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Modeling the Spatial Dynamics of Regional Land Use: The CLUE-S Model

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ABSTRACT / Land-use change models are important tools for integrated environmental management. Through scenario analysis they can help to identify near-future critical locations in the face of environmental change. A dynamic, spatially explicit, land-use change model is presented for the regional scale: CLUE-S. The model is specifically developed for the analysis of land use in small regions (e.g., a watershed or province) at a fine spatial resolution. The model structure is based on systems theory to allow the integrated analysis of land-use change in relation to socio-economic and biophysical driving factors. The model explicitly addresses the hierarchical organization of land use systems, spatial connectivity between locations and stability. Stability is incorporated by a set of variables that define the relative elasticity of the actual land-use type to conversion. The user can specify these settings based on expert knowledge or survey data. Two applications of the model in the Philippines and Malaysia are used to illustrate the functioning of the model and its validation.

Land-use change is central to environmental management through its influence on biodiversity, water and radiation budgets, trace gas emissions, carbon cycling, and livelihoods (Lambin and others 2000a, Turner 1994). Land-use planning attempts to influence the land-use change dynamics so that land-use configurations are achieved that balance environmental and stakeholder needs.

Environmental management and land-use planning therefore need information about the dynamics of land use. Models can help to understand these dynamics and project near future land-use trajectories in order to target management decisions (Schoonenboom 1995). Environmental management, and land-use planning specifically, take place at different spatial and organisational levels, often corresponding with either eco-regional or administrative units, such as the national or provincial level. The information needed and the management decisions made are different for the different levels of analysis. At the national level it is often sufficient to identify regions that qualify as "hot-spots" of land-use change, i.e., areas that are likely to be faced with rapid land use conversions. Once these hot-spots are identified a more detailed land use change analysis is often needed at the regional level.

At the regional level, the effects of land-use change on natural resources can be determined by a combination of land use change analysis and specific models to assess the impact on natural resources. Examples of this type of model are water balance models (Schulze 2000), nutrient balance models (Priess and Koning 2001, Smaling and Fresco 1993) and erosion/sedimentation models (Schoorl and Veldkamp 2000). Most of-

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ten these models need high-resolution data for land use to appropriately simulate the processes involved.

Land-Use Change Models

The rising awareness of the need for spatially-explicit land-use models within the Land-Use and Land-Cover Change research community (LUCC; Lambin and others 2000a, Turner and others 1995) has led to the development of a wide range of land-use change models. Whereas most models were originally developed for deforestation (reviews by Kaimowitz and Angelsen 1998, Lambin 1997) more recent efforts also address other land use conversions such as urbanization and agricultural intensification (Brown and others 2000, Engelen and others 1995, Hilferink and Rietveld 1999, Lambin and others 2000b). Spatially explicit approaches are often based on cellular automata that simulate land use change as a function of land use in the neighborhood and a set of user-specified relations with driving factors (Balzter and others 1998, Candau 2000, Engelen and others 1995, Wu 1998). The specification of the neighborhood functions and transition rules is done either based on the user's expert knowledge, which can be a problematic process due to a lack of quantitative understanding, or on empirical relations between land use and driving factors (e.g., Pijanowski and others 2000, Pontius and others 2000). A probability surface, based on either logistic regression or neural network analysis of historic conversions, is made for future conversions. Projections of change are based on applying a cut-off value to this probability surface. Although appropriate for short-term projections, if the trend in land-use change continues, this methodology is incapable of projecting changes when the demands for different land-use types change, leading to a discontinuation of the trends. Moreover, these models are usually capable of simulating the conversion of one land-use type only (e.g. deforestation) because they do not address competition between land-use types explicitly.

The CLUE Modeling Framework

The Conversion of Land Use and its Effects (CLUE) modeling framework (Veldkamp and Fresco 1996, Verburg and others 1999a) was developed to simulate land-use change using empirically quantified relations between land use and its driving factors in combination with dynamic modeling. In contrast to most empirical models, it is possible to simulate multiple land-use types simultaneously through the dynamic simulation of competition between land-use types.

This model was developed for the national and continental level, applications are available for Central America (Kok and Winograd 2001), Ecuador (de Koning and others 1999), China (Verburg and others 2000), and Java, Indonesia (Verburg and others 1999b). For study areas with such a large extent the spatial resolution of analysis was coarse (pixel size varying between 7 × 7 and 32 × 32 km). This is a consequence of the impossibility to acquire data for land use and all driving factors at finer spatial resolutions. A coarse spatial resolution requires a different data representation than the common representation for data with a fine spatial resolution. In fine resolution grid-based approaches land use is defined by the most dominant land-use type within the pixel. However, such a data representation would lead to large biases in the land-use distribution as some class proportions will diminish and other will increase with scale depending on the spatial and probability distributions of the cover types (Moody and Woodcock 1994). In the applications of the CLUE model at the national or continental level we have, therefore, represented land use by designating the relative cover of each land-use type in each pixel, e.g. a pixel can contain 30% cultivated land, 40% grassland, and 30% forest. This data representation is directly related to the information contained in the census data that underlie the applications. For each administrative unit, census data denote the number of hectares devoted to different land-use types.

When studying areas with a relatively small spatial extent, we often base our land-use data on land-use maps or remote sensing images that denote land-use types respectively by homogeneous polygons or classified pixels. When converted to a raster format this results in only one, dominant, land-use type occupying one unit of analysis. The validity of this data representation depends on the patchiness of the landscape and the pixel size chosen. Most sub-national land use studies use this representation of land use with pixel sizes varying between a few meters up to about 1 × 1 km. The two different data representations are shown in Figure 1.

Because of the differences in data representation and other features that are typical for regional applications, the CLUE model can not directly be applied at the regional scale. This paper describes the modified modeling approach for regional applications of the model, now called CLUE-S (the Conversion of Land Use and its Effects at Small regional extent). The next section describes the theories underlying the development of the model after which it is described how these concepts are incorporated in the simulation model. The functioning of the model is illustrated for two case-studies and is followed by a general discussion.

