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Modelling land use changes in southeastern Spain using a Markovian approach.

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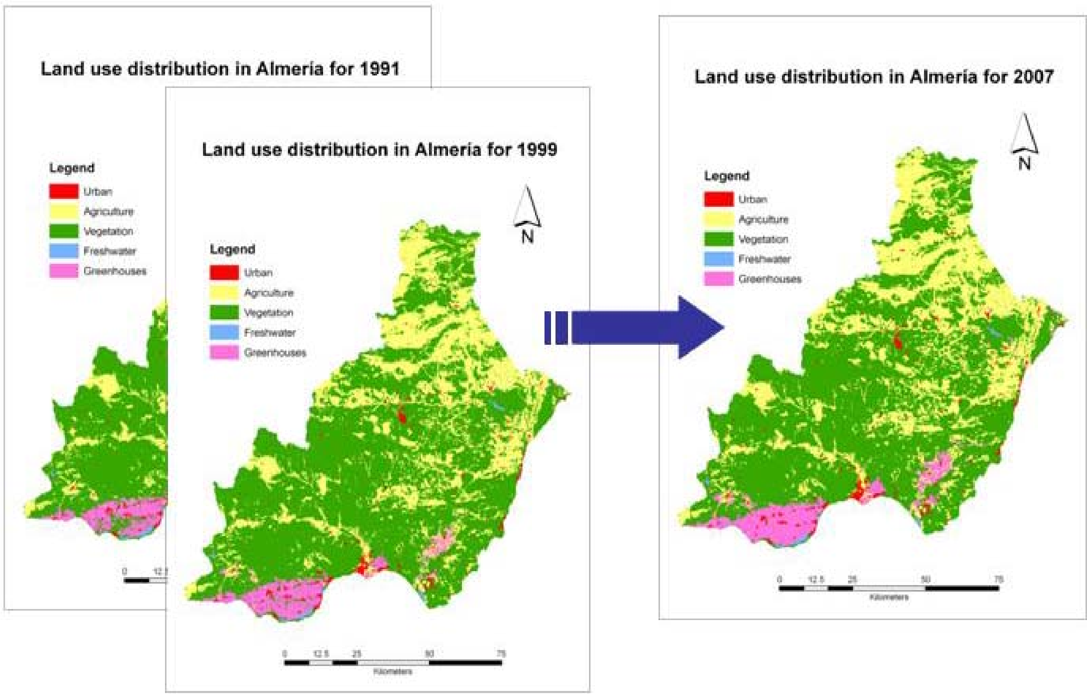

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Modelling land use changes in southeastern Spain using a Markovian approach.

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Abstract

Anthropogenic land-use (LU) activities are altering at high rates the natural ecosystems of the southeast of Spain. Biodiversity is lost, natural resources depleted and ecosystem services reduced. Here, we present the application of a Markovian cellular automata (CA Markov) model to spatially locate land-use changes (LUCs) in the Almería province to detect natural threaten areas. CA Markov has low data requirements and is a friendly use model. It provides visual interpretation of LUCs and facilitates the detection of vulnerable areas threatened by human harmful uses.

A LU projection was done at a provincial and ecosystem level from 1991-1999 to 2007. A validation of the model projections was carried out in 2005 using field data. Accuracies Accuracy results were suitable for the purpose of the analysis although when comparing the LU projection with a null model, the CA Markov showed a high stability in LUC. The reliability of land-use projections was interpolated for the whole province by an indicator kriging. Dynamic areas showed low accuracy values due to either the quality of the inputs, the use of a suitability map that does not takes into account the spatial degree of LUC or both. The CA Markov application presented a spatial extent dependency. For areas with a LU distribution differing from its surroundings, the use of a more detailed spatial extent (regional ecosystems) approach of CA Markov is recommended. However, the provincial approach is needed for governance and planning.

The main LU forces of change detected were urban developments for tourism purposes, greenhouses and other forms of agriculture. The two first, forced the highest vegetation loss in Semi-arid Hollows regional ecosystem. This regional ecosystem contains most of the LUCs of the province for the studied period. Five main areas of the province where the most dynamic: Campo de Dalías, Campos de Níjar, Corridor Tabernas-Sorbas, Almanzora river basin and Watercourse of Chirivel. Landscape equilibrium state was also calculated and resulted that provincial natural vegetation would be isolated in protected areas in 2034 if the current management policies do not change. This showed the need for conservation outside protected areas.

Key words: Almería, Cellular Automata, landscape planning, Markov, regional ecosystems, spatial extent, steady state, vegetation loss.

