Modeling Land Change using One or Two Time Points based Calibration
A Comparison of Factors

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Abstract: One of land change model parameters in calibration step relates to how changes over time and space are considered in the model. A land change model can be calibrated with the state at one time point or with the difference between two time points. The purpose is describing land use and cover (LUC) state patterns, i.e. one time point calibration, and LUC transition patterns, i.e. two time points. For a case study in Spain we obtained the collections of factors for two calibration periods at one time point (dates 2000 and 2006) and the collections of factors for two calibration periods between two time points (periods 1990-2000 and 2000-2006). Evidence likelihood is used to transform the explanatory variables into factors. The objective of this paper is to compare these four collections of factors to show how the choice of reference maps influences the factors and how these factors highlight the change patterns in two different calibration periods and in the calibration of two models. As a following step the detailed results for the different factors and LUC categories are analysed.

1 INTRODUCTION

The validity of the model and its outputs is one of the most important challenges in land change modeling (Paegelow and Camacho Olmedo, 2008; Paegelow et al., 2014). Pontius and Malanson (2005) demonstrate that output varies more as a result of the choice of model parameters than as a result of the choice of the model itself. One of these parameters relates to how changes over time and space are considered in the model, for the purpose of describing LUC state patterns, i.e. one time point calibration, or LUC transition patterns, i.e. two time points calibration (Camacho Olmedo et al., 2013; Kolb et al., 2013).

A model that is calibrated with the state at one time point has certain advantages and disadvantages compared to a model that is calibrated with the difference between two time points. The first approach does not explicitly consider the distribution of land cover resulting from recent past changes and instead assesses the total past changes (Paegelow and Camacho Olmedo, 2005; Villa et al., 2007; Conway and Wellen, 2011; Yu et al., 2011). By contrast, the second approach evaluates the change potential for each possible transition, where the future potential of the space is split into specific transitions across a finite number of LUC categories (Eastman et al., 2005; Sangermano et al., 2010, Wang and Mountrakis, 2011).

When calibrating the model, the patterns of change (or change behaviour) are analyzed by a collection of variables explaining LUC states and/or LUC transitions. From these variables, a collection of factors can be created with a large variety of methods and analyses, as described in previous research into land change modeling (Mas and Flamenco, 2011; Pérez-Vega et al., 2012; Camacho Olmedo et al., 2013, 2015; Kolb et al., 2013; Soares-Filho et al., 2013; Mas et al., 2014; Osorio et al., 2015; Abuelaish and Camacho Olmedo, 2016).

Factors can be created without references to LUC locations, either states or transitions, using transformation methods as natural logarithm, fuzzy, etc. Alternatively, a collection of factors can be made on the basis of information about LUC locations. This is possible if methods such as evidence likelihood are used to create the factors, using the LUC states as the reference areas in one time point calibration, and the LUC transitions in two time points calibration. We chose this option because land change models describing LUC states or transitions must include LUC locations.

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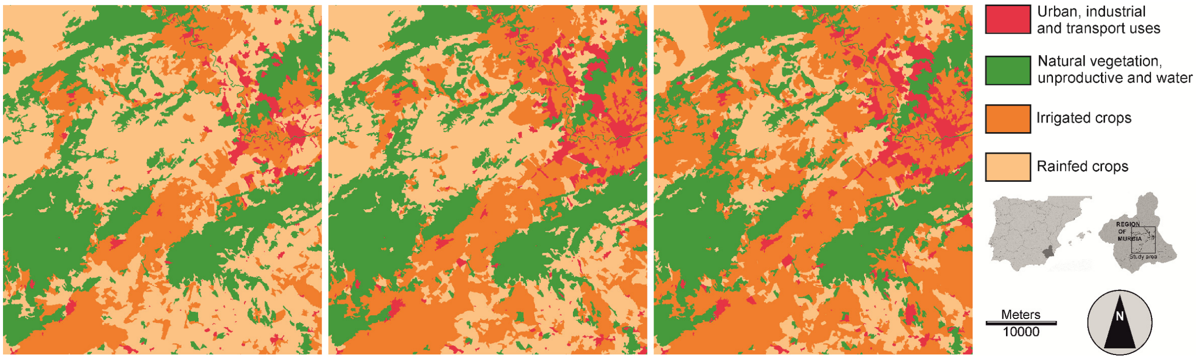

