# Assessing "spatially explicit" land use/cover change models

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## Abstract

Spatially explicit land use/cover change (LUCC) models aim at predicting the location and pattern of LUCC. The simulation involves a spatial procedure which identifies the potential locations of change and eventually replicates the patterns of the landscape. Generally, evaluation is based upon the comparison of the simulated map and a true map of the same date. However, most of the evaluation techniques only evaluate the spatial coincidence between simulated and true changes and do not assess the ability of the model to simulate the landscape patterns. Simulated maps obtained by two models (DINAMICA and Land Change Modeler) were evaluated using a fuzzy similarity index and landscape metrics. Results show that more realistic simulated landscape are often obtained at the expense of location coincidence. When patterns of landscape is an important issue (e.g. Fragmentation), indices taking into account spatial patterns, and not just location, should be used to assess model performance.

*Keywords:land use/cover change, modeling, landscape metrics, assessment*

## 1. Introduction

Over the last decades, a range of "spatially explicit" computational models of LUCC have been developed for the projection of alternative scenarios into the future, for conducting experiments that test our understanding of key processes, and for describing the latter in quantitative terms (Veldkamp and Lambin 2001; Xiang and Clarke 2003). Among these models, process-based models, closely related with geographic information systems, view land use and cover changes as transition process from one state to other states. Typical examples are models based on cellular automata and Markov process models, such as the two models used in the present study.

## 2. Material

We used the programs DINAMICA EGO and Land Change Modeler in IDRISI for LUCC modeling. DINAMICA EGO is a cellular automata-based model which has been applied in a variety of studies, including modeling tropical deforestation (Soares-Filho et al. 2002 and 2006; Cuevas and Mas 2008) and urban growth and dynamics (Godoy and Soares-Filho 2008). Land Change Modeler (available in IDRISI) provides tools for the assessment and projection of land cover change, and their implications for species habitat and biodiversity (Eastman 2006; Gontier et al. 2009; Koi and Murayama 2010). Statistical analysis and graphs were created using R (R Development Core Team 2009).

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Modeling was carried out using the data set supplied with the IDRISI tutorial which consists of land cover (LC) maps and ancillary information from a rapidly changing area in the Bolivian lowlands (Eastman 2009). The data used in the present study are the LC maps of 1986 and 1994 and several maps used as explanatory variables (maps of distance from urban areas, distance from roads, slope, distance from disturbance, elevation).

## 3. Methodology

The present study aimed at: 1) creating modeled LC maps using DINAMICA and LCM; and 2) assessing these maps using two approaches, a) based on the spatial coincidence,, and b) computing landscape metrics.

### 3.1. LUCC Modeling

LUCC are modeled empirically by using past change to develop a mathematical model; and GIS data layers influence the transition potential. The simulation procedures can be sub-divided into the following basic steps:

1) Calibration: The model is calibrated using a map of LUCC obtained through the comparison of LC maps at two different dates (1986 and 1994 in the present case). The quantity of each type of change is computed from a Markov matrix, which is the standard procedure in DINAMICA and LCM. A spatial analysis allows the identification of more likely change locations using a set of explanatory variables. Based upon the relationship between the different transitions and the explanatory variables, maps of change potential are produced for each transition. In the present study, the DINAMICA model uses the map of probability elaborated by the LCM artificial neural network (ANN) in order to obtain comparable results.

2) Simulation: A prospective LC map is created based upon the expected quantity of changes (Markov matrix). DINAMICA and IDRISI use a cellular automata approach in order to obtain a proximity effect and eventually simulate landscape pattern. In IDRISI, the process involves a 3x3 filter which reclassifies pixels to incorporate the effects of neighboring pixels on a current pixel value and there is no option to control the CA behavior. DINAMICA uses two complementary transition functions: 1) the Expander; and 2) the Patcher. The first process is dedicated only to the expansion or contraction of previous patches of a certain class. The second process generates new patches through a seeding mechanism. The user can set parameters to control the size and shape of the simulated patches, such as mean patch size, patch size variance, and isometry. Additionally, a “prune factor” allows simulated changes to occur in less likely areas.

### 3.2. Model assessment

The evaluation of the LC prospective map was based on the comparison between the simulated and the observed (true) map using two approaches: a) the spatial coincidence between modeled and true change; and, b) the spatial pattern of modeled and true change patches.

