Chapter 2
LUCC Modeling Approaches to Calibration

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Abstract In land change modeling, calibration enables the modeler to establish the parameters for the model in order to produce expected outcomes, similar to those observed for the study area over a period in the past or consistent with a given scenario. Depending on the modeling approach, the parameters are set using maps which describe past change or information obtained from experts or stakeholders. These parameters will control the behavior of the model during the simulation with regard to aspects such as the quantity and the spatiotemporal patterns of modeled change. This chapter focuses on different aspects of calibration, such as the selection and transformation of input variables and the different approaches for estimating the parameters of the most common pattern-based models (PBM) and constraint cellular automata-based models (CCAM).

Keywords Calibration · Land use and cover changes · Land change models · Drivers of change · Markov · Change potential maps

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1 Introduction

Calibration is the process whereby the modeler sets the parameters of the model so as to enable it to reproduce outcomes similar to those observed for the study area. The information used for calibration should be at or before the date at which the predictive extrapolation begins (Pontius and Malanson 2005). Calibration is different from verification (also called "internal validation") which refers to the process of certifying the correct internal operation of a model, including debugging and at times sensitivity analysis.

The source of the information used to calibrate the model will depend on the modeling approach. In data-driven models, the modeler carries out an analysis of the data, which typically describes land change over a previous period, in order to obtain the expected pattern of change for the simulation period from this analysis. In knowledge-based models, the information about change patterns is obtained from experts or directly from the agents of change (Fig. 1).

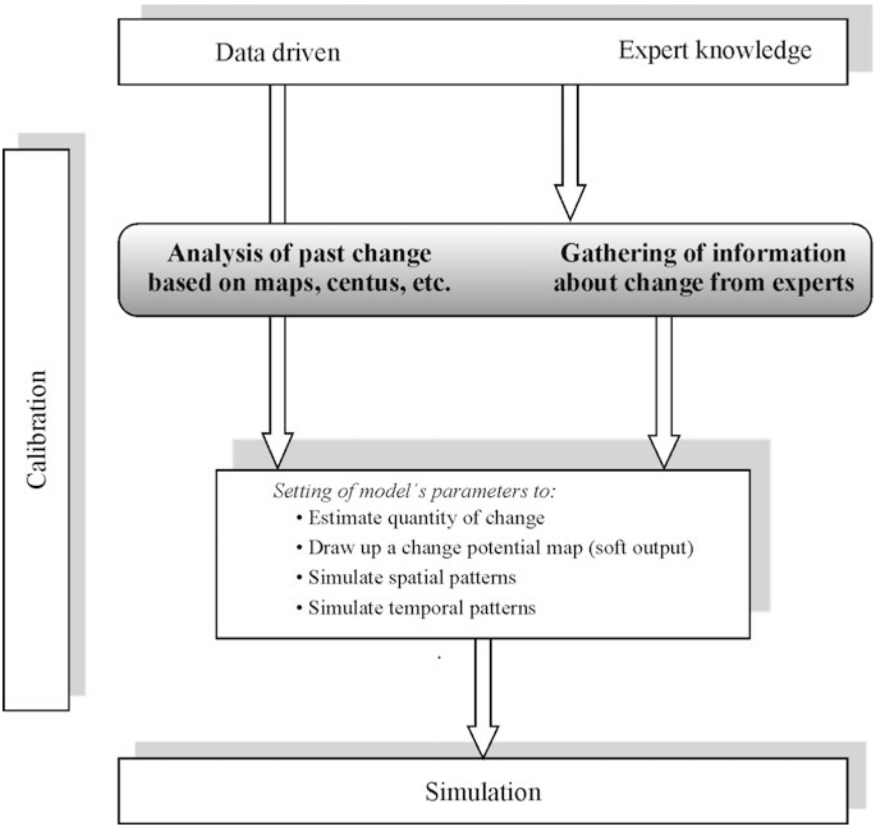

Fig. 1 Flowchart of the general procedure in the calibration stage in LUCC modeling approaches