1. Introduction

Land-use change (LUC) is considered one of the biggest threats to regional and global biodiversity because of the its strong impact on the environment (Vitousek, 1994). Indeed, LUC and climate change are consider to be the main components of the so-called "Global Change" (Sala et al., 2000). At the European level, LUC has been detected as one of the main human forces of biodiversity loss (EPBRS, 2004). And in this context, the Mediterranean biome is where ecosystems disappear faster as new human constructions and activities are developed (Van Eetvelde, 2004). In this area, the traditional agricultural and forest uses configuration maintains a high biodiversity (UICN, 2003).That is the reason why the Mediterranean basin is recognized as one of the most important world biodiversity "hotspots" (Medail and Quezel 1999). The expansion of human land-uses (LU) implies the fragmentation of natural areas and the loss of their biodiversity and natural resources (Meffe and Carroll, 1997). LUCs are, therefore, one of the major forces of biodiversity change in the Mediterranean basin (Sala et al., 2000). From a socio-economic point of view, the reduction of natural ecosystems can be seen as a loss in the environmental services that they supply to the territory (Daily, 1997;Costanza et al., 1997).

Particularly, in the southeastern Spain, the increase in population density and the fast growth of human LUs, represent considerable threats and real challenges for conservation and sustainability policies (Fernández-Revuelta Pérez, 2005). The urbanization linked to coastal tourism (Environmental European Agency, 2005) and the expansion of intensive agriculture are the main LUCs in the region.

The anthropogenic forces that drive these changes act at different spatio-temporal scales, depending on human management capabilities, the future extent and gravity of ecosystem losses can be avoided. Hence, a good understanding of the LU forces and their predictions at proper spatial and temporal scales are of high interest for sustainable management (Vasconcelos et al., 2002). LU models can provide the understanding of LUC and facilitate the detection of threaten natural areas. However, some of the current LUC models are so complete/complex that its operational use by planners and stakeholders is almost not feasible. In this study we present a friendly use LU model possible to use by a broad the extent of potential users, i.e. planners, managers, scientists, etc.

Models are used since early ages to predict future situations and for several disciplines. They have been used as potential tools allowing a better knowledge of the systems. Ecological models have been focused only on the analysis of the evolution of the vegetation (Trani and Giles, 1999;Mendoza and Dirzo, 1999;Trejo and Dirzo, 2000). However, integrated analyses are needed in order to understand the landscape and its LUC dynamics as a whole. In this respect, many authors recommend the use of predictive LU models because they allow the study of the landscape as a whole (Wood et al., 1997;Thornton and Jones, 1998;Veldkamp and Lambin, 2001). These kinds of models have already been used both at global (Alcamo et al. 2004, Nordhaus 1992) and regional scales (Koning et al. 1999, Verburg and Veldkamp 2001, Voinov et al 1999). The tool used for its performance can be based on Remote Sensing Images or on thematic maps integrated on Geographical Information Systems (Lloret et al., 2002;Vasconcelos et al., 2002;Gallego, 2004;Van Eetvelde, 2004;Bielsa et al., 2005) .

LU models are implemented in many different ways. Thus, some models are based on statistics (Schneider and Pontius 2001, Tilman et al. 2001), probabilistic analysis (Wood et al 1997, Weng 2002) or Monte Carlo Analysis, while some others make use of artificial neural networks (ANN) to model the evolution of LU. Nevertheless, these models have a number of drawbacks: stochastic models are meant to be used for short-term predictions (Lambin et al., 2000;Luijten, 2003) and, Monte Carlo and ANN have high computation demands and the need of a calibration before performing operations (Li et al., 2002;Eckhardt et al., 2003) .

Within the broad LU model types, probabilistic models are preferred for analysing spatio-temporal LU dynamics (Logsdon et al., 1996) . These models are also choosen for analysing LU change at regional scales, and their projections are better than those done by linear extrapolations (Aaviksoo, 1993). In this context, markovian approaches are probabilistic regional models that have been profusely used for vegetation dynamics (Aaviksoo, 1993;Balzter et al., 1998;Balzter, 2000), dynamic agricultural uses (Thornton and Jones, 1998) and LU/land cover changes (López et al., 2001;Weng, 2002). Some of the characteristics of Markov probabilities of change are listed below:

- They are based on probability matrices that are easy to compute and they allow for a good simulation on the frequency of changes of the inputs. Its simplicity saves costs and effort by avoiding measurements of a large number of factors and due to their small data requirements (data constrains) (Balzter, 2000;Luijten, 2003).

