raise two important points of view: first, the availability of ecosystem services for different socio-economic groups, and second, the socio-economic groups' views and actions to urban ecosystem services.

8.3.2.1 Research Questions

The aim of this case study is to address these challenges by exploring large coverage, high-resolution, multi-temporal data on vegetation and height information to analyze the urban environment and extract parameters relevant for ecosystem service assessments.

Research questions concerning vegetation differentiation are:

1. How does an intra-annual, multi-temporal dataset of RapidEye images support the classification of urban trees?

   (a) Which improvements can be identified by a multi-temporal intra-annual dataset compared to a standard summertime mono-temporal multi-spectral approach?
   (b) What is the effect of further spectral information from the red edge band?
   (c) How does illumination correction by LIDAR data improve the classification of multi-temporal data featuring differences in illumination?
   (d) Which correlations exist between remotely sensed intra-annual trajectories of trees and data of phenological gardens offering high-resolution phenological timelines?
2. How does a multi-sensor approach of RapidEye images and additional LIDAR derived height information support the classification of urban trees?
3. Which urban ecosystem service gains substantial information from remote sensing derived vegetation information including height information?

The research questions concerning quantification and interaction of a specific urban ecosystem service are:

1. How does the selected urban ecosystem service vary in space and volume?
   (a) What are limits of analysis of summertime bio-phytomass derived by wintertime LIDAR and RapidEye data?
   (b) How does illumination-corrected and non-corrected classification differ in location and volume measurements of each tree species?
   (c) What are the minimum mapping unit and limits of different resolution of ancillary (census) data and tree volume data derived by remote sensing?
2. How does the specific urban ecosystem service affect humans?
3. How can findings of socioeconomic disparities of urban ecosystem services be addressed by different socio-economic groups?

8.3.2.2 Data

To answer these research questions, this study focuses on urban trees within Berlin as they are one of the major urban green sources in Berlin (Berlin Department of Urban Development 2009). A multi-temporal dataset of high-resolution RapidEye satellite images (6.5 m) from 2009 and very high resolution LIDAR (0.5 m) is used to improve classification details of urban tree species as a unique reference base (RapidEye AG 2010) (Table 8.1). Additional socio-economic information on social status is retrieved from the Senate Department of Urban Development.

RapidEye images provide high coverage, high repetition rate, high spatial resolution, and extended multi-spectral features. An intra-annual dataset of five images provides additional phenological information which can be used for in-depth vegetation analysis to benefit from seasonality of vegetation as shown in Fig. 8.2 (Schwartz 2003). Colours of Fig. 8.2 indicate differences in vegetation characteristics for the surrounding of the former Berliner Schloss (Berlin castle). The possible differentiation within the vegetation by a multi-temporal, intra-annual dataset becomes already apparent by visual interpretation (Fig. 8.2).

Table 8.1 Dataset

Multi-spectral	*System*: RapidEye, spaceborne *Geometric Resolution*: 6.5 m; 5 m resampling *Spectral Resolution (nm)*: 450–510 (blue) 520–590 (green) 630–685 (red) 690–730 (red edge) 760–850 (nir) *Swath Width*: 77 km	*Date of acquisition*: 13 April 2009 27 July 2009 16 August 2009 09 October 2009 19 October 2009 *Coverage*: City of Berlin, Germany
LIDAR	*System*: ALTM GEMINI, airborne *Geometric resolution*: Digital Surface Model, 0.5 m Digital Terrain Model, 1 m *Spectral resolution (nm)*: 1,064	*Date of acquisition*: Winter 2007/08 *Coverage*: City of Berlin, Germany

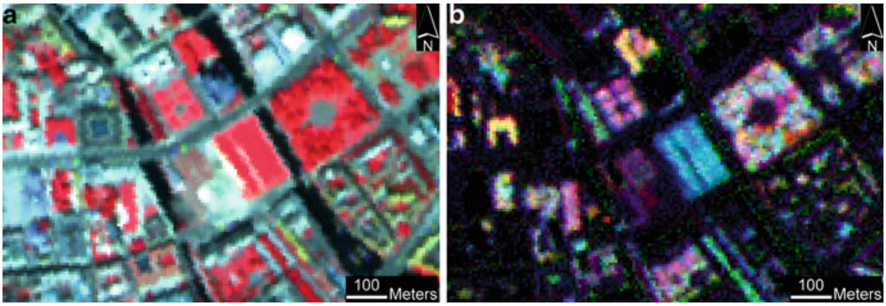

Fig. 8.2 Mono-temporal (*left*) and multi-temporal (*right*) RapidEye satellite image, Berlin.

Differences in height and volume of vegetation are derived by the digital elevation model as shown in Fig. 8.3. The centre of Fig. 8.3 depicts the building "Neue Wache" which is surrounded by chestnut trees.