One of the most important tasks in calibration is the selection and transformation of variables which can explain future changes and the fine tuning of the parameters that control the transition rules. In this chapter, we will review the approaches used to set the parameters used to determine the quantity of modeled change, the relationship between change and its drivers, and the spatial and temporal patterns of change. We will then highlight the related topics and the sources of uncertainty which can affect the process of calibration and the calibration assessment. Authors also describe calibration steps according to LUCC models.[1] Some of them, such as CA_MARKOV, Land Change Modeler (LCM) (both in TerrSet), Dinamica EGO and CLUMondo, are pattern-based models (PBM). By contrast, Metronamica, APoLUS, SLEUTH and LucSim are considered constraint cellular automata-based models (CCAM).

2 Selection of Variables

2.1 LUC Transitions

First, the modeler should choose the land-use change he/she wants to model, the level of detail required in the characterization of the change, the main changes occurring in the study area and the characteristics of the input data. For example, when multi-date maps or classified remotely sensed images are used, the number of map categories will affect the number of mapped transitions. A broad transition (e.g. deforestation) is likely to be mapped more accurately than more detailed transitions such as "pine forest to crop cash agriculture" or "dry forest to temporal agriculture" because most of the confusion between mapped categories occurs between similar land use/cover (forest categories, agriculture categories). In fact, it might be easier to model these two types of deforestation process in a separate way because they respond to different agents, motivations and conditions. The choice of the modeled transitions can also be guided by information from interviews (Voinov et al. 2016). As pointed out by Hewitt (2015), modeled LUC transitions need to be carefully chosen, and a reclassification of LUC categories available in existing cartography should eventually be carried out. Models based on a land systems approach allow us to simulate both LUC conversions and changes in land use intensity (van Asselen and Verburg 2013).

Finally, it is often difficult to model just the few specific transitions that interest the modeler if other transitions also play an important role in the land change dynamic of the entire system. For instance, if a modeler is interested in

[1]See the short presentations in Part V of this book about (in alphabetical order) APoLUS, CA_MARKOV, CLUMondo, Dinamica EGO, Land Change Modeler (LCM), LucSim, Metronamica and SLEUTH. The authors are also grateful to all contributors who helped us understand the different software packages.

deforestation caused by agricultural expansion in a region where important areas of cropland are also being lost to urban expansion, he should also consider the latter transition because it is likely to increase the pressure on forest as a source of land to replace the lost agricultural areas.

Analysis of changes based on LUCC-budget (Pontius et al. 2004, see Technical Notes in Part IV of this book) or intensity analysis (Aldwaik and Pontius 2012) can give useful insights to help the modeler choose the transitions to consider in the model.

2.2 *Explanatory Variables of Change*

The modeler should select the drivers, or explanatory variables that play a role in the land changes. Even in automated approaches, the selection of initial input variables is based on expert knowledge although data availability is often a major limitation. These variables are diverse and describe different aspects of the study area and its context such as accessibility (distance from human settlements, roads, markets…), suitability of the terrain for diverse human activities (slope, elevation, rainfall, soils…), human activities (agriculture, sawmills and human pressure indices such as population density, marginalization), public policies (protected areas, subsidies for cattle ranching or agriculture). It is worth noting that pattern-based models can produce quite accurate prospective maps using only variables, such as slope and distances that do not explain the causes of the change and focus only on its location. By contrast, process-based approach models will concentrate on variables closer to the causes of the change because they seek to simulate the process of change.

Variables can be divided into static and dynamic variables. Static variables do not change over the course of a simulation. Dynamic variables, which value change during the simulation, include distance to roads that will be built according to a schedule or whose construction is simulated in the model. Such models, called ¨road constructor¨ in some software packages are calibrated by identifying zones of attraction, such as valuable timber areas, and zones of resistance to the path of roads such as flooded or rugged terrains. Other dynamic variables are distances to specific LUC areas, to settlement projects or to conservation units and are usually calibrated using the first date of the calibration period, based on the assumption that the changes observed during the calibration period are explained by the landscape configuration at the beginning of the period.