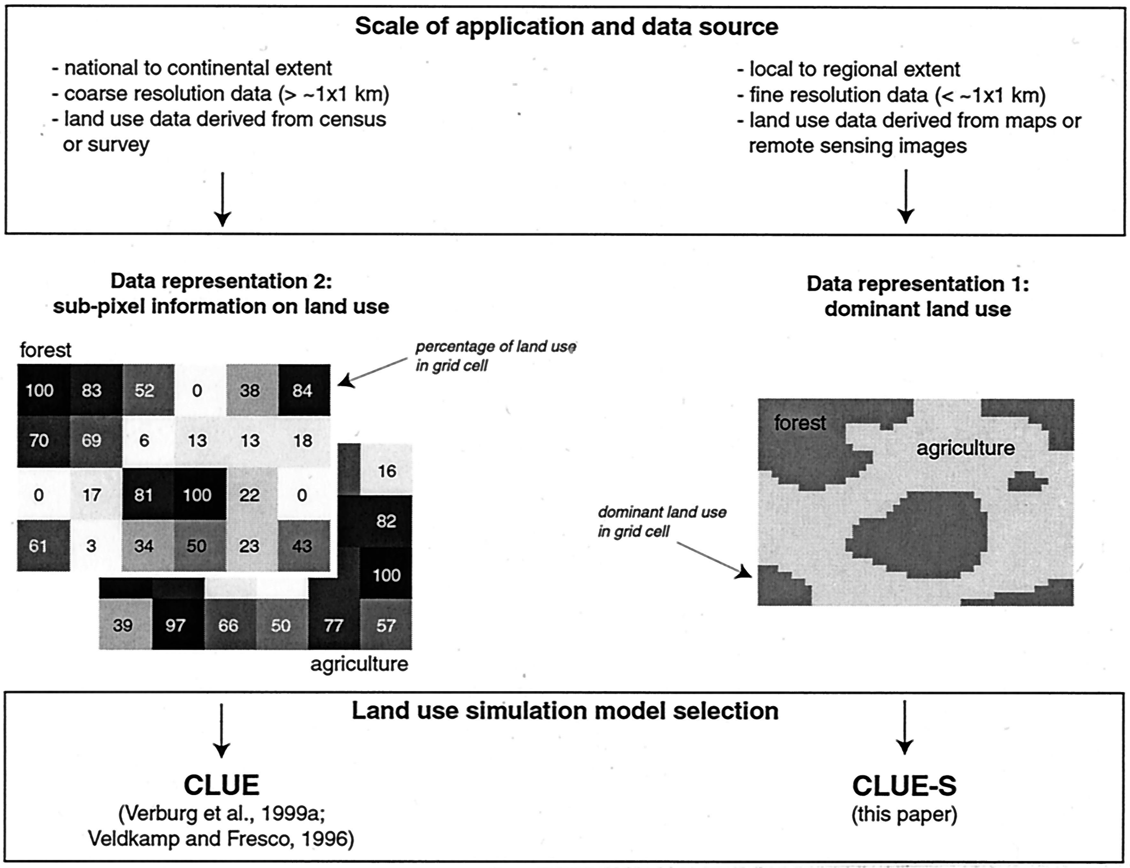

Figure 1. Data representation and land-use model used for respectively case-studies with a national/continental extent and local/regional extent.

Characteristics of Land-Use Systems

This section lists the main concepts and theories that are prevalent for describing the dynamics of land-use change being relevant for the development of land-use change models.

Land-use systems are complex and operate at the interface of multiple social and ecological systems. The similarities between land use, social, and ecological systems allow us to use concepts that have proven to be useful for studying and simulating ecological systems in our analysis of land-use change (Loucks 1977, Adger 1999, Holling and Sanderson 1996). Among those concepts, connectivity is important. The concept of connectivity acknowledges that locations that are at a certain distance are related to each other (Green 1994). Connectivity can be a direct result of biophysical processes, e.g., sedimentation in the lowlands is a direct result of erosion in the uplands, but more often it is due to the movement of species or humans through the landscape. Land degradation at a certain location will trigger farmers to clear land at a new location. Thus, changes in land use at this new location are related to the land-use conditions in the other location. In other instances more complex relations exist that are rooted in the social and economic organization of the system. The hierarchical structure of social organization causes some lower level processes to be constrained by higher level dynamics, e.g., the establishments of a new fruit-tree plantation in an area near to the market might influence prices in such a way that it is no longer profitable for farmers to produce fruits in more distant areas. For studying this situation another concept from ecology, hierarchy theory, is useful (Allen and Starr 1982, O'Neill and others 1986). This theory states that higher level processes constrain lower level processes whereas the higher level processes might emerge from lower level dynamics. This makes the analysis of the land-use system at different levels of analysis necessary.

Connectivity implies that we cannot understand land use at a certain location by solely studying the site characteristics of that location. The situation at neighboring or even more distant locations can be as important as the conditions at the location itself.

Land-use and land-cover change are the result of many interacting processes. Each of these processes operates over a range of scales in space and time. These processes are driven by one or more of these variables that influence the actions of the agents of land-use and cover change involved. These variables are often referred to as underlying driving forces which underpin the proximate causes of land-use change, such as wood extraction or agricultural expansion (Geist and Lambin 2001). These driving factors include demographic factors (e.g., population pressure), economic factors (e.g., economic growth), technological factors, policy and institutional factors, cultural factors, and biophysical factors (Turner and others 1995, Kaimowitz and Angelsen 1998). These factors influence land-use change in different ways. Some of these factors directly influence the rate and quantity of land-use change, e.g. the amount of forest cleared by new incoming migrants. Other factors determine the location of land-use change, e.g. the suitability of the soils for agricultural land use. Especially the biophysical factors do pose constraints to land-use change at certain locations, leading to spatially differentiated pathways of change. It is not possible to classify all factors in groups that either influence the rate or location of land-use change. In some cases the same driving factor has both an influence on the quantity of land-use change as well as on the location of land-use change. Population pressure is often an important driving factor of land-use conversions (Rudel and Roper 1997). At the same time it is the relative population pressure that determines which land-use changes are taking place at a certain location. Intensively cultivated arable lands are commonly situated at a limited distance from the villages while more extensively managed grasslands are often found at a larger distance from population concentrations, a relation that can be explained by labor intensity, transport costs, and the quality of the products (Von Thünen 1966). The determination of the driving factors of land use changes is often problematic and an issue of discussion (Lambin and others 2001). There is no unifying theory that includes all processes relevant to land-use change. Reviews of case studies show that it is not possible to simply relate land-use change to population growth, poverty, and infrastructure. Rather, the interplay of several proximate as well as underlying factors drive land-use change in a synergetic way with large variations caused by location specific conditions (Lambin and others 2001, Geist and Lambin 2001). In regional modeling we often need to rely on poor data describing this complexity. Instead of using the underlying driving factors it is needed to use proximate variables that can represent the underlying driving factors. Especially for factors that are important in determining the location of change it is essential that the factor can be mapped quantitatively, representing its spatial variation. The causality between the underlying driving factors and the (proximate) factors used in modeling (in this paper, also referred to as "driving factors") should be certified.