8.3.2.3 Methods

As a first step, the literature review concentrates on urban remote sensing, tree physiology, volume modelling, urban ecosystem services, and spatial statistics combining social census data with parameters derived by remote sensing. Furthermore, a field survey is conducted to map reference data on urban trees in the city of Berlin. Homogeneous structured patches of the same tree species are identified and

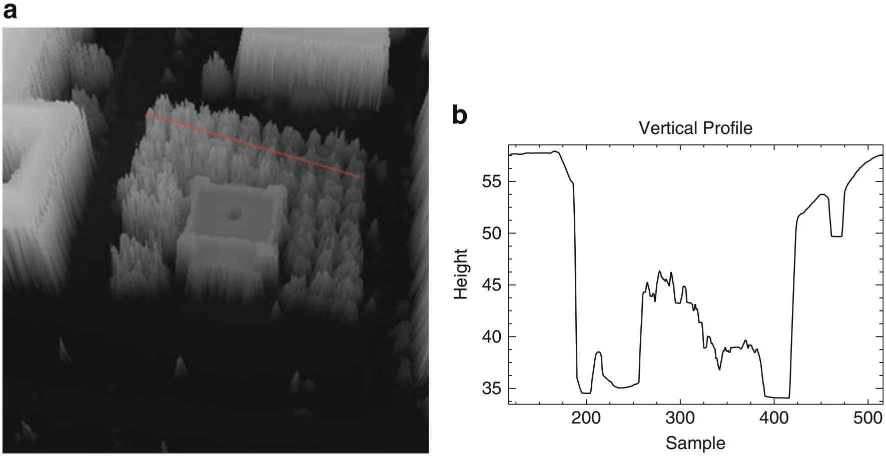

Fig. 8.3 Digital surface model (*left*) with vegetation height profile (ROI), Berlin

located. For each vegetation patch, additional attributes such as a visual assessment of the understory and the degree of mixing of different types of vegetation and impervious surface are mapped to account for their manipulation of the spectral reflectance of the vegetation.

Pre-processing of the multi-spectral and LIDAR data includes geometric and illumination corrections. A high-resolution digital surface model of 0.5-m spatial resolution is used for orthorectification of each RapidEye image. Secondly, each image is co-registered in space using airborne orthofotos of 0.1-m spatial resolution. Further, solar illumination correction is conducted by an IDL-programmed module called c-correction which is based on the slope-aspect correction of multi-spectral scanner data by Teillet (Canty 2010; Teillet et al. 1982).

For the automatic classification of trees, an iterative process is applied using support vector machines (SVMs) (Fig. 8.4) (compiled by the author Tigges). The RapidEye image from summer is used as a reference line since this is a standard period of time for remote-sensing-based classification of vegetation. Additional images of different phenological phases are then added one by one to evaluate potential improvements in the classification process. Additional information of the red edge is added as a final step to identify the effect of further spectral information on multi-spectral remote sensing. SVMs are used as classifiers for image analysis since they proved to be able to handle high data dimensionality of multi-temporal data stacks as well as to adapt to the urban environment regarding small patches of vegetation.

Volume data of vegetation is then derived by a difference model of a LIDAR digital surface model (first return) and a digital terrain model (last pulse) (Hyyppä et al. 2000; Wagner et al. 2004). Small inner crown holes as part of the DSM data are filled by convolution filters. Further accuracy assessment and correction derive true summertime bio-phytomass above ground. Remote-sensing derived

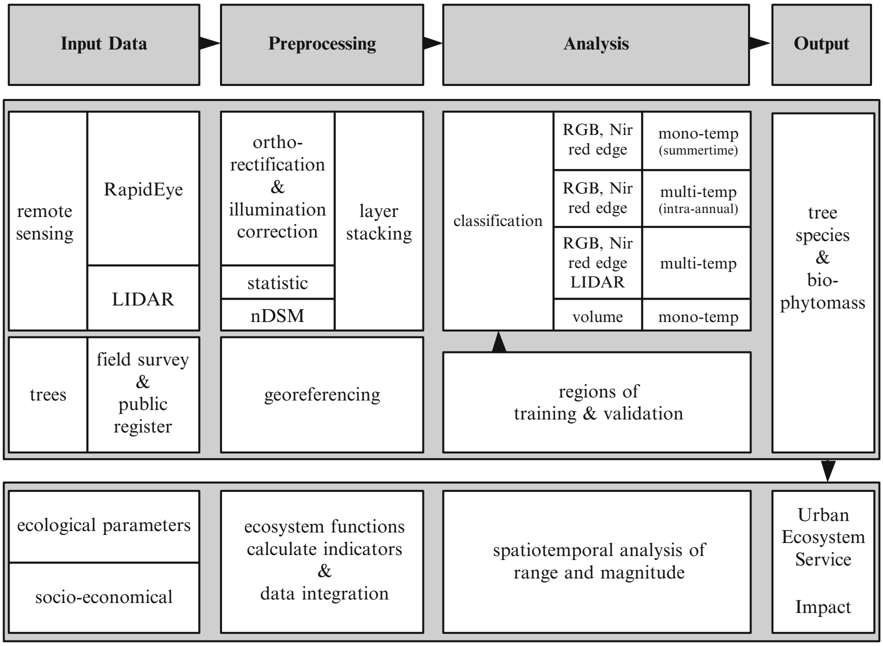

Fig. 8.4 Workflow

information on tree species and bio-phytomass is then augmented by additional ecological parameters to identify indicators for ecosystem functions of trees. In a next step this information on ecosystem functions of trees is analysed with socio-economic information to define indicators for ecosystem services. Spatial statistics and analysis are then conducted using geographical information systems to derive the spatiotemporal characteristics of range and magnitude of the urban ecosystem service.

8.3.2.4 Preliminary Results

To explore the possibilities of the above-described RapidEye data in terms of differentiation of tree species, a separability test of different tree species has been conducted. Results are illustrated by a test site located at the Kottbusser Damm in Berlin. The site is characterized by a set of honey locust, plane trees, and chestnut trees, with each set covering an area of approximately 2,500 m^2. A transformed divergence separability measure for Gaussian statistics is used as a statistical measure where values above 1.9 indicate good separability while values below 0.5 indicate insufficient separability (Richards and Jia 1999). The test is applied to two datasets. First, a mono-temporal RapidEye layer stack of July is used for testing, which includes the red, green, blue, and nir-infrared channels. This time period and selected channels stand for a traditional dataset used for vegetation analysis in remote sensing. Secondly, a multi-temporal, intra-annual RapidEye layer stack is used for separability testing (Table 8.1).