- In general, Markov transition probabilities matrices are easy to implement and they allow for a good simulation (Wood et al., 1997).
- However, they are dependent on the initial state of the inputs and historical processes are not taken into account (Aaviksoo, 1993).
- A constant state probability which represents the steady state of a landscape (Balzter, 2000;Commission on Geosciences, 2001) can be computed
- They lack of spatial knowledge (Lambin, 1997),

In this context, a markovian approach was chosen for the analysis of LUC and to result in a more spatially dependent approach, a cellular automata (CA) model based on Markov transition matrices was selected. Cellular automata are dynamic models discrete in time, space and state and they are used to model landscape dynamics and changes in LU (Balzter et al., 1998). Especially, Cellular Automata Markov (CA Markov) is a probabilistic model that provides a spatially detailed analysis and quantitatively describes future trends in order to indicate the direction and magnitude of LU changes (Weng, 2002). Also, stochastic rules used for the matrix building are supported when applying a cellular automata to ecological systems (Phipps, 1992).

The aim of this work was i) to test an easy to use model for detecting LU change in Mediterranean ecosystems. This model should be an efficient tool for conservation management and ii) to detect particularly vulnerable ecosystems and natural endangered areas threaten by future LUCs.

CA Markov quantified and located transformations for the South-East of Spain. The CA markovian probabilities of LU change were projected and the main forces of change explored. Finally, recommendations for conservation management were derived from the model performance and results. The specific objectives of the study were: i) to spatially detect and quantify LU changes over the short term, ii) to analyze the performance of the CA Markov model at different spatial extents, iii) to evaluate the final state of the landscape if the LU management policies do not change, iv) to locate the areas where especial management attention should be focus.

2. Materials and Methods

2.1. Study area and current situation

The study area comprises the whole province of Almería, which is the most South-Eastern province of the Iberian Peninsula (Fig. 1). The province of Almería has an area of approximate 8.770 km^2 and about 580.000 inhabitants (year 2004). Its economy is based on intensive agriculture on flat areas, as well as coastal tourism and mining. Agriculture has been intensified to the extent that this activity is nowadays referred as 'agriculture factory' (Sánchez-Picón, 2005). Tourism has increased to 1.460.000 the amount of visitors since the past five years (www_1). From a biodiversity point of view, the province is a specially rich and unique area within Europe (Medail and Quezel, 1999;Cabello Piñar, 2002). Its more than 2.700 plant species (Sagredo, 1987) include 20% of the Iberian endemic plant genera as well as some African and Asian disjunctions not present in the rest of Europe. It also contains several priority habitats for conservation (Directive 92/47/CEE). However, this richness is being threatened by the expansion of human LUs on natural landscapes.

During the last 25 years the standard of living in the province has significantly improved (Sánchez-Picón, 2005). This economical improvement had as a consequence the abandonment of some areas and intensification of the human activities in others, rural exodus (Aznar Sánchez, 2005) , ecosystem loss and habitat fragmentation. The main causes of these environmental impacts are the greenhouse expansion (Mota et al., 1996) and tourist urbanizations (Caro Gómez and Teruel Moreno, 2005). This, in turn, is leading to the isolation of protected areas (Piquer Rodríguez et al., 2004). The existing surface of protected areas is known as the Natural Network of Protected Areas of Andalucía (RENPA) and it covers 33% of Almería. During the coming years, RENPA will be reinforced by the European Natura 2000 Network up to 52% of the province surface (www_2). Therefore, as a preservation measure, the knowledge of future LU changes that can harm Natura 2000 sites is of a high importance.

Figure 1. Location of Almería province (SE Spain) in the European context.

2.2. Data sets

2.2.1. LU data

In this study, the LU maps of Almería for the years 1991 and 1999 are selected as the basis of the analysis (Fig.2). These datasets, produced by the regional government, were elaborated based on orthoimages and photo interpretations of Landsat-TM and IRS-Pan data at a scale of 1:50.000. The final product is presented in vector format and it has a global error of 5.6% for a 95% confidence interval (www_3). These data sets have 3 levels of detail and up to 120 classes. In order to perform simple LU projections, the LU classes were aggregated into a 5-class category: urban, agriculture, natural vegetation, freshwater and greenhouses. Under the urban class, urban nucleus, rural settlements, roads and quarries were included. Natural vegetation was referred just as vegetation. Under the agriculture class, non-irrigated and irrigated lands were included. Notice that all intensive agricultural practices below plastic were included in the class greenhouses and not under agriculture. Rivers, water reservoirs and marshes were aggregated to the class freshwater. LU classes and some area metrics for the province of Almería are showed in Table 1.