Other system properties that are relevant for land-use systems are stability and resilience, concepts often used to describe ecological systems and, to some extent, social systems (Adger 2000, Holling 1973, Levin and others 1998). Resilience refers to the buffer capacity or the ability of the ecosystem or society to absorb perturbations, or the magnitude of disturbance that can be absorbed before a system changes its structure by changing the variables and processes that control behavior (Holling 1992). Stability and resilience are concepts that can also be used to describe the dynamics of land-use systems, that inherit these characteristics from both ecological and social systems. Due to stability and resilience of the system disturbances and external influences will, mostly, not directly change the landscape structure (Conway 1985). After a natural disaster lands might be abandoned and the population might temporally migrate. However, people will in most cases return after some time and continue land-use management practices as before, recovering the land-use structure (Kok and others 2002). Stability in the land-use structure is also a result of the social, economic, and institutional structure. Instead of a direct change in the land-use structure upon a fall in prices of a certain product, farmers will wait a few years, depending on the investments made, before they change their cropping system.

These characteristics of land-use systems provide a number requirements for the modelling of land-use change that have been used in the development of the CLUE-S model, including:

- Models should not analyze land use at a single scale, but rather include multiple, interconnected spatial scales because of the hierarchical organization of land-use systems.
- Special attention should be given to the driving factors of land-use change, distinguishing drivers that determine the quantity of change from drivers of the location of change.
- Sudden changes in driving factors should not directly change the structure of the land-use system as a consequence of the resilience and stability of the land-use system.

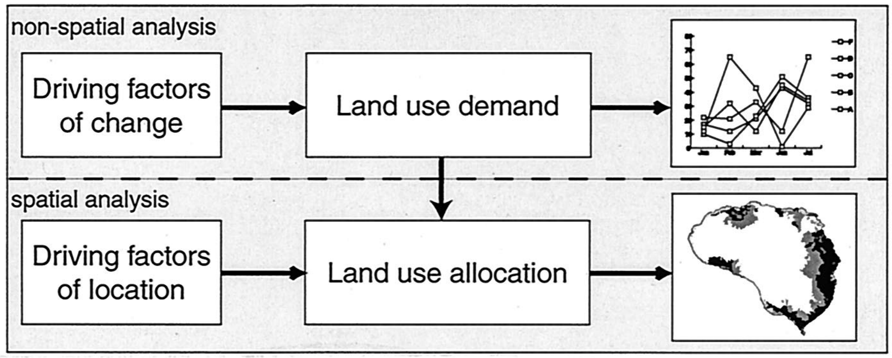

Figure 2. Overview of the modeling procedure.

- The model structure should allow spatial interactions between locations and feedbacks from higher levels of organization.

Model Description

Model Structure

The model is sub-divided into two distinct modules, namely a non-spatial demand module and a spatially explicit allocation procedure (Figure 2). The non-spatial module calculates the area change for all land-use types at the aggregate level. Within the second part of the model these demands are translated into land-use changes at different locations within the study region using a raster-based system.

For the land-use demand module, different alternative model specifications are possible, ranging from simple trend extrapolations to complex economic models. The choice for a specific model is very much dependent on the nature of the most important land-use conversions taking place within the study area and the scenarios that need to be considered. Therefore, the demand calculations will differ between applications and scenarios and need to be decided by the user for the specific situation. The results from the demand module need to specify, on a yearly basis, the area covered by the different land-use types, which is a direct input for the allocation module. The rest of this paper focuses on the procedure to allocate these demands to land-use conversions at specific locations within the study area.

The allocation is based upon a combination of empirical, spatial analysis, and dynamic modelling. Figure 3 gives an overview of the procedure. The empirical analysis unravels the relations between the spatial distribution of land use and a series of factors that are drivers and constraints of land use. The results of this empirical analysis are used within the model when simulating the competition between land-use types for a specific location. In addition, a set of decision rules is specified by the user to restrict the conversions that can take place based on the actual land-use pattern. The different components of the procedure are now discussed in more detail.

Spatial Analysis

The pattern of land use, as it can be observed from an airplane window or through remotely sensed images, reveals the spatial organization of land use in relation to the underlying biophysical and socio-eco-

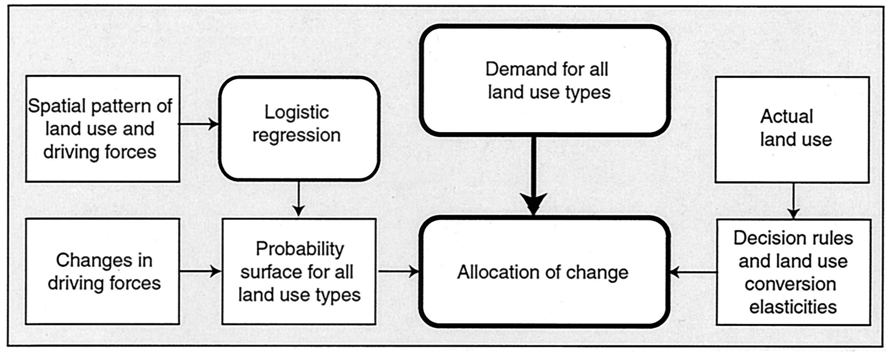

Figure 3. Schematic representation of the procedure to allocate changes in land use to a raster based map.