Results indicate a high variability concerning a mono-temporal dataset. The transformed divergence value of chestnut trees and honey locust is likely to be highly insufficient for classification purposes. A strong increase in value is shown (Table 8.2) in class honey locust, plane trees, as well as chestnut trees using a multi-temporal approach. These results reach the transformed divergence value of above 1.9 for good separability. The results underline the advantage of using a multi-temporal and intra-annual dataset for vegetation separability of tree on a species level.

The possibility of achieving a deeper understanding regarding the level of tree species by using a multi-temporal intra-annual dataset are also underlined by the identified exemplary trajectories of plane tree, chestnut tree, and honey locust (Fig. 8.5). All of them show similar trajectories in terms of increasing reflectance till summer (date 2 of Fig. 8.5) and decreasing till October (date 4 and 5 of Fig. 8.5). Nor do they indicate significant differences in reflectance due to differences in illumination and nor in understorey and degree of sealing. In result, spectral divergence in time is most likely due to differences in species which will be further explored to improve vegetation classification.

Table 8.2 Separability test of selected tree species

Class 1	Class 2	Transformed divergence, mono-temp	Transformed divergence, multi-temp
Gleditsia triacanthos (honey locust)	Platanus × hispanica (plane tree)	1.2	**2.0**
Platanus × hispanica (plane tree)	Aesculus hippocastanum (chestnut tree)	1.3	**2.0**
Aesculus hippocastanum (chestnut tree)	Gleditsia triacanthos (honey locust)	0.4	**2.0**

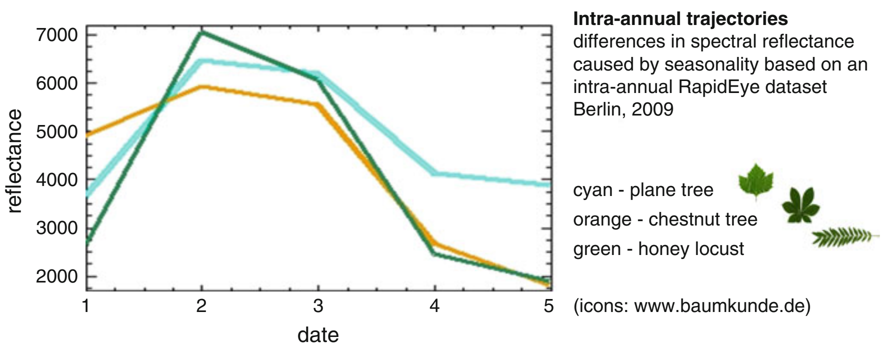

Fig. 8.5 Intra-annual changes in spectral reflectance of tree species

8.3.2.5 Benefits and Challenges

Preliminary results on the possibilities of a multi-temporal, multi-spectral, and high-spatial-resolution dataset for a differentiated classification of urban vegetation on the level of tree species seem very promising. Additional information gained from the third dimension out of the LIDAR data will most likely add a substantial component for precise information for differentiating urban vegetation. In a next step, the derived information will then be used to map ecosystem services, in particular those, which are heavily influenced by the vegetation volume, such as air pollution filtering.

Results derived by remote sensing, however, have to be discussed regarding their spatial resolution, their comparability across space, and changes in time. As vegetation parameters are derived by an intra-annual dataset of spectral information, spatial differences in phenology of the same vegetation species might affect the classification process. This was indicated in a field survey of vegetation phenology in Berlin 2006 where significant phenological differences of the same trees species were found, which were related to microclimatic characteristics of the urban heat island effect (Henniges and Chmielewski 2007; Mimet et al. 2009). Furthermore, the dataset of this case study is limited to very few stages of the phenological cycle of vegetation. Another challenge in the field of remote sensing will remain shadow and mixed pixels due to spatial resolution and differences in solar illumination. The spatial range of a specific ecosystem service will be limited to the nearby surrounding of trees, because long-distance impact will need a more complex modelling approach and information. Furthermore, long-term changes of climate as well as demographic change cannot be considered in this study. While climate change will most likely modify intra-annual dynamics such as leaf fall or leaf unfolding, the demographic change is expected to modify the urban population's perspective on ecosystem services. Only an interdisciplinary perspective will allow approaching the question of access to ecosystem services among different socio-economic groups and the transfer of the derived new insights into locally adapted decision-making.

8.3.2.6 Outlook

One reason for differences in spectral reflectance of trees is seasonality. This will produce specific trajectories of spectral reflectance. Are these intra-annual changes similar to ground-truth trajectories of phenology gardens? Positive results would be a first step to a generic approach which might be transferred to other regions and types of trees. Inter-annual data supports an improved classification up to the level of tree species. Further improvements are expected by including the above-introduced LIDAR data, which will support the differentiation of vegetation according to their height. Area-wide, comparable and up-to-date results on a species level and bio-phytomass may then be an indicator for air pollution filtering, carbon storage or pollen emission. Particularly in urban areas, this could be of high interest for epidemiological studies; for example, allergic reactions to birch pollen or secondary organic aerosol can cause respiratory symptoms. An analysis could reveal new insights on spatio-temporal patterns of urban ecosystem services for different socio-economic groups. Furthermore, the aim to reduce CO_2 emissions could be supported by a measure of urban CO_2 storage of trees since the physiology of tree species shows differences on CO_2 storage dynamics. Beside other factors such as climate change, soil condition, and irrigation, a generic classification on a species level a remote sensing approach could provide information for monitoring CO_2 storage dynamics on a large scale. Thus, Berlin and its different tree species could serve as a laboratory relevant for different ecosystem services at the human-environment interface in urban areas.