Figure1: LUC in 1990 (left), 2000 (middle) and 2006 (right) in the Murcia region in southern Spain. Source: Corine Land Cover.

Our goals are therefore to obtain and compare factors in order to show how the choice of LUC reference maps influences the factors, how these factors represent the change patterns in two different calibration periods, how these factors represent the change patterns in the two models calibrated in different ways, and, finally the specific behavior of the different LUC categories and factors.

We illustrate the procedure using the TerrSet software (Clark Labs, 2016). For a case study in Spain, we obtained the collections of factors for two calibration periods at one time point (dates 2000 and 2006) and the collections of factors for two calibration periods between two time points (periods 1990-2000 and 2000-2006). Evidence likelihood is used to transform the explanatory variables into factors. We then compared these four collections of factors so as to gain a better understanding of change patterns.

2 TEST AREA AND DATA SETS

Figure 1 shows the specific study area, which covers 2,300 square kilometers in the province of Murcia (southern Spain). The two types of calibration are based on land use and cover data for the different time periods and the related explanatory variables. The maps of land use and cover (LUC) have four categories from the Corine Land Cover (CoORdination of INformation of the Environment, Instituto Geográfico Nacional, Spain) dataset: urban, industrial and transport uses; natural vegetation, unproductive land and water; irrigated crops; rainfed crops. In the rest of this article we refer to these categories as urban, natural, irrigated and rainfed. Corine maps at 1990 (t0), 2000 (t1) and 2006 (t2) are used for model calibration. The explanatory variables are topographic variables, protected areas, territorial accessibility (roads diversity and quality), distance to roads and distance to hydrographic network (Gómez and Grindlay, 2008).

The study area has undergone profound territorial and economic transformations in the recent past. The most important change has been the transition from rainfed crops to irrigated crops, due to the development of water-related infrastructures and the increase in the water supply (Gómez Espín et al., 2011). Urban growth is a secondary change driven by the development of transportation and communication infrastructures.

3 METHODS

3.1 Obtaining Factors

Evidence likelihood is used to transform the explanatory variables into factors. This procedure analyzes the relative frequency of the different categories of a given variable within the areas of LUC states or LUC transitions. It is an efficient means of introducing categorical variables into the analysis, and it accepts continuous variables that have been binned into categories.

The reference areas represented in binary maps are therefore different for model calibration based on one time point or two time points. For one time point, the reference area is the most recent land use category, i.e. the LUC state. For two time points, the reference area is a map showing the changes that have taken place between two points in time, i.e. LUC transitions. This option aims to preserve the nature of the state of the categories and the nature of the changing categories. From now on, we refer to areas corresponding to an LUC state or an LUC transition as 'reference maps'.

We obtained four reference maps for each LUC category. In the first calibration period t0 – t1, the reference map for one time point is a set of binary categorical LUC maps (one for each category) at t1, and for two time points is a set of binary categorical LUC maps (one for each transition) between t0 – t1. In the second calibration period t1 – t2, the reference map for one time point is every LUC state at t2 and for two time points is every LUC transition between t1 – t2 (Table 1). Figure 2 shows the reference maps for irrigated crops as an example.

Table 1: Reference maps for evidence likelihood in one time point and two time points based calibration in both calibration periods.