During the last decade, the amount of available information increased dramatically. Many government agencies have made their information available online, often in a digital GIS compatible format. Remote sensing data is also increasingly, often freely, available. The quality of the imagery has also improved greatly: high spatial resolution images are now common and recently launched satellite constellations enable space agencies to produce images with both high spatial and temporal resolution. Another challenging new source of information is volunteered geographic information which produces a large amount of firsthand information (Goodchild 2007; Jokar Arsanjani et al. 2013).

When selecting the variables to be integrated into the model, different strategies are often carried out in which the drivers are analyzed using statistical indices, expert knowledge, reviews of the literature and workshops with stakeholders. Step-by-step regression models help select the variables with the highest explanatory power. Many other indices are used to evaluate the strength of the relationship between two variables such as for example the average of the absolute value of the weights of evidence (Mendoza Ponce et al. 2017) or the importance of weight (Sangermano et al. 2012). In some models based on the assumption of the independence of the explanatory variables, indices such the Cramer index, chi square, correlation index, Kappa index and joint information uncertainty are used to detect correlated explanatory variables (Mas et al. 2014). Based on these analyses, one or various variables among the correlated variables are discarded from further analysis to reduce correlation. For example, Almeida et al. (2005) used the criterion proposed by Bonham-Carter (1994) and considered two variables as correlated when they had Cramer's Coefficient and Joint Information Uncertainty values of over 0.5.

2.3 *Variable Transformation*

Variables often have to be adapted into a suitable format for the analysis procedure. For instance, some statistical methods, such as weights of evidence (see Technical Notes in Part IV of this book), require categorical input variables. Thus, continuous variables such as distances should be transformed into bins. By contrast, when using methods such as logistic regression or multilayer perceptron (see Technical Notes in Part IV of this book), modelers try to avoid categorical variables because each category is managed as a dummy binary variable, increasing the dimensionality of the model. Categorical variables can be transformed into continuous ones using the Evidence Likelihood transformation based on the relative frequency of cells belonging to the different categories within areas of change. In logistic regression, the transformation of explanatory variables through algebraic operations such as exponential, quadratic, logarithmic or power, can be done to achieve linear relationships with the logit of the dependent variable. The creation of suitability maps using fuzzy transformation and weighting can also be considered as variables transformation.

3 Parameters to Calibrate

3.1 Quantity of Changes

The main objectives of a land change model generally include the prediction of the quantity of change that may occur in the future.

In past trend-based models, the rate of change is obtained from the analysis of change which occurred during a previous period, the "calibration period". As pointed out by Chen and Pontius (2011), the selection of the calibration period often depends on data availability and can have an important influence on the predictive performance of the model. Broadly speaking, in short period calibration there is a risk of extrapolating change quantity in exceptional moments, while if trends are analyzed over longer intervals, the extreme tendencies tend to be averaged out. For example, Fig. 2 illustrates annual deforested area in the Brazilian Amazon between 1989 and 2015 and average rate computed for periods of three and five years. The rates calculated over longer periods do not present the large fluctuations observed in yearly data. However, there is no fixed rule as to the appropriate calibration period when the rate of change seems erratic. Temporal resolution includes the number of available dates and time intervals. As the most commonly used approaches include only two training dates, the choice of training dates is crucial. The dataset showing the annual deforested area in the Brazilian Amazon (Fig. 2) offers the possibility of computing many rates of change using two training dates. Model output will vary greatly depending on the pair of training dates selected, due to the large fluctuations in the rate of deforestation over time. Paegelow et al. (2014) highlighted the impact of different training dates on the accuracy of a model based on a dataset like this. In this book, Paegelow examines the potential errors resulting from only considering two past dates in Markov projections.