8.4 Modelling of LUC and Ecologic Impacts

8.4.1 State of the Art

LUC – as a major influence on the urban environment – has been analysed in the past by a variety of different modelling techniques, out of which we in the following will concentrate on the predominant urban models, namely system dynamics (SD), cellular automata (CA), and multi-agent systems (MASs).

SD in an urban context was firstly applied in the 1960s (Forrester 1969; Lowry 1964) with rather simple assumptions, such as housing develops in relation to the place of work, however it was pioneering work. Within SD, the system-describing components are interlinked by differential equations in the form of stocks and flows and show a nonlinear behaviour. While SD are generally not spatially explicit, their strength is the dynamic behaviour due to implemented feedbacks between the system components (Dhawan 2005; Sterman 2000). SD represents a qualified tool to reproduce population dynamics and respective decisions and behaviours. Today, system dynamics play an important role in modelling ecological parameters under inclusion of (socio)economic parameters, such as biodiversity, soil functions, or carbon cycle, which is particularly relevant in terms of ecosystem services and environmental impact assessments (Costanza and Voinov 2004; Seppelt 2003).

Spatially explicit models for urban land cover and land use change gained importance in the 1980s when computer-based processing became more accessible and affordable and increasingly remote sensing techniques were applied to derive data on the urban land cover and land use. These "newer" models of both, cellular automata and multi-agent systems, frequently use raster information to describe the spatial organisation of land use within a city or urban region.

The basic idea of cellular automata (CA) is that cells holding discrete numbers of land use states depend on neighbouring cell states (Engelen et al. 1997). All cells change their state simultaneously for each time step according to the same rules. The dynamic behaviour of CA models result from implemented transition rules in form of neighbourhood functions. In doing so, all cell states are incorporated to determine the probability for a cell transition. Contributing factors are physical conditions, proximity to transportation networks, and restrictions due to planning standards (Barredo et al. 2003). Neighbourhood effects regarding different land uses are integrated as distance-decay functions defining attraction or repulsion (White and Engelen 1993). The neighbourhood for each cell is equal and predefined. Since Tobler (1979) proposed the use of CA as a tool for geography, CA has been widely used and continuously improved towards user-friendly urban simulation tools like the software package Metronamica (Riks 2007). In fact, CA models are predominant for LUC simulations. They are very suitable to simulate the spatial allocation of LUC due to the possible integration of diverse spatial factors affecting LUC, such as political constraints, economical conditions, and physical characteristics. However, CA models are mostly lacking the representation of dynamic behaviour based on the causal relation between drivers and LUC. Frequently, they rely on quantification of change in land use classes (the driver for CA) by simple methods such as trend exploration or regression-based trends (Ti-yan et al. 2007) while individual or group-specific behaviour of city dwellers is still not detailed enough considered in CA.

MASs explicitly address the agents who act and organize themselves within a spatially explicit urban environment. Originating from artificial intelligence (AI) (Bousquet and Le Page 2004) agents in MAS are autonomous and defined as individuals, interest groups, or organizational units (such as households, landowners, or farms). Each agent or agent group has specific characteristics or preferences to solve the predefined problem of the MAS (Loibl and Toetzer 2003). Decision-making by agents, such as the choice of a land use cell, is based on interactions with other agents and their environment. In this way, agents are able to enlarge their knowledge of the environment by communication and learning. The environment is often described by a grid, in which cells define the spatial conditions (Batty 2007). MASs are powerful tools to address human decision-making in a spatial context, especially in small-scale considerations of only few land use classes. MASs address, for example, residential relocations of households affecting residential land (Haase et al. 2010; Loibl et al. 2007) or shifts of arable land due to different behaviours of farmers (Valbuena et al. 2008). MASs quickly become too complex for integrated LUC modelling with a detailed land use classification

We conclude that different model approaches imply different advantages and disadvantages for LUC modelling depending on the research question. Combining the approaches seems promising for improving the reproduction of real LUC processes, especially in terms of an integration of demographic, social, economic, political, and ecological driving forces. A few recent model approaches benefit from combining different techniques (Batty 2007; Fang et al. 2005; He et al. 2008). However, studies on ecosystem services and ecological impacts due to LUC are snap shots in time rather than a dynamic time series study. Existing models interlinking dynamic LUC and ecosystem services or ecosystem functionalities are leading the way for an integrative citywide perspective on urban ecology (Rutledge et al. 2008; Van Delden et al. 2007).

Numerous inductive investigations on urban ecology on the small scale (as shown in this book) prove the effects on the environment due to structural differences in the same land use. Especially, in residential areas, ecological effects vary greatly depending on the structure and density of land use. Consequently, a more detailed differentiation of urban land use classes is needed. Further, the development of European cities proves the imperative of a wider perspective of LUC. Shrinking cities and the comeback of urban nature have to be considered and unilateral growth models have to be enhanced to adapt LUC models to the current needs (Buzar et al. 2007; Kabisch 2005; Kasanko et al. 2006).