	First calibration period	Second calibration period
One time point	2000 ($_{t1}$)	2006 ($_{t2}$)
	LUC state	**LUC state**
Two time points	1990 ($_{t0}$) – 2000 ($_{t1}$)	2000 ($_{t1}$) – 2006 ($_{t2}$)
	LUC transitions	**LUC transitions**

In this study we discarded the transitions affecting small surface areas, and grouped together the transitions involving the same final category, a common procedure in transitions modeling. It is important to remember therefore that we are comparing LUC states with almost all, but not all, the LUC transitions. In the practical application only the following transitions are modeled: natural/irrigated/rainfed to urban; rainfed to natural; natural/rainfed to irrigated; natural to rainfed. By far the most important change in the area we studied is the transition to irrigated crops, which is followed some way behind by urban growth.

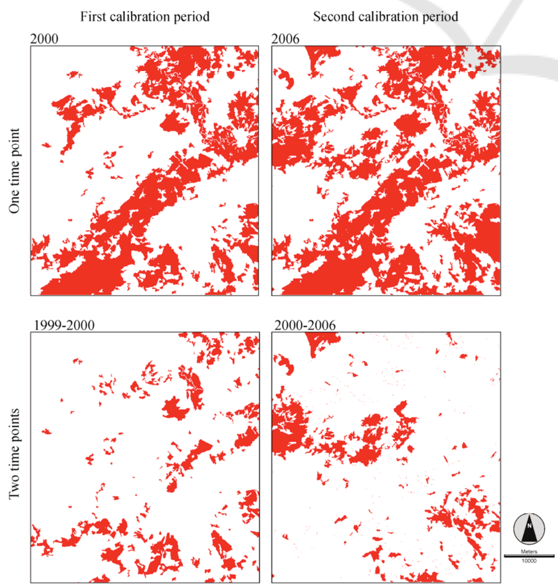

Figure 2: Reference maps for evidence likelihood of the LUC state of irrigated crops in 2000 and in 2006 (above) and of the LUC transition to irrigated crops over the periods 1990-2000 and 2000-2006 (below).

Using these reference maps we obtained four collections of factors for each LUC category: for one time point and for two time points, and both of these for two calibration periods.

3.2 Assessment Methods

The Pearson correlation, a classical method for assessing the congruence of quantitative data, was used for comparing factors. Instead of looking for a causality relationship between pairs of data, the Pearson correlation tries to establish whether there is a relationship between them. Values range from -1 to +1. High positive/negative Pearson values indicate a direct/indirect relationship between two data. Low positive/negative values indicate a lack of relationship.

The Pearson correlation was calculated between all pairs of factors for the one and two time points based models and for the two calibration periods. Factors are quantitative data from 0.0 to 1.0. The higher the Pearson coefficient, the stronger the correlation of factors. We consider values of over 0.8 to be very strong correlations.

4 RESULTS AND DISCUSSION

4.1 Collection of Factors

For one time point and for two time points, and for each of the two calibration periods, the collections of factors were obtained for each LUC category. As an example, Figures 3 and 4 show the collection of factors derived from the elevation variable and from the slope variable in the reference maps for irrigated crops.

4.2 Comparison of Four Collections of Factors

In Figure 5, the Pearson correlation values for every pair of factors (each square corresponds to one comparison) is showed. Each cross tabulation matrix is composed of one column per factor grouped by LUC category (above) or per LUC category grouped by factors (below) and by four rows: One time point based model (first and second calibration period), Two time points based model (first and second calibration period), First calibration period (one and two time points based model), Second calibration period (one and two time points based model).

In Figure 5 (above), the collections of factors for the urban category are all very similar. This means that transitions patterns to this category are very close to the state pattern for this category in both calibration periods. The only exceptions are the elevation and aspect factors. As an example, if we focus on the Pearson correlation values for elevation factors related to the urban category, we can see that for 2000 and 2006 the situations are almost identical (first row); the transitions between 1990-2000 and 2000-2006 are not so close (second row); the state in 2000 is very similar to the transitions over the period 1990-2000 (third row); and the state in 2006 is less similar to the transitions that took place over the period 2000-2006 (fourth row).