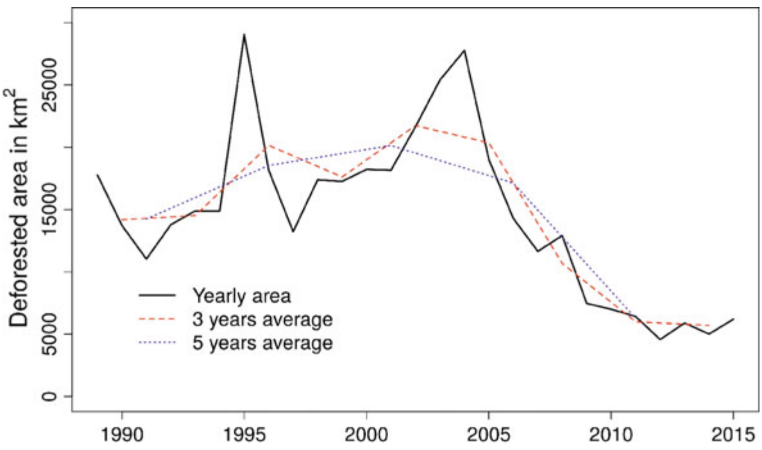

Fig. 2 Deforested area in the Brazilian Amazon (1989–2015). *Source* INPE, Brazil

Many LUCC models are based on Markov chains. As detailed in the technical note in Part IV of this book, a transition matrix for the calibration period can be obtained by overlaying two LUC maps and transforming them into an annual Markov chain probability matrix. This matrix indicates the probability of transition from one category to another over one year and allows us to project the estimated areas of each LUCC transition. There are several methods for obtaining the annual matrix. The method based on the eigenvector and eigenvalues of the original matrix (see equation in Takada et al. 2010 or Mas et al. 2014) can prove problematic: (1) if they produce one or several matrices with complex or negative numbers and (2) when there are two matrices in the results (even if they do not contain complex or negative numbers). These matrices cannot be interpreted as probabilities (Takada et al. 2010).

To overcome the limitations of Markov projection due to the assumption of stationarity of the transition probabilities over the calibration and simulation periods, Collins et al. (1974) calculated dynamic transition probabilities by using different transition matrices at certain time intervals or computing dynamic transition probabilities by postulating rules of behavior for LUC categories.

Markov chains are used in population projection: Population is divided by age and the transition matrix indicates death and birth rates for each group (Shryock and Siegel 1976). It seems logical that the number of births and deaths will depend on the size of the population in each age group and their corresponding birth and death rates. A large population will have more births than a small population with the same birth rate. However, the application of this logic to LUCC rates is far from straightforward. Suppose that there is a large forest region with an annual deforestation rate of 5%. A Markov projection will project a decrease in the total deforested area each year, because the 5% rate will be applied to a diminishing forest area. Nevertheless, the area deforested annually will probably depend on many others factors (e.g. market or population-related) and not on the area of remaining forest, as least until remaining forest areas are very small and confined to inaccessible areas.

Moreover, the Markov assumption that a constant proportion of a given category will present a certain transition at each time step will result in extrapolations reaching a state of equilibrium in terms of the area of each category (Petit et al. 2001), an equilibrium that is rarely observed in true situations. Runfola and Pontius (2013) proposed the Flow matrix, which expresses the sizes of the transitions among categories between two dates as an alternative to the Markov matrix.

If the past-trend-based projection seems to be a risky option due to the large fluctuations in change over time, the modeler can try to model the quantity of change. This can be done by external models using exogenous variables. For example, Barni et al. (2015) calculated the rate of deforestation in a non-spatial numerical model which takes into account planned road building and a migration factor that simulated increased deforestation by expected migrants to the region after road building. This model was calibrated using observed past trends. Vieilledent et al. (2013) also modeled deforestation including the effect of population density.

Models such as CLUMondo represent land-use change in a different way from area-based demand. Input for this model comes in the form of exogenous demands for goods and services, which can be supplied by different land systems characterized by their land cover and their land management intensity. This means that increasing demand for crop products can lead to a combination of expansion in agricultural area and intensification of existing cropland.

Table 1 shows the approaches used by eight popular software packages to estimate the quantity of change. Markov chain is the most common approach, particularly in pattern-based models.