nomic conditions. These observations can be formalized by overlaying this land-use pattern with maps depicting the variability in biophysical and socioeconomic conditions. Geographical Information Systems (GIS) are used to process all spatial data and convert these into a regular grid. Apart from land use, data are gathered that represent the assumed driving forces of land use in the study area. The list of assumed driving forces is based on prevalent theories on driving factors of land-use change (Lambin and others 2001, Kaimowitz and Angelsen 1998, Turner and others 1993) and knowledge of the conditions in the study area. Data can originate from remote sensing (e.g., land use), secondary statistics (e.g., population distribution), maps (e.g., soil), and other sources. To allow a straightforward analysis, the data are converted into a grid based system with a cell size that depends on the resolution of the available data. This often involves the aggregation of one or more layers of thematic data, e.g. it does not make sense to use a 30-m resolution if that is available for land-use data only, while the digital elevation model has a resolution of 500 m. Therefore, all data are aggregated to the same resolution that best represents the quality and resolution of the data.

The relations between land use and its driving factors are thereafter evaluated using stepwise logistic regression. Logistic regression is an often used methodology in land-use change research (Geoghegan and others 2001, Serneels and Lambin 2001). In this study we use logistic regression to indicate the probability of a certain grid cell to be devoted to a land-use type given a set of driving factors following:

$$Log\left(\frac{P_i}{1 - P_i}\right) = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} \ldots\ldots + \beta_n X_{n,i}$$

where P_i is the probability of a grid cell for the occurrence of the considered land-use type and the X's are the driving factors. The stepwise procedure is used to help us select the relevant driving factors from a larger set of factors that are assumed to influence the land-use pattern. Variables that have no significant contribution to the explanation of the land-use pattern are excluded from the final regression equation.

Where in ordinal least squares regression the R^2 gives a measure of model fit, there is no equivalent for logistic regression. Instead, the goodness of fit can be evaluated with the ROC method (Pontius and Schneider 2000, Swets 1986) which evaluates the predicted probabilities by comparing them with the observed values over the whole domain of predicted probabilities instead of only evaluating the percentage of correctly classified observations at a fixed cut-off value. This is an appropriate methodology for our application, because we will use a wide range of probabilities within the model calculations.

The influence of spatial autocorrelation on the regression results can be minimized by only performing the regression on a random sample of pixels at a certain minimum distance from one another. Such a selection method is adopted in order to maximize the distance between the selected pixels to attenuate the problem associated with spatial autocorrelation. For case-studies where autocorrelation has an important influence on the land-use structure it is possible to further exploit it by incorporating an autoregressive term in the regression equation (Overmars and others 2002).

Based upon the regression results a probability map can be calculated for each land-use type. A new probability map is calculated every year with updated values for the driving factors that are projected to change in time, such as the population distribution or accessibility.

Decision Rules

Land-use type or location specific decision rules can be specified by the user. Location specific decision rules include the delineation of protected areas such as nature reserves. If a protected area is specified, no changes are allowed within this area. For each land-use type decision rules determine the conditions under which the land-use type is allowed to change in the next time step. These decision rules are implemented to give certain land-use types a certain resistance to change in order to generate the stability in the land-use structure that is typical for many landscapes. Three different situations can be distinguished and for each land-use type the user should specify which situation is most relevant for that land-use type:

1. For some land-use types it is very unlikely that they are converted into another land-use type after their first conversion; as soon as an agricultural area is urbanized it is not expected to return to agriculture or to be converted into forest cover. Unless a decrease in area demand for this land-use type occurs the locations covered by this land use are no longer evaluated for potential land-use changes. If this situation is selected it also holds that if the demand for this land-use type decreases, there is no possibility for expansion in other areas. In other words, when this setting is applied to forest cover and deforestation needs to be allocated, it is impossible to reforest other areas at the same time.
2. Other land-use types are converted more easily. A swidden agriculture system is most likely to be converted into another land-use type soon after its

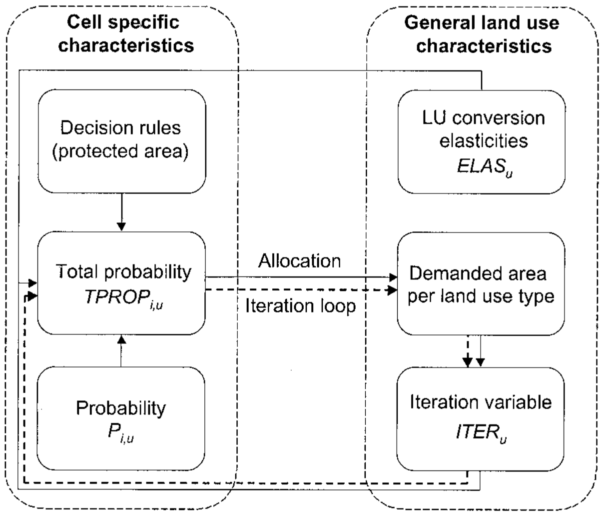

Figure 4. Representation of the iterative procedure for land-use change allocation.

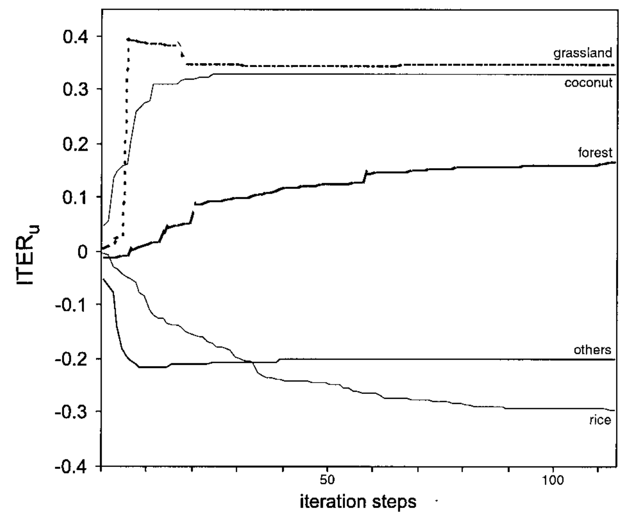

Figure 5. Change in the iteration parameter ($ITER_u$) during the simulation within one time-step. The different lines represent the iteration parameter for different land-use types. The parameter is changed for all land-use types synchronously until the allocated land use equals the demand.

initial conversion. When this situation is selected for a land-use type no restrictions to change are considered in the allocation module.