The factors for the natural vegetation, unproductive and water category and the factors for irrigated crops vary more sharply: transition patterns in the first calibration period are not similar to those in the second. Transitions are not very close to the state pattern in either period. With respect to irrigated crops, in the second calibration period the transitions patterns are quite different from the state pattern. This is due to elevation, distance to a main irrigation channel and distance to a network of ditches. Finally, for the collection of factors for rainfed crops, a high dissimilarity is present in transition patterns for both calibration periods and with respect to the state pattern, particularly in the first calibration period. However, it is also important to emphasize that the state patterns are stable for all

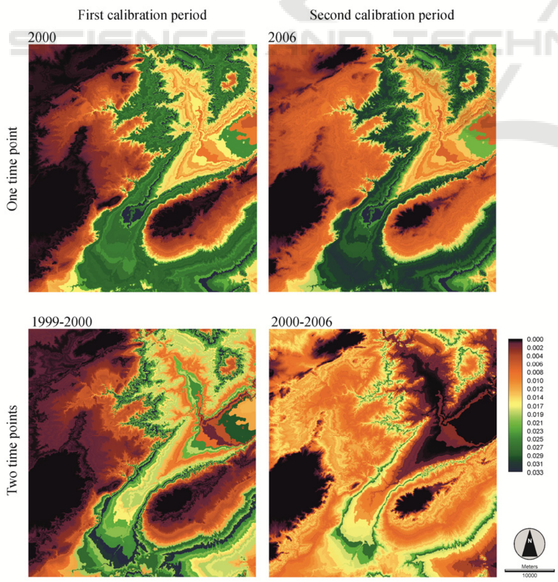

Figure 3: Irrigated crops and elevation. Evidence likelihood of the LUC state for irrigated crops in 2000 and 2006 derived from the elevation variable (above) and of the LUC transition to irrigated crops over the periods 1990-2000 and 2000-2006 derived from the elevation variable (below).

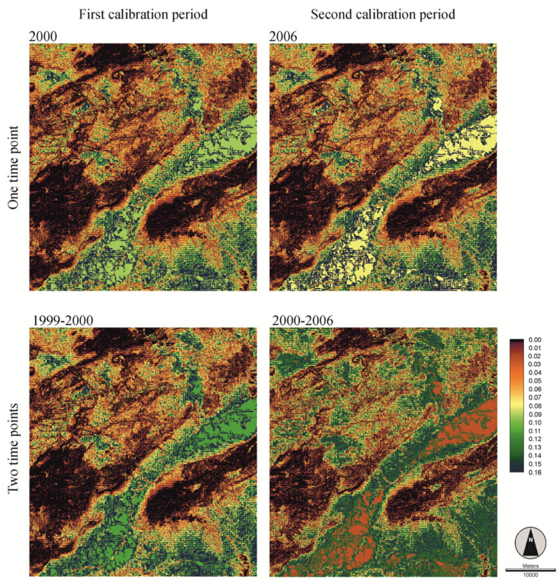

Figure 4: Irrigated crops and slope. Evidence likelihood of the LUC state for irrigated crops in 2000 and 2006 derived from the slope variable (above) and of the LUC transition to irrigated crops over the periods 1990-2000 and 2000-2006 derived from the slope variable (below).

categories (first row in Figure 5, above, one time point based model).

In brief, if we compare the two calibration methods, there is a medium to high linear relationship between LUC transitions and LUC states, which is higher in the first calibration period in all the categories except for one. Looking at each category, the urban patterns are very stable while at the opposite extreme, the patterns for rainfed crops show high variation. The situation also varies a great deal in the natural category and in irrigated crops: the transition patterns are not very stable and are not very similar to the state pattern.