3.2 Function Describing the Relationship Between Change and Drivers

In many pattern-based models, the allocation of change is generally based on maps of change potential which indicate, for each transition, the propensity of change (see Chap. 3 about simulation). This map is usually based on a data-driven analysis of past patterns of change with respect to the explanatory variables. In this way, the map of change potential reflects the changes in the distribution of land-use that occurred during the calibration period. There are many methods used to establish the relationship between the change observed during the calibration period and the variables. The most commonly used are brute force, logistic regression, weights of evidence, decision tree, multilayer perceptron and genetic algorithm (for some of these methods see Technical Notes in Part IV of this book). Some authors combine various methods such as weights of evidence and genetic algorithms (Soares et al. 2013). These methods can be distinguished by their ability to fit non-linear relationships. High flexibility is not always an advantage due to overfitting. When the model is overfitted to specific conditions of the calibration period it is unable to predict the next period (simulation step) correctly. These methods are mainly data-driven. However, the map of change potential can also be partially or totally based on expert knowledge as in Overmars et al. (2007) who drew up their map on the basis of expert advice from agronomists. Some of the methods, such as the weights of evidence in Dinamica EGO, enable users to adjust the importance attributed to expert knowledge from a totally statistical, data driven approach (no modification of the computed values of the weights) to an exclusively expert knowledge approach (complete edition by the expert). A hybrid approach, combining data-driven and expert knowledge, can be obtained with a partial modification of the weights (Mas et al. 2014).

One alternative to the change potential map is a suitability map that expresses the appropriateness of a location for each type of LUC. This map is frequently created using a multi-criteria analysis (see Technical Note in Part IV of this book). The chapter on simulation (see Chap. 3) provides a complete discussion of both the change potential and suitability approaches.

Table 1 Approaches used to estimate the quantity of change in eight software packages

	Pattern-based models (PBM)				Constraint CA-based models (CCAM)		
	CA_Markov TerrSet	LCM TerrSet	Dinamica EGO	CLUMondo	Metronamica and APoLUS	SLEUTH	LucSim
LUC/ continuous variable	LUC	LUC	LUC	LUC	LUC	LUC and Urban Growth	LUC/ Continuous variables
Time points	1 or 2	2	2	1	2	Min 4, no maximum	1 or 2
Estimation of change quantity	Markov	Markov, external	Markov, external	Exogeneous demand for goods and services	External	CA growth rule parameters	Markov

Table 2 Main approaches used for the analysis of drivers. Additionally, models may use tools to help understanding LUC and setting model´s parameters

	Pattern-based models (PBM)				Constraint CA-based models (CCAM)		
	CA_Markov TerrSet	LCM TerrSet	Dinamica EGO	CLUMondo	Metronamica and APoLUS	SLEUTH	LucSim
Data driven statistical approach		Logistic regression	Weight of evidence	Logistic regresion		Cellular automata	
Data driven machine learning		Multiplayer perceptron sim weight	Genetic algorithm	May be used to generate suitability map external to model		Brute force, Genetic algorithm	Decision trees
Knowledge driven approach	Multicriteria evaluation		Weight edition	Expert based parameterization several parameters	Empirical, trial and error tested against benchmarks.	CA rules are hard coded, but adjust	No

In CA constrained-based models, calibration involves parameter values for the neighborhood (van Vliet et al. 2013). For instance, models such as Metronamica and APoLUS compute a total transition potential combining the neighborhood effect, accessibility, suitability and zoning (see the technical note about the NASZ model in Part IV of this book). Usually, calibration proceeds systematically by fitting the simulated and the real maps for the calibration period as well as possible for each of the parameters. The procedure for evaluating goodness of fit involves visual inspection, cell-by-cell comparison measures such as Ksim (van Vliet et al. 2011) and spatial pattern indices such as fractal dimension or clumpiness.