3. There is also a number of land-use types that operate in between these two extremes. Permanent agriculture and plantations require an investment for their establishment. It is therefore not very likely that they will be converted very soon after into another land-use type. However, in the end, when another land-use type becomes more profitable, a conversion is possible. This situation is dealt with by defining the relative elasticity for change ($ELAS_u$) for the land-use type into any other land use type. The relative elasticity ranges between 0 (similar to Situation 2) and 1 (similar to Situation 1). The higher the defined elasticity, the more difficult it gets to convert this land-use type. The elasticity should be defined based on the user's knowledge of the situation, but can also be tuned during the calibration of the model.

Competition and Actual Allocation of Change

Allocation of land-use change is made in an iterative procedure given the probability maps, the decision rules in combination with the actual land-use map, and the demand for the different land-use types (Figure 4). The following steps are followed in the calculation:

1. The first step includes the determination of all grid cells that are allowed to change. Grid cells that are either part of a protected area or under a land-use type that is not allowed to change (Situation 1, above) are excluded from further calculation.
2. For each grid cell i the total probability ($TPROP_{i,u}$) is calculated for each of the land-use types u according to: $TPROP_{i,u} = P_{i,u} + ELAS_u + ITER_u$, where $ITER_u$ is an iteration variable that is specific to the land use. $ELAS_u$ is the relative elasticity for change specified in the decision rules (Situation 3 described above) and is only given a value if grid-cell i is already under land use type u in the year considered. $ELAS_u$ equals zero if all changes are allowed (Situation 2).
3. A preliminary allocation is made with an equal value of the iteration variable ($ITER_u$) for all land-use types by allocating the land-use type with the highest total probability for the considered grid cell. This will cause a number of grid cells to change land use.
4. The total allocated area of each land use is now compared to the demand. For land-use types where the allocated area is smaller than the demanded area the value of the iteration variable is increased. For land-use types for which too much is allocated the value is decreased.
5. Steps 2 to 4 are repeated as long as the demands are not correctly allocated. When allocation equals demand the final map is saved and the calculations can continue for the next yearly timestep.

Figure 5 shows the development of the iteration parameter $ITER_u$ for different land-use types during a simulation.

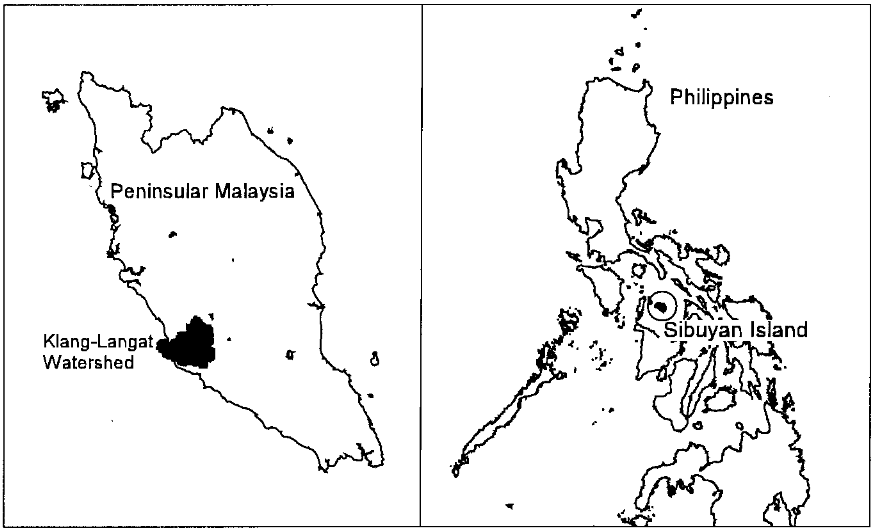

Figure 6. Location of the case-study areas.

Multi-Scale Characteristics

One of the requirements for land-use change models are multi-scale characteristics. The above described model structure incorporates different types of scale interactions. Within the iterative procedure there is a continuous interaction between macro-scale demands and local land-use suitability as determined by the regression equations. When the demand changes, the iterative procedure will cause the land-use types for which demand increased to have a higher competitive capacity (higher value for $ITER_u$) to ensure enough allocation of this land-use type. Instead of only being determined by the local conditions, captured by the logistic regressions, it is also the regional demand that affects the actually allocated changes. This allows the model to "overrule" the local suitability, it is not always the land-use type with the highest probability according to the logistic regression equation ($P_{i,u}$) that the grid cell is allocated to.

Apart from these two distinct levels of analysis there are also driving forces that operate over a certain distance instead of being locally important. Applying a neighborhood function that is able to represent the regional influence of the data incorporates this type of variable. Population pressure is an example of such a variable: often the influence of population acts over a certain distance. Therefore, it is not the exact location of peoples houses that determines the land-use pattern. The average population density over a larger area is often a more appropriate variable. Such a population density surface can be created by a neighborhood function using detailed spatial data. The data generated this way can be included in the spatial analysis as another independent factor. In the application of the model in the Philippines, described hereafter, we applied a 5 × 5 focal filter to the population map to generate a map representing the general population pressure. Instead of using these variables, generated by neighborhood analysis, it is also possible to use the more advanced technique of multi-level statistics (Goldstein 1995), which enable a model to include higher-level variables in a straightforward manner within the regression equation (Polsky and Easterling 2001).