In general, the landscape is dominated by agriculture and vegetation although during the last 10 years there has been a steep increase of the surface occupied by greenhouses and urban areas. The fragmentation of the provincial LU also increased from 1991 to 1999. Finally, the initial vector data sets were rasterized because the CA Markov analysis is performed in a raster environment. A 30x30m grid was used during the rasterization in accordance with the Landsat TM pixel size.

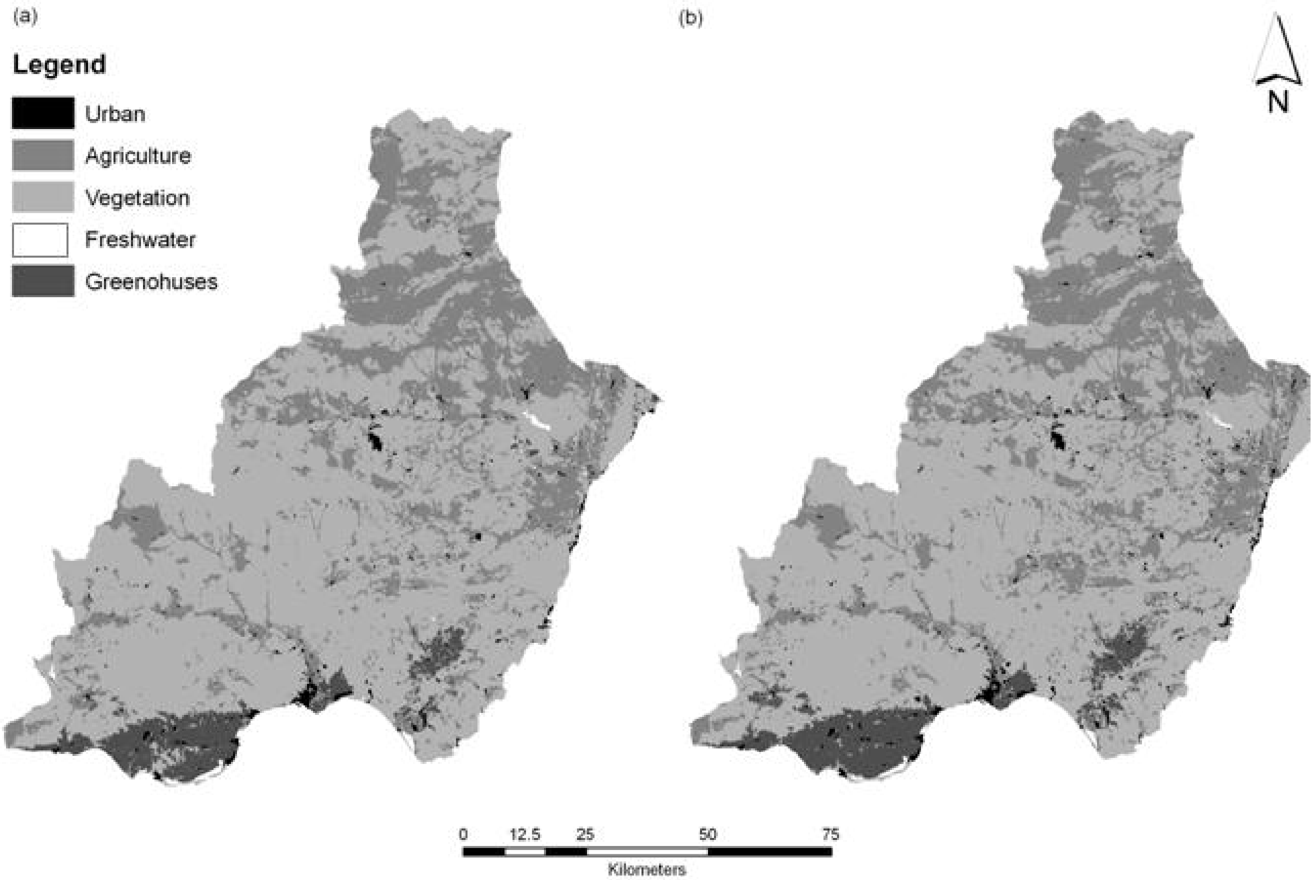

Figure 2. Land-use data sets 1991 (a) and 1999 (b)