In order to assess the spatial coincidence between simulated and true changes, we used the fuzzy similarity test based on the concept of fuzziness of location, in which a representation of a cell is influenced by the cell itself and by the cells in its neighborhood (Hagen 2003). Two-way comparison was conducted, applying the fuzziness to the simulated and the true maps of change in turn. As random maps tend to score higher, we picked up the minimum fit value from the two-way comparison. In order to assess the spatial configuration of simulated and true changes, we calculated, for each transition, the amount of change with respect to the map of change probability. For this, a map of susceptibility categories was first obtained by reclassifying susceptibility maps into 10 categories and overlaying this with the maps of changes. Additionally, some metrics used to characterize landscape were computed, such as the number and the size of the patches (mean and standard deviation) and total edge (mean and standard deviation). In the present study, as we are interested in assessing landscape pattern simulation rather than predictive performance, we simulated a 1994 LC map from the model calibrated over the period 1986-94 (i.e. the simulation and calibration periods are the same).

## 4. Result

### 4.1. LUCC Modeling

During 1986-94, the main LUCC transitions were the conversion to anthropogenic disturbance of:

Transition 1:Deciduous mature forest.
Transition 2: Savanna.
Transition 3: Amazonian mature forest.
Transition 4: Woodland savanna.

Only these 4 principal transitions were modeled using as explanatory variables the distance from 1986 urban areas, the distance from roads, the slope, the distance from 1986 disturbance, the elevation and the 1986 LC map. The two programs were used to build 1994 simulated LC maps (Figure 1). In the case of DINAMICA, various settings of prune factors, patch sizes and isometry were tested.

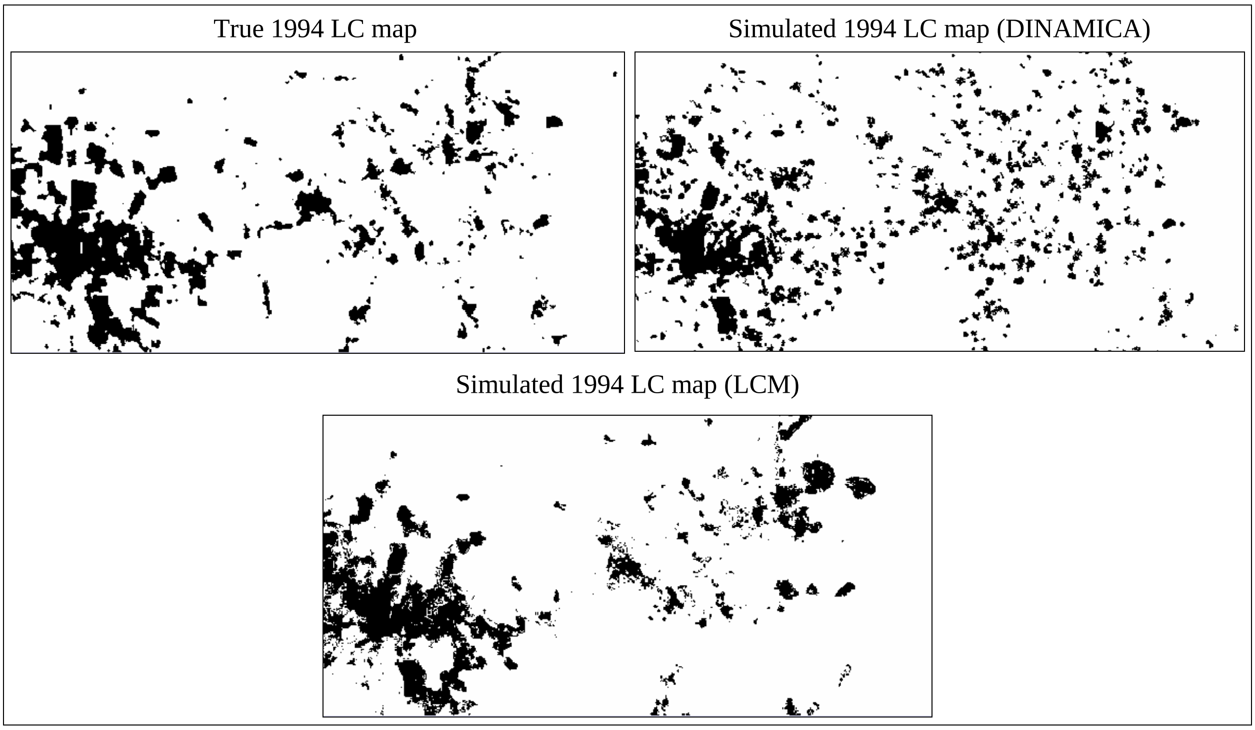


Figure 1: True 1994 LC map and modeled maps by DINAMICA and LCM (Zoom on the Southeastern part of the study area, only the category anthropogenic disturbance is represented)