Table 1. Land-use classes and driving factors evaluated for Sibuyan Island

Land-use classes	Driving factors (location)
Forest	Altitude (m)
Grassland	Slope
Coconut plantation	Aspect
Rice fields	Distance to town
Others (incl. mangrove and settlements)	Distance to stream
	Distance to road
	Distance to coast
	Distance to port
	Erosion vulnerability
	Geology
	Population density (neighborhood 5×5)

Application of the Model

In this paper, two examples of applications of the model are provided to illustrate its function. These

Table 2. Beta values[1] for regression results of the spatial distribution of land use on Sibuyan Island

	Forest		Coconut		Grassland		Riceland	
Driver	Beta	Exp(B)	Beta	Exp(B)	Beta	Exp(B)	Beta	Exp(B)
Constant	−1.9807		0.5773		−0.7451		−1.6334	
Geology								
Diorite rock	1.9942	7.3462						
Ultramafic rock	2.7080	14.9985	−0.6853	0.5040	−3.2608	0.0384		
Ultramafic sediment	2.0517	7.7808			−1.0998	0.3330		
Metamorphic sediment	0.7127	2.0396	1.1387	3.1227	−0.8919	0.4099		
Erosion								
Moderate erosion	−1.8234	0.1615	1.0056	2.7334	1.2767	3.5848		
No erosion	−1.1811	0.3069	−0.5085	0.6014				
Elevation	0.0027	1.0027	−0.0021	0.9979	−0.0012	0.9988	−0.0253	0.9750
Slope			0.0405	1.0413	0.0208	1.0211	−0.1244	0.8830
Aspect	0.0023	1.0023	−0.0022	0.9978				
Distance to road			−0.0005	0.9995	−0.0005	0.9995	0.0005	1.0005
Distance to town	0.0001	1.0001	−0.0002	0.9998	0.00007	0.9999		
Distance to stream					−0.0008	0.9992		
Distance to coast	0.0003	1.0003	−0.0006	0.9994	0.0003	1.0003		
Population density	−0.00066	0.9935	0.0009	1.0009	−0.0011	0.9989	0.0008	1.0008
ROC value	0.9368		0.9160		0.8225		0.914	

[1]All variables significant at $p < 0.01$.

Exp(B) values indicate the change in odds upon one unit change in the independent variable. When Exp(B)>1 the probability increases upon an increase in the value of the independent variable, when exp(B)<1 the probability decreases.

examples are derived from model applications in Sibuyan Island, the Philippines, and the Klang-Langat watershed in Malaysia. Figure 6 gives the location of both case-studies. The scenarios presented are not necessary the most realistic, but are made in such a way that they provide information on the functioning of the model.

Study Areas

Sibuyan Island. Sibuyan is located in Romblon province which is part of the Visayas region of the Philippines. The island measures 28 km east to west at its widest point and 24 km north to south, with a land area of approximately 456 km^2, surrounded by deep water. In the center of the island lies a large protected area (Mount Guiting-Guiting Natural Park). It is characterized by its steep mountain slopes, covered with forest canopy. The land surrounding the high mountain slopes gently to the sea and is used for natural and plantation forest and agricultural, mining, and settlements. Modeling land-use change in this case-study is especially relevant to evaluate the potential impact of land-use change on the protected area.

Klang-Langat watershed. The Klang-Langat watershed is located on the boundary of the states of Selangor and Negeri Sembilan, Malaysia and contains the urban area of Kuala Lumpur. The watershed represents the most urbanized region in Malaysia. In total the Klang-Langat region has a population of 4.18 million (1999), which accounts for 20% of the country's total population. Land-use change analysis is of extreme interest in this region due to the high dynamics, rapid urbanization, and loss of remaining natural areas.

Spatial Analysis

The land-use types analyzed in the Sibuyan case-study and the driving variables that were assumed to represent the driving factors on the island are listed in Table 1. For each of the land-use types a logistic regression is run. Table 2 presents the results of these regressions. The spatial distribution of all land-use types could well be explained by the selected driving variables as indicated by the high ROC test statistics (scale 0.5–1). From the table it can be seen that not all driving factors that were considered (Table 1) were actually included in the regression models.

Simulation Results

For Sibuyan a baseline scenario was run assuming a continuation of present trends of land-use change determining the demand. No protection of the natural area was assumed. Decision rules included a "no change" setting for the "other" land-use type and prevented conversion to forest in previously non-forest grid cells, a relatively high value for the elasticity parameter of coconut plantations and low values of this parameter for riceland and grassland. The results of

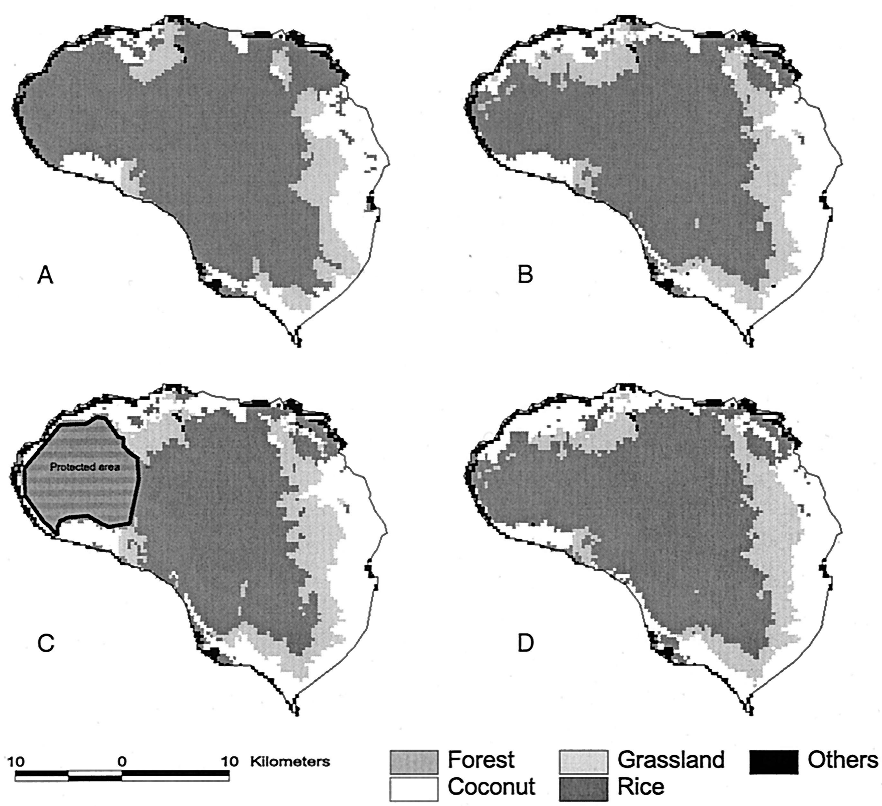

Figure 7. Simulation results. **A**, Land-use situation at the start of the simulations in 1997; **B**, Simulation result for the baseline scenario in 2017; **C**, Simulation result for 2017 with the protection of the north-western forest area; **D**, Simulation result for 2017 with adapted decision rules for coconut.

this baseline scenario for the period 1997 to 2017 are shown in Figure 7A and 7B.