8.4.2 Case Study

8.4.2.1 Research Questions

The aim of this project is to tackle the above-mentioned challenges by applying a combined model approach based on system dynamics, cellular automata, and an ecological impact model. We intend to uncover the functional chain of demographic change, LUC, and consequential ecological impacts. Furthermore, we are interested in how those effects might influence LUC decisions again. By improving the causal relation of LUC through integrating a residential choice algorithm, we expect more adaptable and dynamic model behaviour. Due to the use of finer residential land use classes, a housing market perspective is enabled, a deeper insight into LUC effects is offered, and finally, land use patterns are reproduced more accurately. Furthermore, we aim to integrate a mechanism enabling growth and shrinkage for our model in Berlin. Appropriate model scenarios help to identify possible future paths for Berlin. These objectives lead to the following research questions:

1. How does the model quality improve by combining system dynamics and cellular automata model approaches and integrating sophisticated population dynamics?
   (a) Which are the main drivers of LUC and how sensitive are they?
   (b) How do household shifts due to demographic change influence urban LUC in terms of growth and shrinkage?
2. Which impacts on selected ecosystem services due to LUC are identifiable and how might they affect LUC and vice versa?
   (a) How do food providing land uses develop and where do changes take place?
   (b) Are changes in green space provision affecting land use decisions?
   (c) How is the sealing rate going to develop?
3. How does LUC express for Berlin's metropolitan area under consideration of growth, shrinkage, and baseline scenarios for the year 2022?
   (a) What development of urban-suburban relations can be predicted under consideration of different scenarios?

(b) Are the increase in detached and semi-detached housing in the outskirts and the development of inner-city brownfields proceeding? If so, in which intensity?
(c) Which developments are expectable on the former airport sites Tempelhof and Tegel and how might the surrounding of the new international airport in Schönefeld be affected?
(d) How do recent planning constraints address identified LUC processes?

8.4.2.2 Study Area

In order to improve the understanding of urban-suburban interrelations, the study area is defined by the metropolitan area of Berlin. Thereby, the administrative border of Berlin is exceeded and parts of the federal state of Brandenburg are involved (Fig. 8.6). In total, the case study involves an area of almost 5,370 km^2 and includes almost 4.3 million inhabitants (SOBB 1991–2008). Berlin as one of the biggest European agglomerations represents a city where urban development trends of socialist and western cities occur and contrasting processes of simultaneous shrinking and growth are revealed.

LUC since the reunification of Germany is characterized by an increasing demand to be “living in the green”. Numerous developments of detached and semi-detached houses have displaced former arable land, accompanied by an outward-directed migration of family households towards Berlin’s hinterland. Against this, the population numbers of Berlin declined rapidly and vacancy rates of inner-city block structures and prefabricated multi-storey houses (from socialist time) increased. The collapse of the GDR economy was accompanied by the abandonment of industrial sites and the increase in inner-city brownfields. New commercial areas, however, emerged on valuable green and arable land. In the last decade, Berlin has transformed into a smart growing city not least due to its favourable living conditions (a relaxed housing market, low living costs) and its cultural meaning. Young people especially, are attracted across national borders and form a new reurbanisation trend, which is supported by the positive net migration.

Land-use patterns as depicted in Fig. 8.6 show a dominance of forest and arable land in the study area in 2007. Only 25% describe built-up areas, of which 32% depict detached and semi-detached houses. All listed land use classes are integrated in the presented LUC model. The city of Berlin is used for model calibration, whereas the total study area is used to assign the model quality. Different land use maps for Berlin and the metropolitan area (ranging from 1992 to 2008) are derived from satellite images (own interpretation of IRS_P6 image) and aerial photographs (Berlin Department of Urban Development 2009; Brandenburg State Office for Environment 2010). Besides, census data, economic parameters, and spatial planning information is used (Berlin Department of Economy Technology and Women 2010; Regional Planning Department Berlin Brandenburg 2010; Statistical Office Berlin Brandenburg 2010).