## 4.2. Model assessment

The fuzzy similarity index indicates that coincidence between the true changes and the changes modeled by LCM is much higher than with DINAMICA using little tolerance (fuzzy tolerance distance < 1000 m). This result was expected as LCM tends to collocate simulated changes only in the areas with higher change potential. Since DINAMICA makes an attempt to create patches and simulates change in less likely areas (if the prune factor value is set high), the coincidence between the true and simulated changes is likely to be lower. However, with higher fuzzy tolerance values, DINAMICA presents a higher score because it has some (fuzzy) coincidence of simulated patches located in less likely areas. This does not occur with LCM that restricts the simulated change to the more susceptible areas only. Therefore, DINAMICA presents a better coincidence "as a broad picture" whereas LCM exhibits a better coincidence on a per-pixel comparison or with little fuzzy tolerance.

Table 1 shows that with DINAMICA it was possible to obtain for each transition simulated patches of change that present broadly the same size as true patches of change. In the case of LCM, the simulation produced some very large patches corresponding to the higher susceptibility areas, resulting in larger values for the mean and the standard deviation of patch size. A similar pattern can be observed for patch edge lengths. However, there are fewer patches on the true change map than on either of the simulated change maps. The map modeled with LCM has 47% fewer patches than the true map.

Table 1: Landscape metrics for true and simulated maps

| Metric | Transition | True Changes | DINAMICA | LCM |
|---|---|---|---|---|
| Number of patches | Transition 1 | 332 | 204 | 192 |
| | Transition 2 | 326 | 208 | 190 |
| | Transition 3 | 666 | 615 | 299 |
| | Transition 4 | 1017 | 804 | 547 |
| Patch size (mean / standard deviation) | Transition 1 | 5.7 / 6.9 | 9.3 / 9.3 | 9.7 / 36.2 |
| | Transition 2 | 9.8 / 18.4 | 15.4 / 21.3 | 16.7 / 41.7 |
| | Transition 3 | 17.1 / 46.3 | 18.5 / 23.5 | 36.1 / 162.1 |
| | Transition 4 | 19.4 / 45.6 | 24.5 / 32.4 | 35.4 / 151.6 |
| Patch edge length (mean / standard deviation) | Transition 1 | 1058.1 / 802.4 | 1551.5 / 1262.8 | 1417.2 / 2936.7 |
| | Transition 2 | 1465 / 1835.6 | 2097.1 / 2056.8 | 2133.2 / 3690.2 |
| | Transition 3 | 1856.8 / 2604.1 | 2245.4 / 2240.3 | 3107.9 / 9325.7 |
| | Transition 4 | 2233.2 / 3343.9 | 2889 / 3184.5 | 3240.2 / 9436.7 |

Figure 2 shows that true changes do not occur only in more susceptible areas and that this tendency depends on the transition. For example, transition 3 occurred mainly in the more susceptible area whereas transition 2 is frequent even in areas with medium susceptibility. The changes simulated by LCM are limited to the areas with higher susceptibility. The setting of the prune factor allowed DINAMICA to generate a map with a distribution of change closer to the observed change.