The results show that deforestation is expanding in the uplands, while coconut plantations expand in the lowland areas. The zone of grasslands in between the coconut plantations and the forest gradually moves uphill.

Connectivity

The model is able to simulate connectivity between locations originating from feedbacks over a higher level of organization. This can be illustrated by simulating the hypothetical protection of part of the forest area. In this example strict protection of the western part of the forest is assumed. If this area is protected while the demand for the different land-use types remains equal, other parts of the island will face land-use change instead. The results of this scenario run are shown in Figure 7C. Instead of the deforestation in the now protected north-western part of the island more deforestation is found on the eastern and southern slopes of the island and close to the boundaries of the protected area.

Model Sensitivity

The model is sensitive to the user specified decision rules that steer the conversions based on the actual land-use pattern. The influence of the elasticity to change ($ELAS_u$) is shown as an example in Figure 7D. Instead of assuming a high inelasticity towards change for coconut plantations ($ELAS_u = 0.8$), a more dynamic behavior of the spatial distribution of coconut plantations was tested ($ELAS_u = 0$). The figure shows that more areas that were already under coconut at the start of the simulation are now abandoned for other land-use types. A larger area of new coconut plantations at other locations, as compared to the baseline result (Figure 7B), compensates this decrease. When land-use data for different years are available it is possible to calibrate the model by changing these settings.

Model Validation

For the Klang-Langat watershed data for two years were available, which made a validation of model performance possible. Simulations are started in 1989 and a comparison between model performance and real changes is made for 1999. The model for Klang-Langat simulates land-use change for nine land-use types, synchronously. Urban areas, oil palm and rubber plantations, and forests are the most important land-use types in this area. Also for Klang-Langat the model is parameterized with a considerable number of driving factors.

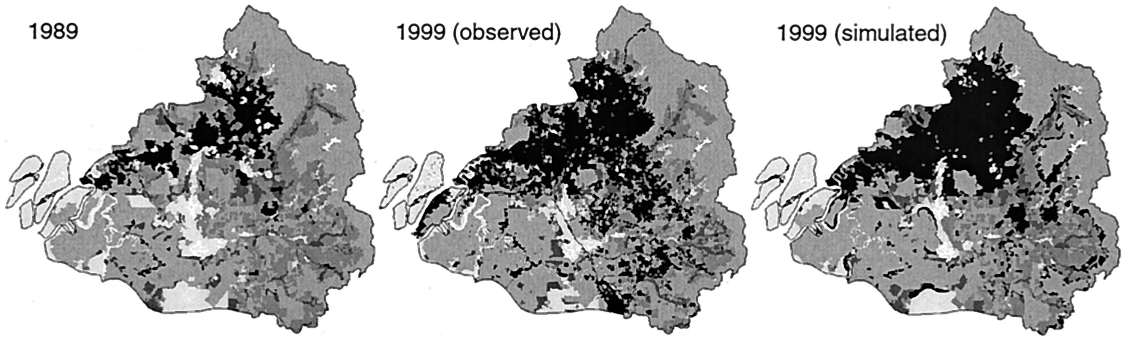

Figure 8. Land-use situation in the Klang-Langat watershed in 1989 and 1999 and simulated land use in 1999. Different grey shades indicate the nine different land-use types in the model. Black is urban area. The study area has a total extent of 4,300 km^2. Each grid-cell is 150 m.

Because of the dominance of urbanization in this area, a number of driving factors related to this process have been included, such as the accessibility of the area by different road types. Figure 8 shows the land-use distribution in 1989 and 1999 and the simulated land-use pattern in 1999. Validation methods for this type of studies include the calculation of the Kappa statistic (Cohen 1960), the recently derived special Kappa statistics to evaluate the ability of the model to simulate location (Pontius 2000), while the fuzzy equivalent of the Kappa statistic evaluates the fuzziness of location and category of the simulated land-use patterns (Hagen 2002). In this study we use the multiple resolution procedure (Costanza 1989) to evaluate the model performance over a range of resolutions. This multiple resolution procedure quantifies the degree of matching or similarity between complex spatial patterns. Model validation by a simple percentage of cells that are correct at the basic grid-size ignores the "near misses" and two maps with the same percent correct could exhibit very different patterns in their residuals (misses). The multiple resolution method tells us whether the pattern is relatively well matched. An expanding "window" is used to gradually degrade the resolution of the comparison. At each of these degraded resolutions the correspondence between the simulated and observed land-use pattern is calculated.

Figure 9 shows the goodness of fit for different window sizes for the simulations of land use in the Klang-Langat watershed. Two different lines indicate simulations with different settings for the relative elasticity ($ELAS_u$). Although the fit is relatively low at the basic grid-size, there is clearly a better correspondence in the overall pattern as the fit increases with window-size. The two validation lines indicate that simulations performing best at the most detailed level are not always the best at the aggregate level. The overall fit of

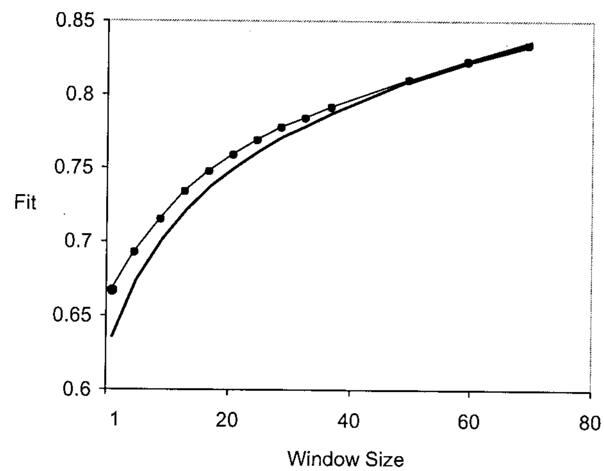

Figure 9. Plot of fit versus window size (n × n grid-cells of 150×150m each) for simulated land use in the Klang-Langat watershed compared to observed land use in 1999. The two lines indicate different settings of the relative elasticity ($ELAS_u$).