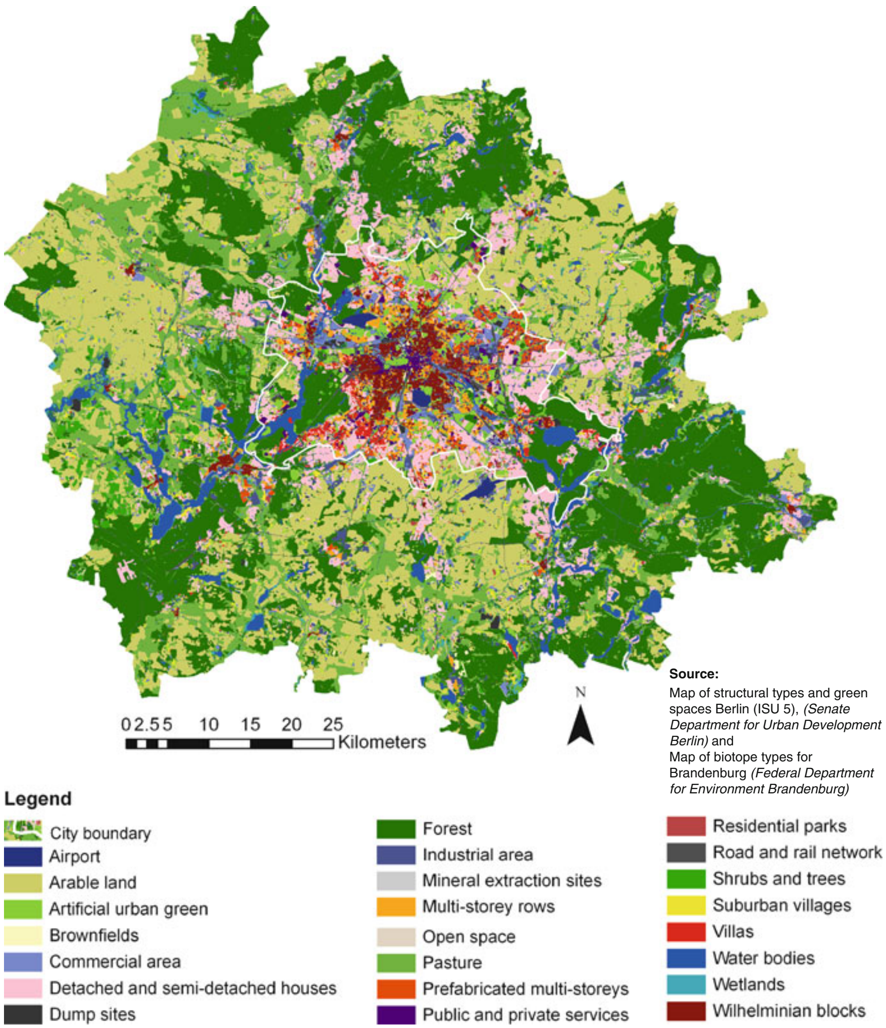

Fig. 8.6 Land use map of the study area in 2007

8.4.2.3 Methods

Figure 8.7 gives an overview of the introduced model structure, its components, their relations and content, plus the model inputs. By changing the parameters of the input data, different scenarios are implemented, such as population growth or shrinkage. The quantitative LUC is calculated using system dynamics and the spatial allocation then is determined by cellular automata. Spatial effects on the urban environment are finally identified in the ecological impact model. Feedback loops are implemented to additionally measure the effects on LUC as a consequence of its ecological impacts (c.f. broken lines).

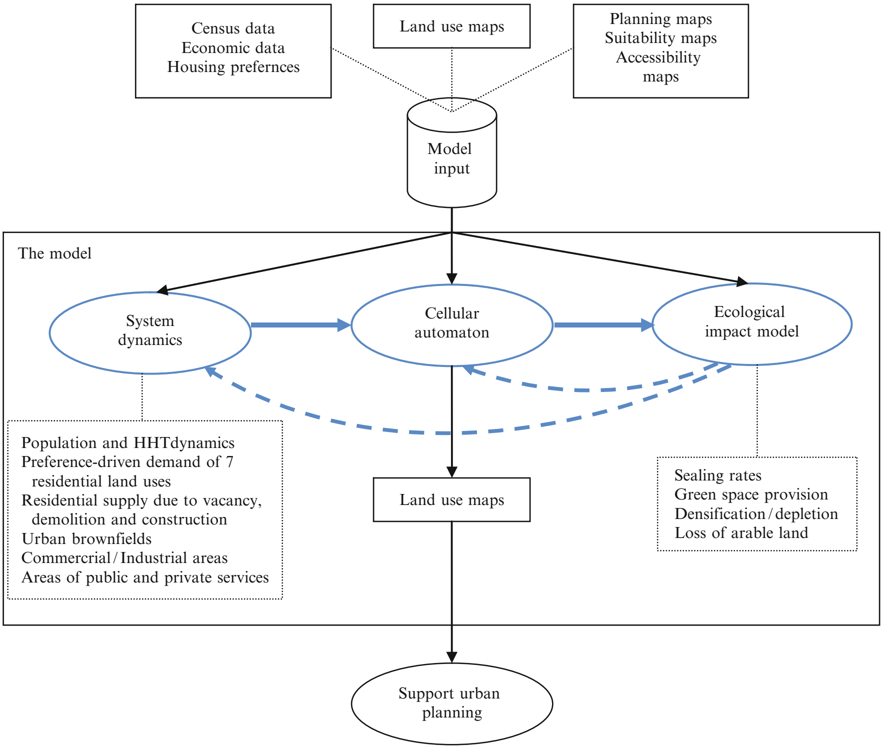

Fig. 8.7 Model approach

System Dynamics

We use system dynamics to calculate the demand for living space in each residential use including population dynamics with regard to the second demographic transition (Kaa 2004). Therefore, population shifts of eight age cohorts are determined by the demographic variables fertility, mortality, and migration. Using a dynamic transition matrix, the population of each cohort is distributed over seven household types. Respective housing preferences are used to determine the residential choice with reference to varying residential uses in terms of structure and form. The demand for living space in each residential use is calculated by the mean living space per capita and household type and the number of housing demanders. For the calculation of living space supply, we integrated the construction rate, vacancy rate, and demolition rate as a function of demand. The given site conditions for each residential use depend on demand and supply shifts. These affect residential choice, which starts a closed feedback loop. As well as using seven residential use types in the model approach; commercial area, industrial area, and public and private services are derived as a function of population and the economic variables GDP and employees by economic sectors. Further, we calculate the shifts of (urban) brownfields within system dynamics.

Cellular Automaton

We use CA to compute the spatial allocation of LUC with respect to neighbourhood effects between land use types, which are formalized in transition rules. Planning decisions, local suitability, and the availability of infrastructure are integrated in form of raster maps using a uniform grid as used for the initial land use map. All maps were prepared in GIS. We implemented a cell size of $50 \times 50\ m^2$ for the challenging study area size to capture local dynamics in detail. The simulated changes of the SD model for 11 land use classes constitute the input for the CA. Those 11 active classes affect LUC of 7 passive classes, representing the potential sites for urban growth, which are (1) artificial urban green, (2) forest, (3) shrubs and trees, (4) pasture, (5) arable land, and (6) open space. The remaining four classes are constant uses, such as water bodies. The regional development plan giving back the protected green areas and the suggested development axes for built-up areas as well as zoning plans protecting inner-city parks are integrated. For the spatial characterization of accessibility, we integrated the road network of federal streets and freeways, the network of regional and city trains, and all local rail stations.