In Figure 5 (below), the Pearson values are grouped by factors. Only factors common to at least two LUC categories are shown. A quick overview confirms that the state patterns are stable for all categories (first row, one time point based model). Aspect is the factor with the highest values in both calibration periods and both models, followed by distance to secondary road, except in the rainfed crops category. Elevation and aspect seem to be the most sensitive factors. They show widely varying behavior, with high, medium and low Pearson values, which means that transition patterns and state patterns are not regular with respect to these variables. With regards to distance to main irrigation channel, the transition patterns for irrigated crops are not regular, although the most irregular are those for

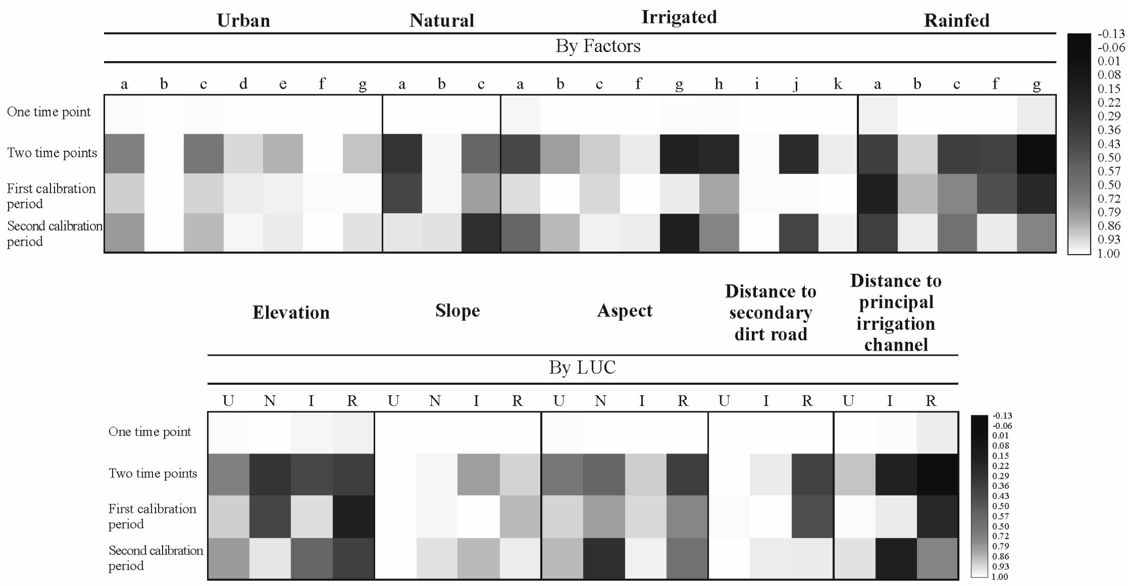

Figure 5: Representation of Pearson correlation values for each pair of factors (each square corresponds to one comparison). Each cross tabulation matrix is composed of one column per factor grouped by LUC (above) and per LUC grouped by factors (below), and of four rows: One time point based model (first and second calibration period), two time points based model (first and second calibration period), first calibration period (one and two time points based model), second calibration period (one and two time points based model). Factors legend (above): elevation (a), slope (b), aspect (c), accessibility to main road (d), accessibility to human settlements (e), distance to secondary road (f), distance to main irrigation channel (g), distance to secondary irrigation channels (h), distance to network of rivers and streams (i), distance to network of ditches (j), distance to water catchments (k). LUC legend (below): urban (U), natural (N), irrigated (I) rainfed (R).

rainfed crops. In brief, when looking at the different factors, the homogeneity or heterogeneity of LUC locations can lead to widely varying behavior. Previous researchers observed a relationship between environmental and accessibility factors and the initial conditions in which LUC changes are carried out (Lambin et al., 2001; Yu et al., 2011 Osorio et al., 2015).

For a better understanding of these patterns, we focused on the collection of factors for irrigated crops. Figures 6 and 7 present the histograms (ha) for the LUC state for irrigated crops in 2000 and 2006 and for the LUC transition to irrigated crops over the periods 1990-2000 and 2000-2006, by elevation intervals and by slope intervals.