The LucSim model uses a decision tree algorithm to determine a set of transition rules. Calibration data is split into training and testing data to avoid overfitting (see the short presentation about LucSim in Part V of this book). When calibrating the SLEUTH model, the model simulates a map of land-use at the end of the calibration period, carrying out a large number of simulations to assess its consistency. Thirteen performance metrics are used to assess the coefficient values. The best five coefficients are selected using brute force or a genetic algorithm (Silva and Clarke 2002, Clarke in this book) (Table 2).

3.3 Spatial Patterns

Spatial patterns involve the distribution, shape and size of the change patches in the landscape. Cellular automata (CA) are often used to enable the creation of small groups of cells which underwent change, simulating spatial patterns such as agriculture extension and urban growth (see Technical Notes in Part IV of this book). CA is a popular spatial simulation tool due to its simplicity, its ability to reproduce complex emergent dynamics and its affinity with raster GIS format (Torrens and O'Sullivan 2001). Calibration involves identifying the parameters which control the CA behavior based on training data. Torrens and O'Sullivan (2001) pointed out the need for stronger calibration techniques for CA because they are often calibrated by manual tuning.

A few studies incorporate landscape pattern metrics into the calibration procedure to establish the parameters for CA. For instance, Silva and Clarke (2002) determined the parameters of SLEUTH model CA by brute force, trying many combinations of the control parameters and computing measures of the goodness of fit between the simulated pattern and the real one. Soares-Filho et al. (2002) used a trial-and-error method to calibrate CA using landscape indices. Due to the large number of simulations involved, these methods are computation intensive. Li et al. (2013) proposed a pattern-calibrated method based on landscape metrics for calibrating CA using genetic algorithms. Liu et al. (2014) proposed an index called landscape expansion index (LEI) to calibrate a CA able to simulate infilling, edge-expansion and outlying urban growth patterns. Certain models such as Dinamica EGO have a mechanism for controlling the distribution of change with respect to the change potential and avoid restricting the simulated change to the highest change potential cells. This mechanism is controlled by a parameter which should be determined during calibration. Mas et al. (2015) used a genetic algorithm to calibrate this parameter along with CA parameters.

Finally, some models are based on objects rather than on cells. For example, Houet et al. (2014) carried out landscape simulations at fine resolution, based on elementary units (agricultural parcels) represented by vector-based objects.

Spatial patterns also involve the identification of zoning effects related with incentives or constraints in land-use regulation policies such as subsidies for cattle ranching or conservation. The zoning effect is often controlled by a coefficient to adjust the change potential in these areas. Highly restrictive zoning may result in a deterministic and unrealistic model. These patterns are also identified and quantified during calibration.

At another level, the spatial pattern may involve the identification of sub-regions, which present different processes and patterns of change. For instance, when a study area includes both mountainous and flood plain areas, different rates and patterns of change can be expected even for the same transition. In such cases, it may be useful to split the study area into various sub-regions in which independent calibration processes are carried out. For instance, Mas (2016) used a Geographically Weighted Regression model to identify sub-regions with different patterns of deforestation and carried out an independent calibration in each region.

3.4 Temporal Patterns

Temporal patterns include the sequence of land-use observed in the landscape. For example, when Houet et al. (2014) simulated LUCC they took into account farming practices such as crop successions. Chang and Mas (2017) develop a model of a slash and burn agriculture landscape in which a fallow period is necessary after a few years of cropping. This temporal behavior is generally calibrated using information from the literature or interviews, as a multi-date database with a high temporal resolution (e.g. yearly map) is often not available.

4 Calibration Evaluation

Calibration can be evaluated using the same methods as used to validate the model (see Chap. 4 about validation). For instance, for the past-trend pattern model, the change potential map can be compared with the changes that took place during the calibration period. Change can also be simulated from the beginning of the calibration period to create a simulated map for the end of this period. The simulated and observed (true) maps can then be compared. However, this evaluation only provides information about the goodness-of-fit of the calibration procedure. As we will see in the next section, this goodness-of-fit is not always a good indication of the predictive power of the model.

5 Source of Uncertainty

There are many sources of uncertainty that can obstruct the calibration of the model.