Ecological Impact Model

This part of the model describes the spatial analysis of impacts on the urban environment due to LUC. The simulated land use maps of the CA are imported into GIS and evaluated with respect to the scenario implications. At this stage the analysis focuses on quantitative changes and spatial dynamics in terms of the degree of sealing, the green space provision for city dwellers within the neighbourhoods, the loss of arable land, and the developments of urban densification versus depletion. Those indicators are further used to identify changes regarding the provision of ecosystem services, such as food provision, recreation, and climate regulation. The output of the model contains risk maps detecting local impacts and losses of services. As used in preventive planning, we will incorporate those maps in the preceding model components (SD and CA) to include the feedback and analyze resulting effects on LUC.

8.4.2.4 Selected Results and Discussion

Several simulation runs provided a better model quality regarding land use patterns due to the underlying SD implications which is described by statistical accuracy measures. Effects of demographic change on LUC are measurable, especially the change in the household composition with decreasing family households versus increasing single households; this expresses obvious demand shifts in certain residential uses. Residential choice is sensitive to changed demand-supply relations, affecting the side conditions of the residential uses, such as living costs and green space provision (Lauf et al. in press). Due to the detailed residential land use classification, the associated inclusion of construction, vacancy and demolition rates and the integration of the class urban brownfields, shrinkage processes in Berlin are reproducible, as seen in the housing stock of prefabricated multi-storey houses from socialist times (Fig. 8.8 and Table 8.3).

The following results refer to a simulation run from 1992 to 2022 under baseline assumptions: a low population growth is determined especially by immigration of younger age cohorts. The increasing number of single person households leads to a growing demand for accommodation in inner-city (Wilhelminian) block structures. Despite a decline of family households, the space consumption of detached and semi-detached houses increases. The vacancy in prefabricated multi-storey houses increases at 7%, whereas the vacancy in Wilhelminian blocks continuously decreases.

A closer look at Fig. 8.8 reveals five major significant trends:

1. Inner-city consolidation
2. Spreading of detached houses
3. Massive changes caused by airport developments
4. Renaturation in prefabricated multi-storey neighbourhoods and
5. Increase in commercial areas and public and private services.

Table 8.3 gives a detailed overview of the land use development until 2022 and shows which land use transitions occurred in the model run. Focusing on the green and open land use, a loss of over 6,400 ha is shown. Of these, almost 53% is arable land; 12%, pasture; 2%, shrubs and trees; 13%, forest; and 20%, open space. The number and area of brownfields, however, increase. This is due to the massive changes in the surrounding area of the airport Tempelhof, with the consequence of a tremendous amount of released land. This is in the first instance, defined as brownfields. Still, this fact should be kept in mind when valuable soils are transformed to built-up areas.

8.4.2.5 Outlook

Future work will focus on scenario simulation and the assessment of land use changes on the urban environment in particular on urban ecosystem services. With extreme scenarios, model consistency will be tested. Implications defining a growth and shrinkage scenario will be realized under integration of different planning constraints. Furthermore, land use effects on before-described ecosystem services will be analyzed and evaluated within risk maps. These maps will then be reintegrated in the SD and CA model to obtain a full response model by which the likely shift of land use decisions as a consequence of its own impacts on the environment can be determined. Finally, the results will be discussed with local authorities to integrate the findings into current decision-making processes.