If we compare these two variables, we can conclude that irrigated crops behave in a more homogenous manner with respect to slope (only some slope intervals are affected) than to elevation, which explains the different Pearson values commented above. Figure 6 shows that irrigated crops were located at lower elevations in the first calibration period, 1990-2000, and that the new irrigated fields planted from 2000 to 2006, went up to higher elevations, in other words, transitions occurred at different altitudes. However, we do not know if this is a general dynamic or if it is due to the particular behavior of one of the LUC origin categories (natural or rainfed). We must remember that, in this study, we grouped some transitions (natural/irrigated/rainfed to urban; natural/rainfed to irrigated) together. Although this is a common procedure in modeling, it does not allow us to distinguish between the categories that have been grouped together.

Figures 6 and 7 show absolute surface area values (ha), which means that comments must also be relativized with respect to the surface areas of the reference maps. We assume that an LUC state or an LUC transition with a larger area offers more robust statistical representativeness. This means that the factors that are created and their patterns should be more stable. On the other hand, if the surface areas of the reference maps of LUC states and of LUC transitions are similar in size, the patterns should also be more similar, because the LUC transitions are included in the LUC state for the same calibration period.

Figure 8 presents the surface area (ha) for the reference maps for all the LUC categories. As commented earlier, we decided not to model very small transitions or grouped heterogeneous transitions. For the natural category and the rainfed category, the surface areas of LUC states and LUC

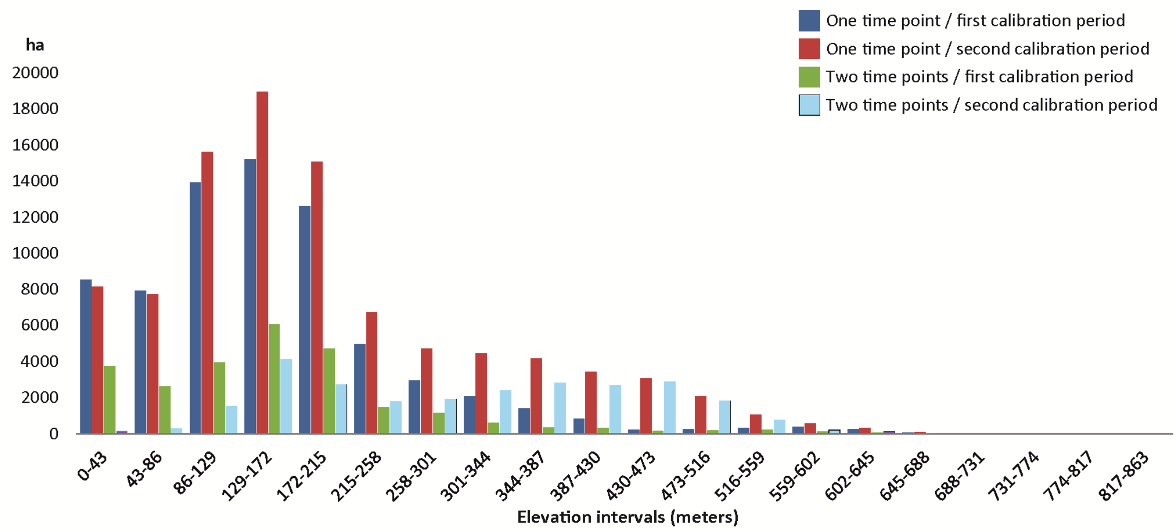

Figure 6: Histograms (ha) for the LUC state for irrigated crops in 2000 and 2006 and for the LUC transition to irrigated crops over the periods 1990-2000 and 2000-2006, by elevation intervals.