the model runs presented for the Klang-Langat watershed is not very high, which can also be seen from Figure 8. The new urbanization developments in the central and southern part of the watershed are not well captured in the model. This might be explained by the relatively poor quality of the data for some of the driving factors of land-use change used in the model. No information has yet been included describing the demographic characteristics and governmental planning regions within the area, whereas this type of information is considered important for the land-use change processes in this region. Better quality data and incorporation of this type of important factors could improve the results of this model run.

Discussion

The results of the model runs above indicate that the model is capable of representing land-use change in accordance with the characteristics of complex systems described earlier in this paper.

The results are not simple linear extrapolations of trends: connectivity between locations and competition between land-use types cause the outcomes of the model to be complex patterns, typical of non-linear systems. Setting the decision rules of the elasticity towards conversion creates stability in the land-use pattern. The results show that the model is sensitive to the settings of these decision rules. Care should therefore be taken while specifying these rules. For land-use types that are known to have different spatial behavior different land-use classes should be created. This can be the case in forested areas were a lot of regrowth of secondary vegetation is found. Primary forest can only decrease on its present area whereas secondary vegetation will show a more dynamic spatial behavior: some secondary vegetation might be cleared for agriculture while at the same time new secondary regrowth occurs on abandoned lands or logged-over primary forest. Similar differences can be found in rice growing systems. A lowland rice field with permanent irrigation facilities will show totally different dynamics and relations with driving forces than upland rice cultivation. Subdivision of this type of land-use classes should be considered for appropriate modeling of the dynamics of these land-use types.

The setting of the elasticities for conversion are now based on expert knowledge and can be modified by calibration of the model, if a second data set for land use is available. A sensitivity analysis has shown that these settings have an important influence on the resulting land-use patterns as they are directly related to the trajectories of change and land-use histories. This specification needs, therefore, considerable attention. Future research should find methods to help the definition of these conversion elasticities, based on the analysis of historic land-use data and/or better insights into the decision-making process of the actors of land-use change.

The model structure clearly represents the hierarchical organization of land-use systems, allowing for a continuous iteration between regional level demands and local-level land suitabilities. In addition, driving factors operating at spatially aggregated analysis levels can be taken into account. In this sense, the model has an appropriate structure to study the scalar dynamics of land-use systems. The exact interactions and feedbacks between scales and the causal processes underlying these interactions are, however, still largely unknown and are an important topic of research (Gibson and others 2000, Root and Schneider 1995, Wilbanks and Kates 1999). It is especially difficult to comprehend the link between the decision-making process by the individual actors of land-use change and the emerging patterns of land use (Geoghegan and others 1998, Mertens and others 2000). When the system-based approach described in this paper is combined with actor-oriented studies (e.g., Bilsborrow and Okoth Ogondo 1992) and agent-based modeling (Bousquet and others 1998, Manson 2000) it is possible to gain further understandings in the multi-scale dynamics of the land-use system.

The CLUE-S model is clearly different from models solely based on an empirical analysis of land-use change (e.g., Mertens and Lambin 1997, Pijanowski and others 2000). The advantage of this model is the explicit attention for the functioning of the land-use system as a whole, the capability to simulate different land-use types at the same time and the possibility to simulate different scenarios. Models that rely heavily upon statistical relations between land use and driving factors are frequently criticized for their lack of causality (Irwin and Geoghegan 2000, Kaimowitz and Angelsen 1998, Lambin and others 2000b). The selection of driving factors for the CLUE-S model should, therefore, be based on the theoretical relationships between driving factors and land use. Only driving factors are taken into account for which a theoretical relationship with land use is known, in order to avoid spurious correlations. We have chosen not to base the selection of variables on one single theoretical framework because of the differences in dominant processes between case-studies. In some case-studies is will be possible to base the selection of driving factors solely on economic theory, but in other cases other processes are important as well. In such situations we need to also incorporate factors based on other theories. The use of expert knowledge is essential, both for the determination of the dominant processes and selection of the potential driving variables as well as for the evaluation of the outcomes of the regression analysis.

Conclusion

The model can easily be applied to a wide range of study areas and land-use change situations. The main limitation of applying the model is its incapability to simulate land-use dynamics in areas without a land-use change history, e.g. deforestation in a pristine forest area. This is because the model uses empirically-derived relations based on existing land-use patterns for the allocation of land-use change. The only possible way around this limitation is the use of empirical relations derived in an area with very similar characteristics.

The model is suitable for scenario analysis and the simulation of trajectories of land-use change. For different scenarios the model can therefore identify critical areas of land-use change (hot spots). Scenarios can be used to evaluate the impact of macro-level changes, such as price developments of agricultural products and/or changes in demographic characteristics or consumption patterns. Other scenarios can be used to evaluate the effects of local level conditions, such as nature reserve protection, on the surrounding region.

The possibility to simulate different scenarios makes the model a powerful tool for natural resource management. When projections of future land use are compared with the location of vulnerable places in the light of biodiversity, landscape stability, and/or food production, it is possible to target interventions. A dynamic coupling with specific models simulating the effects of land-use change for landscape features should, therefore, be established. The incorporation of feedback mechanisms between the CLUE-S model and these impact models will also improve the land-use simulations. A typical example is the feedback between land degradation and land use: land-use change affects land degradation through erosion and sedimentation patterns. In its turn, land degradation will affect future land-use possibilities.

The visualization of the dynamics under different development pathways make the model also a powerful tool for participatory land use planning and stakeholder negotiations (Harms and others 1993). The presented methodology should therefore be seen as a new tool that supplements existing methodologies for improved environmental management.

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