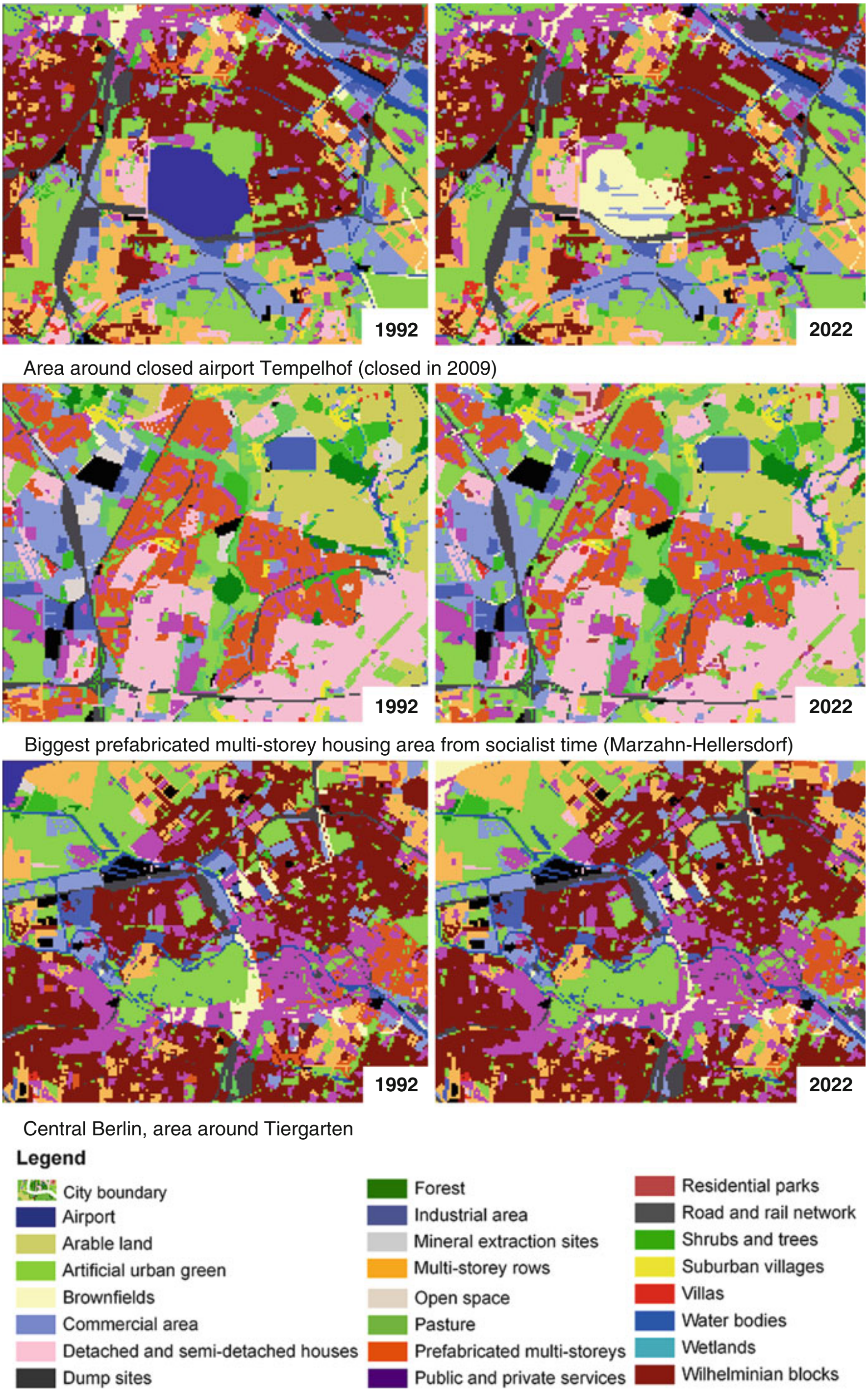

Fig. 8.8 Land use change for selected areas of Berlin's metropolitan area in 1992 (observed) and 2022 (simulated) for a baseline scenario

Table 8.3 Cross table of cell transitions for selected land use classes for a simulation run of 30 years (1992–2022) under baseline assumptions

Map 1992/ Map 2022	Artificial urban green	Brown fields	Multi-storey prefab	Post-war rows	Pre-war blocks	Villas	Detached houses	Residential park	Services	Commercial area	Cell count LU map 1992
Arable land	354	244		52			13,183	5,401	178	2,030	527,543
Pasture	96	352		77	349	347		35	134	1191	293,690
Shrubs and trees	15	67		13	98	26	1	2	6	177	34,205
Forest	277	319		86	6	47	2	137	237	1625	684,934
Open space	5,182	29		1	18	23	9	2	37	239	5,565
Artificial urban green	81,580	3			12		943	18			88,959
Brownfields	26	1,181		68	72	20		312	680	765	3,208
Multi-storey prefab	1,241	542	12,005	27	460		1	581	18	23	14,951
Post-war rows	251			29,234			1	1	4		29,611
Pre-war blocks	500	34		32	28,422		50	75	26	117	29,375
Villas	168	18				17,746				9	18,001
Detached houses	33						153,585			1	153,660
Residential park											0
Services	291	194		5	67		85	45	20,430	260	21,956
Commercial area	3	63			38				12	47,126	47,499
Industrial area	30	86		52	7	21	5	312	34	349	26,710
Suburban village											21,747
Airport	125	2,637		21	31	2	75	15	255	272	5,196
Cell count LU map 2022	90,172	5,772	12,005	29,668	29,580	18,232	167,940	6,936	22,051	54,189	3,868,800

8.5 Conclusions

Starting with the high relevance of the environment, and in particular, ecosystem services in urban areas (McGranahan and Satterthwaite 2003); (Alberti 2005; Cadenasso et al. 2006a; Cadenasso et al. 2007; Grimm et al. 2000; Pickett et al. 2008), we have pointed out the need for augmenting already existing information on today's ecosystem service provision and for modelling urban land use processes to assess likely future impacts on ecosystem services.

We have presented two studies that investigate the potential of sophisticated and up-to-date technologies in remote sensing and spatial modelling. The overall goal of these two studies is an improved understanding of the provision of urban ecosystem services and the underlying processes of land use change. Our studies are focused on the city of Berlin as an example for a densely populated city; however, we believe that the investigated techniques and methodical approaches are to a far degree transferable to similar urban systems.

Initial insights of these studies reveal the following findings: (1) High-temporal and spatial resolution remote sensing data combined with height information can add an additional perspective on urban vegetation for further analysis of ecosystem service provision; (2) Human choices on urban land use heavily impact the provision of urban ecosystem services; and most importantly, (3) Sophisticated and up-to-date technology in the two fields of remote sensing and spatial modelling may offer a large benefit for the analysis of the urban human-environment system when they are integrated.

Thus, we want to conclude that the integration of environmental and socio-economic data, acquired by different methods including remote sensing, is already a major field of research in urban ecology and particular in urban ecosystem service analysis (Pickett et al. 2008). In the future, this will most likely or rather hopefully continue to further develop into the integration of not only data but also methods and concepts to address today's challenges in the urban environment, such as assessing and analysing urban ecosystem service provision driven by land use changes.

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