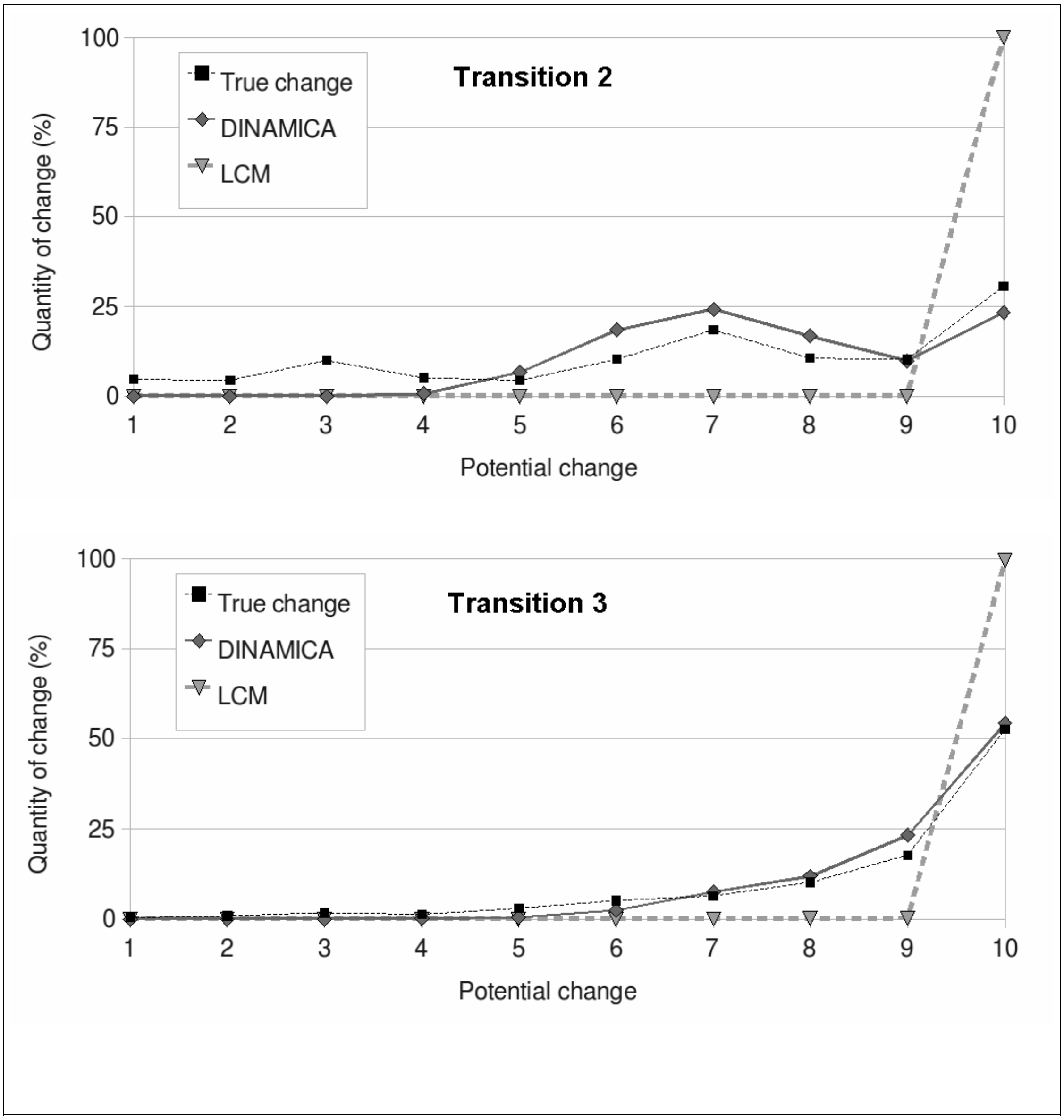


**Figure 2**. Distribution of change in categories of change susceptibility.

## 5. Discussion

DINAMICA was able to generate more realistic prospective LC maps with respect to landscape pattern because it provides parameters to control the CA behavior. However, the best manner of producing a prospective LC map, where simulated changes fit better with the true changes, is by thresholding the susceptibility map, because the majority of the changes occur in the more likely locations. The realism of the landscape pattern in the prospective LC map is obtained at the expense of the accuracy of the locations of the change. This is particularly obvious when models simulate the occurrence of changes in unlikely areas. The prune factor in DINAMICA also allows the occurring of change in less likely areas. When modeling aims at producing LC maps that can represent a possible future given a certain scenario, the accuracy of the spatial allocation of change is not necessarily a critical issue. For example, in the assessment of LUCC

on biodiversity, it can be important to know that homogeneous forest areas will be perforated by small agriculture fields although the exact location of the fields remain unknown.
However, the common procedures of assessment of a prospective LC map are based upon the spatial coincidence of the simulated map and a "true" observed map. Therefore, the modeling and the assessment procedures have to be adapted to the critical feature the model has to achieve. When landscape pattern is an important feature, the computing of landscape metrics can provide valuable insights to evaluate the model performance.

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