Table 1. Proportion of LU in Almería for 1991 and 1999

LU	1991 Area (%)	Mean Patch Size	Median Patch Size	1999 Area (%)	Mean Patch Size	Median Patch size
Urban	1.2	24.67	7.75	1.46	20.71	6.05
Agriculture	27.44	189.59	11.60	28.6	172.26	9.95
Vegetation	67.78	1040.35	12.27	65.69	772.16	11.04
Freshwater	0.22	47.93	1.79	0.26	4.49	0.43
Greenhouses	3.36	155.10	7.96	3.99	56.13	2.17

2.2.2. Regional ecosystems data

Predominance of certain LU types are detected for particular landscapes and activities in the province. This leads to different landscape processes depending on the spatial scale and extent of analysis. For instance, urbanization tends to increase at the coastal area; while remote areas are likely to stay unchanged. This means that, nature will suffer from human activities more intensively were new activities will develop. In order to differentiate patterns of LU distribution within provincial landscapes and to study the different spatial human affections to nature, the Regional Ecosystem zonation of Almería was used (Cabello et al., 2006). The use of eco-regions allows the detection of patterns and the distribution of environmental resources (Loveland and Merchant, 2004;Jongman et al., 2006). And therefore, it facilitates the spatial analysis of LUC affecting the provincial ecosystems (Fig. 3 and Table 2).

Table 2. Regional Ecosystems main characteristics

Regional Ecosystems	Potential Vegetation	Province Surface (%)
High mountains (HM)	Oromediterranean scrublands and pine woodlands	1
High Plateau (HP)	Mediterranean sclerophylous oak forests	6
Betic Mountains (BM)	Mediterranean sclerophylous and semideciduos oak forests	38
Semiarid Mountains (SAM)	Mediterranean sclerophylous oak forests, Maquis and Iberoafrican arborescent shrubland	13
Semiarid Hollows (SAH)	Iberoafrican arborescent shrubland, maquis and semiarid scrublands	42

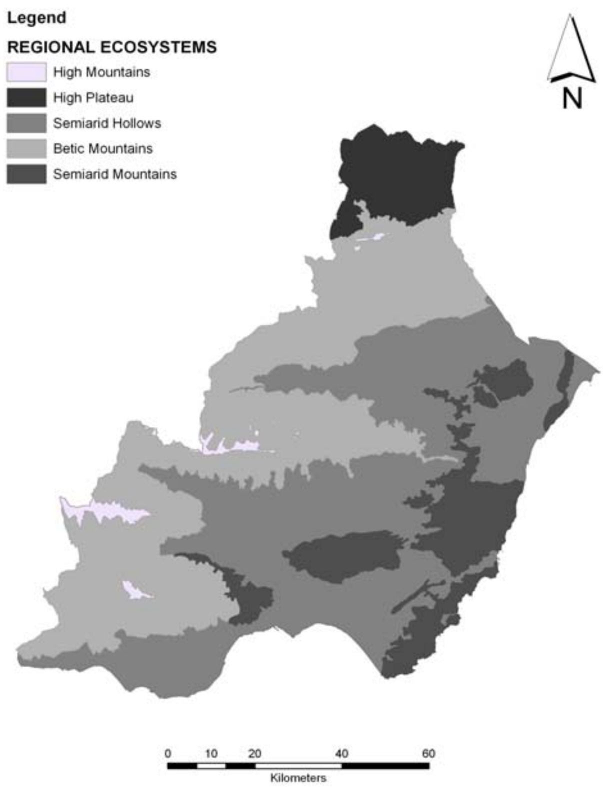

Figure 3. Regional Ecosystem map for Almería province

Dynamic regional ecosystems suffering LUC can be damaged earlier by human uses. Therefore, to detect and focus LUC analysis in those most dynamic regional ecosystems, a vegetation lost rate was calculated for each of them. The use of the rate of vegetation change as defined by Puyravaud (2003) allows the identification of the ecosystems with the highest rate of vegetation loss. Table 3, which summarises the results of this analysis, shows that the Semiarid Hollows (SAH) and the Semiarid Mountains (SAM) are the two most dynamic ecosystems in Almería. Thus, these regional ecosystems will receive special attention during the subsequent analysis.

Table 3. Natural and seminatural area loss in the late XX century in Almería

Regional ecosystem	Natural vegetation loss 1991-1999		
	Annual rate (r)[1]	Lost area	
	% per year	%	Surface (ha)
Semiarids Hollows	-0,0079	6,11	13,226
Semiarids Mountains	-0,0032	2,52	2,538
Betic Mountains	-0,0013	1,04	2,453
High Plateau	-0,0013	1,00	255
High mountains	-0,0008	0,63	76

(1) Puyravaud annual rate of vegetation lost (Puyravaud 2003)

2.3. Modelling LU change

The CA_Markov model, available in IDRISI Kilimanjaro software (Eastman, 2003), was used to project the distribution of LUs in Almería for the years 2005 and 2007. The LU projections for 2005 were validated with data collected in the field whereas the projections for the year 2007 were used to map LUC and identify the areas where human activities are threatening natural ecosystems.