First, difficulties may arise in identifying the causal relationships between the land change processes and the explanatory variables used during calibration. In certain cases, the true drivers of land change are not identified or are not available. However, it is often impossible to establish a strong relationship between the land change and a particular set of variables due to the complexity of land change. Land change is related with environmental, socio-economic, historical and cultural drivers and acts as a complex system. Brown et al. (2004) argue that the failure to incorporate detailed information (e.g. survey-based) about household or community structures can create a specification bias because LUCC processes may be different for different types of households or communities. Additionally, in a large or heterogeneous area, different drivers may be active in different places, which makes finding causal explanations difficult (Walker et al. 2000).

Data inputs can also be a serious source of uncertainty. Land-use changes are often obtained from remote sensing data and accuracy assessments show that image processing often produces a large number of errors due to spectral confusion and other limitations. Consequently, the estimated rate of change and its spatial distribution can show a large amount of error that will propagate in subsequent processing. Change obtained from other sources such as interviews or volunteered geographical information can also show many errors or bias (Foody et al. 2013). Similarly, the explanatory variables used in the model may also have errors or be outdated. When using aggregated data such as census data, models can suffer from the modifiable areal unit problem where the shape and size of data aggregation (e.g. municipalities) affects the results of statistical analysis (Openshaw 1984).

Another source of uncertainty is the non-stationarity of the land change processes. As shown in Fig. 2, the rate of change can present large fluctuations over time. This lack of consistency can make the change patterns during the calibration and simulation periods very different. The non-stationarity of the land change process involves not only the rate of change but also the nature and the spatial distribution of the changes. For instance, agriculture can undergo drastic changes in response to demand for new crops. It is possible that the new crops may be grown on land with adverse environmental conditions where previously no crops could be planted, so rendering the change potential map obsolete. For instance, Mas et al. (2004) reported that the variation in the relative importance of the explanatory variables of deforestation in a tropical region of Mexico between the calibration period, dominated by cattle ranching, and the simulation period, when rice cultivation was introduced, led to errors in predicting the location of deforestation.

Finally, uncertainty can be the result of the design of the model itself. The model ignores important exogenous dynamics (e.g. price fluctuations, new market emergency) and oversimplifies certain relationships. For example, logistic regression can only model an S-shaped relationship between land change occurrence and an explanatory variable, when the true relationship may be an optimal range.

6 Concluding Remarks

Calibration enables modelers to set the model parameters that will control the behavior of the simulation with respect to aspects such as the quantity of change, its spatial distribution and spatio-temporal patterns such as the size and shape of patches and the succession of land-use categories over time. Many approaches are used to calibrate land change models including statistical analysis (mainly regression models and weights of evidence), machine learning (neural networks and genetic algorithms) and expert knowledge. Van Vliet et al. (2016) carried out a review of calibration approaches reported in recently published applications of land change models. They found that statistical analyses and automated procedures are the most common approaches, while expert knowledge and manual calibration are less frequently used.

Houet et al. (2016) distinguish two contrasting modeling approaches: (1) a path-dependent approach aimed at mimicking past changes into the future by applying the calibration procedure to a past period. In this first approach, the amount of change can be modified and incentives or constraints maps can be incorporated to produce different scenarios. These models enable researchers to simulate trend-based scenarios and explore various alternative land management scenarios when the quantity and the processes of change do not differ significantly from observed past changes. (2) A non path-dependent approach which assumes that LUCC models are used to spatially represent pre-defined contrasted scenarios. In this case, the parameterization of the future quantity of change does not depend on input maps which represent past changes. However, the parameterization of the allocation of future changes is usually defined by change potential maps obtained by observing past changes. In both modeling approaches, calibration is therefore a critical step. Success in calibrating the model will depend on the stationarity of change, especially in the path-dependent approach.

New applications of land change models involving the evaluation of land-based policies will require increasingly process-based models, able to model complex processes with feedbacks within and between the socioeconomic and biophysical systems across scales (National Research Council 2014). The improvement of land change models is likely to draw on multidisciplinary and interdisciplinary developments and drastically change the way models are calibrated.

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