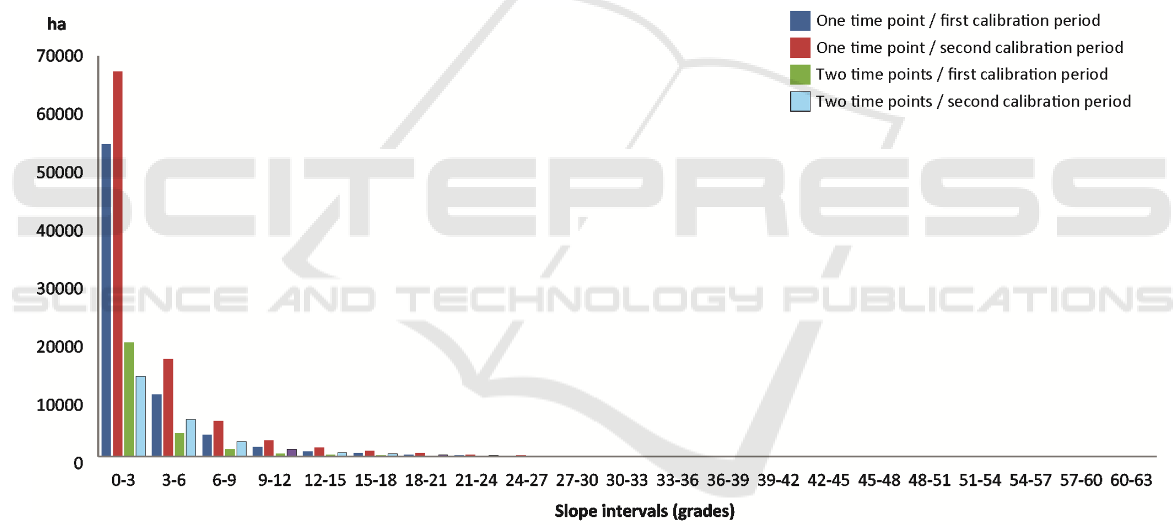

Figure 7: Histograms (ha) for the LUC state for irrigated crops in 2000 and 2006 and for the LUC transition to irrigated crops over the periods 1990-2000 and 2000-2006, by slope intervals.

transitions vary greatly and may therefore show a different pattern in the extracted factors. Besides, LUC transitions to these categories in both calibration periods affect only a small proportion of the study area (<900 ha in the natural category, <400 ha in the rainfed crops category). In fact, LUC transitions to the natural category correspond to less than 2% of the natural LUC state, and LUC transitions to the rainfed category correspond to less than 1% of the rainfed LUC state. Therefore, modeling LUC transitions may not be statistically representative.

For irrigated crops, even if the surface areas of LUC state and LUC transitions vary greatly, they still correspond to 26,386 and 26,026 ha or 36% and 27% of the LUC state for irrigated crops in the two calibration periods respectively. The total surface area covered by urban areas is lower than the other categories, but LUC transitions, with 4,513 and 2,969 ha in the two calibration periods, correspond to 38% and 20% of urban LUC states respectively. This means that modeling LUC transitions for these categories can be statistically representative.

Valuable additional information can be obtained by assessing the coincidence between the reference