2.3.1 Model methodology

The CA Markov is a combination of the markovian transition probabilities and a cellular automaton used to allocate the different LU types. The functioning of the model is described in figure 4. First, the Markov application inputs two LU raster datasets, beginning and end date of the analysis period, as well as the proportional error of the LU datasets (ε), i.e. global error of the LU inputs. The model used supposes that the proportional error is the same for both inputs and therefore taken into account just once. It results then in a transition probability matrix, an area transition matrix and a set of suitability images. The transition probability matrix is the probability of each LU to change to any of the LUs present in the landscape. The area transition matrix is the proportion of pixels of each LU class that will change to another LU. The suitability image is a set of binary images (one for each LU) that contains the spatial location of the LU classes and it is generated by default by the markov model. This image is used as an input by the CA to allocate the new changing cells of use, surrounding the initial LUs. Other CA inputs are the markov area matrix and the LU map to project LUs forward. The CA Markov results in a spatially distributed LU map in raster format.

In this study two spatial extents and dates will be analysed: the ecosystem (semiarid areas) and the provincial level; and for the years 2007 and 2005 (when validation takes place). Different spatial extents are expected to have differences in landscape processes and in human affection to ecosystems. At the ecosystem level the main forces that generate changes in the landscape will be studied (LU change forces). At the provincial level 3 analyses were done. Detection of forces of change, a map of the spatial location of LUCs from 1991 to 1999 and the time when the landscape reaches its equilibrium in terms of LUC.

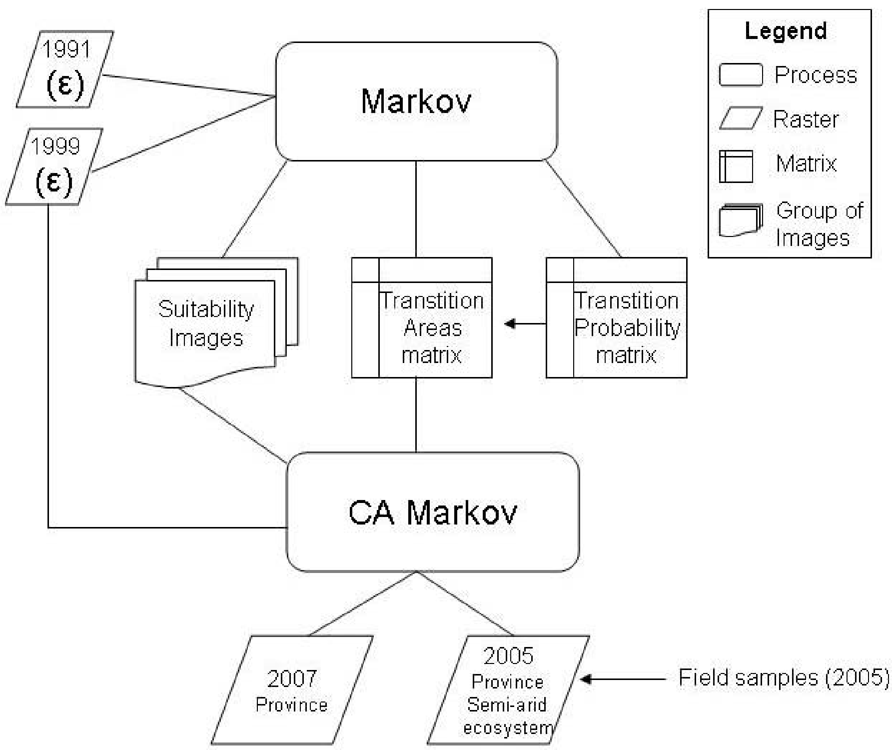

Figure 4. CA Markov model function in the used software.

Markov transition matrices

Markov transition matrices are based on the cross-tabulation of the inputs and from there the probability matrices of change are generated. More precisely, the Markov transition probabilities matrices for the change in time equal to the time step between the two inputs are calculated as follows: When the time interval between the two inputs (τ), t1 and t2, is the same as the time interval to project forward in the model (t), the probabilities of change are calculated as in equation 2. Let $P_{i,j,\tau}$ be the probability of transition from LU i to LU j in time interval τ, and $n_{i,j}$ the number of pixels that change from one LU to another one. Notice that the matrix **P** is row-standardized; this means that the sum of each row equals one.

$$\mathbf{P}_{i,j,\tau} = \frac{n_{i,j}}{\sum^{i} n_{i,j}} \qquad \text{(Eq.2)}$$

The transition probabilities computed in this way are used to project the distribution of LUs for the next time step (López et al., 2001;Syphard et al., 2005;Paegelow and Camacho Olmedo, 2005). In our case, that means that these probabilities give the LU situation for the year 2007 because our input time step is of 8 years.

In order to validate the LU projections, the transition probabilities for the year 2005 were computed too ($\mathbf{P}_{i,j}$). In this case, the projection time interval is different from the "default" time step ($t \neq \tau$) therefore the probabilities need to be adjusted according to Eq. 3

$$\mathbf{P}_{i,j} = 1\text{-}\exp[\ln(1\text{-}\mathbf{P}_{i,j,\tau})]/\tau \qquad \text{(Eq.3)}$$

The transition probability matrices can be corrected for potential errors in the input datasets ($P_{i,j}{}^{\varepsilon}$). Indeed, most of the LU maps are not error-free and therefore have a indicator of their quality (accuracy) that can be used to correct the transition probability matrices Eq. 4

$$\mathrm{P}_{i,j}{}^{\varepsilon} = \begin{cases} \mathrm{P}_{i,j} \cdot (1-\varepsilon) & \text{when i = j} \\ \mathrm{P}_{i,j} \cdot 1 - \mathrm{P}_{i,j} \cdot (1-\varepsilon) \Big/ \sum\limits_{\forall i \neq j}^{i} \mathrm{P}_{i,j} & \text{when i} \neq \text{j and } \sum\limits_{\forall i \neq j}^{i} \mathrm{P}_{i,j} \geq 0 \\ 1 - \mathrm{P}_{i,j} \cdot (1-\varepsilon) \big/ (N-1) & \text{when i} \neq \text{j and } \sum\limits_{\forall i \neq j}^{i} \mathrm{P}_{i,j} = 0 \end{cases} \qquad \text{(Eq.4)}$$

Where ε is the proportional error and N is the number of LU classes.

The transition area matrices, which quantify the amount of LUC between the times t and t+1, can be easily computed from the probability matrices and the LU distribution for the year t:

$$A_{i,j}^{(t+1)} = P_{i,j}^{(t+1)} \cdot A_i^t \qquad \text{(Eq.5)}$$

where $A_{i,j}^{t+1}$ is the area that change from LU class i to class j in the period t to t+1, $P_{i,j\,(t+1)}$ is the probability of change from class i to class j in the period t to t+1 and A_i^t is the area of class i at the time t.

Cellular Automata Module

The CA Markov model uses the areas transition matrix (Eq.5) and a suitability map to perform the spatial allocation of the different LU types. More specifically, a moving window is used to spatially allocate the cells that will change their LU type. Different size of the moving window will result in different LU allocations. Thus, the optimal window size for LU projections was searched analysing several landscape metrics. As a result of this analysis, the median weighted patch size was determined as the best landscape indicator for the moving window size (see Table 2). The median patch size gives the median value for all the patches of the LU data set. The median was chosen against the mean as we were dealing with a skewed area data distribution (Thorne and Giessen, 2000;Moore and MacCabe, 2003;Levin and Fox, 2004). The skew coefficient for the 1999 median patch size was 56.29. Therefore, from this analysis it was agreed to use a 5 x 5 Moore neighbour filter, which is a squared window with 5 x 5 cells whose area coincides with the median weighted patch size for 1999. The CA Markov was executed for 2005 and 2007 in order to get spatial LUs distribution of the province and semi-arid ecosystems.

Landscape equilibrium state

The Markov matrices can also be used to derive the final state (or steady state) of a landscape in case that the current LU policies do not change. According to the Markovian theory, the transition probability matrix for the n^{th}-time step is equal to the n^{th}-power of **P** (being **P** the first probability matrix computed from the initial input datasets). If the matrix **P** is primitive then, the sequence of powers of **P** asymptotically approaches a matrix **T** whose rows (t) are the steady state of the landscape (Lipschutz, 1965):

$$\xrightarrow[\text{n -Time steps}]{\mathbf{P},\ \mathbf{P}^2,\ldots,\ \mathbf{P}^n,\ldots,\ \mathbf{T}} \mathbf{T} \approx \lim_{n\to\infty} \mathbf{P}^n$$

According to Caswell (1989), **P** is primitive if $\mathbf{P}^{n^2-3\cdot n+2}$ is larger than 0. If this is the case, then the Perron-Frobenius Theorem states that P has an eigenvalue equal to 1 (λ_1, dominant eigenvalue) and that the eigenvector corresponding to this eigenvalue is t, the steady state of a landscape.