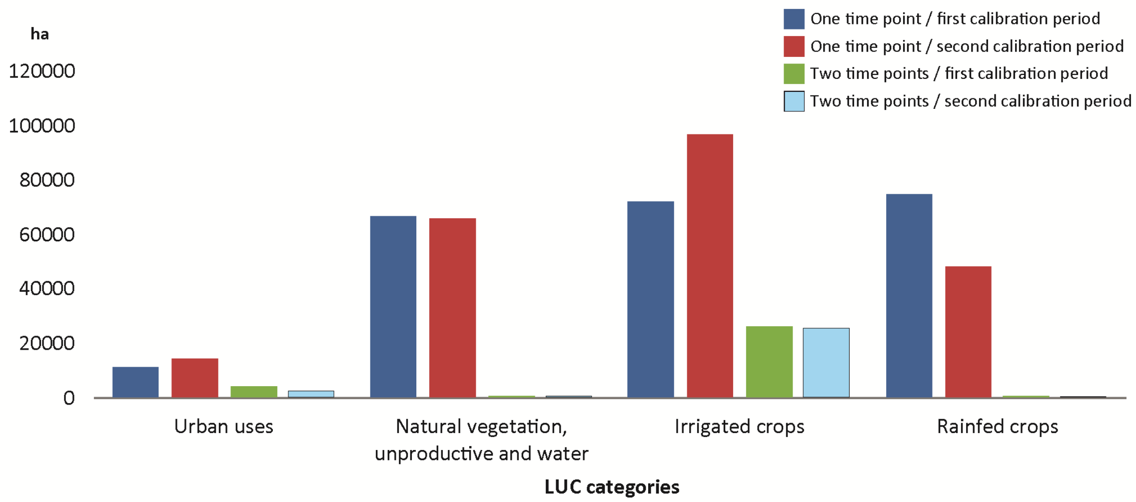

Figure 8: Surface area (ha) of reference maps for the different LUC categories.

maps for the two calibration periods. As commented in section 3.1., there is no coincidence between the areas of the reference maps in the two time points based model. In the one time point based model, the coincidence between the area in the first calibration period with respect to the area in the second calibration period is 100% for urban areas, 97.71% for the natural category, 97.51% for irrigated crops and 63.86% for rainfed crops. However, the coincidence between the areas in the second calibration period with respect to the area in the first calibration period is 79.97% for urban areas, 98.66% for the natural category, 73.20% for irrigated crops and 98.84% for rainfed crops.

This study can be continued by comparing and assessing the soft-classified maps obtained by the different calibration based models. Camacho Olmedo et al. (2013) compared suitability maps (one time point based model) and transition potential maps (two time point based model) in one calibration period. The applied assessment method showed moderate-to-high correlation values between them, inchange-prone areas, for all categories except one. They assessed the predictive ability of soft-classified maps with respect to real maps, and confirmed that a two time points based model outperformed a one time point based model in the case of modeling urban growth because the transition potential map for urban growth captured urban change more accurately than the suitability map did, while the opposite was true for the other categories.

Current research into land change models tends to range from pattern-based models, which are calibrated on the basis of trends observed in the past, to models that try to simulate general processes of change by integrating expert knowledge (NRC, 2013; Mas et al., 2014; Osorio et al., 2015).

5 CONCLUSIONS

A land change model can be calibrated with the state at one time point or with the difference between two time points. These approaches therefore involve modeling either LUC states or LUC transitions. The first approach implicitly includes all past changes, while the second considers past changes that occurred during a recent period. The calibration of land change models by one time point or two time points, i.e. states or transitions, gives different results. The choice of reference maps affects the similarity or dissimilarity of factors.

Factors obtained from the LUC state (one time point based model) in two calibration periods show a high linear relationship. The state pattern is therefore stable. The one time point based calibration model could therefore be accurate at modeling categories in which transitions affect a proportionally small area and also when patterns of change vary in recent periods. This "total past trend" based calibration is more likely to capture historic patterns of change and simulations over longer time.

Factors obtained from LUC transitions (two time points based model) in two calibration periods show highly varied values, from non-linear to highly linear relationships between them. Modeling LUC transitions can be statistically representative when they correspond to a proportionally larger area and when patterns of change are maintained over two successive periods. This "two past trend" based calibration is more likely to capture recent patterns of change and simulations over shorter periods.

A multi-temporal approach, integrating data about more than two training dates, could resolve potential errors resulting from only considering two past dates or by considering the total past, and would be more appropriate for creating forecasting scenarios. However, a choice must be made between using states or transitional data in the calibration of the models. Depending on multiple parameters, including form and intensity of dynamics, the two approaches may be complementary.

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