Using these properties it is also possible to calculate the time when the landscape reaches its final state (T). Because the final state of a landscape is an asymptotic limit, it is more appropriate to calculate the time steps needed to converge to the final state with a given confidence interval (CGER 2000). This can be done with the Eq. 9

$$t_{step}=\ln([100/(100-\mathrm{CI})]-\rho) \qquad \text{(Eq. 9)}$$

Where CI is the Confidence interval and ρ is the damping ratio (Caswell, 1989) which is the ratio of the dominant eigenvector (λ_1) divided by the absolute value of the second largest eigenvalue ($|\lambda_2|$) (Eq. 10).

$$\rho=\frac{\lambda_1}{|\lambda_2|} \qquad \text{(Eq.10)}$$

A confidence interval (CI) of 95 was chosen for the calculation of the time steps to reach the final state of the landscape.

2.3.2. Validation

In order to validate the CA Markov projections, an extensive field data campaign was done during 2005. A stratified probability field sampling scheme was selected for the validation. Field samples covered each regional ecosystem and were focused on agriculture and vegetation areas as they contain most of the biodiversity. In this way, 240 points were prepared for sampling. They covered the coast very intensively as it was assumed that this is the area where most of the human activities take place. The point sampling size was of 30 x 30 meters according to the pixel size of Landsat TM (Franklin et al., 1991;Janssen and Van der Wel, 1994;Stehman and

Czaplewski, 1998). The spatial support region of the sampling unit was defined as 250x250 meters and it was considered to be homogeneous for the surrounding sample points. When more than two LUs were found to coexist in the same support region the one affecting nature the most, was set as the use for that unit. The labelling protocol consisted on assigning to each sampling unit one of the 5 aggregated LUs defined in the LU maps section.

The confusion matrix (Congalton, 1991), the kappa index (Cohen, 1960) were selected as the main accuracy measurements. The so-called producer and user accuracies were also used to get class-specific accuracies.

In addition to these map accuracy indicators, the statibility of the projections was tested using the "null model approach". The LU data from 1999 was compared with both, the LU projection for 2005 and the field work data. We assume that in case the comparison results are very similar, the projection model will be predicting more stability than future changes. Similarities among the maps will be analyzed in terms of area, i.e. disagreement due to quantity, and in terms of the cell-to-cell comparison, i.e. disagreement due to location (Pontius et al., 2004).

Finally, a reliability map of the LU projections was done using a so-called indicator kriging (Steele et al., 1998). This type of kriging performs an interpolation of the accuracies after they have been coded as 1 if the map has the same class as the one identified during the field work or 0 if the map has another class.

2.3.3 LU dynamics at two spatial extents

Different spatial extent analysis will imply differences on the processes influencing the landscape systems (Kok et al., 2001). Therefore, the analysis of the landscape at different spatial levels is needed for an effective LU planning (Verburg and Veldkamp, 2001). Especially, in Almería most of the activity is concentrated in the two semiarid and dynamic ecosystems of study. From an analytical point of view, it was expected that a more spatially detailed study gives a more realistic adjustment of the markov model. In order to test the performance of the model at different spatial extents it was run for an ecosystem and provincial level for 2005. The ecosystem level application consisted in the calculation of each LUs area (Ae) when the model was executed exclusively for a regional ecosystem. The provincial application assessed the general execution of the model for the whole province of

Almería and afterwards the regional ecosystem of study was extracted for its future LU area calculation (Ap).

3. Results and Discussion

3.1. Model performance

Following the Eq. 2 and 4, we computed the transition probability matrix for 2007. Markov transition probabilities of change for 2005 derive from the 2007 matrix probabilities of change using the equation 3 and 4 and therefore will not be discussed as it presents similar tendencies. The Markov matrix for 2007 (Table 4) showed that all the classes are stable in time, i.e. the matrix has high diagonal values. Urban and greenhouses are the classes with the lowest stability as it is a developing activity in the province. Table 4 also shows that the main LU conversion is towards the class agriculture, followed by vegetation and then by greenhouses. The transition probabilities illustrate that most of the LUC are oriented towards the increase of the production of agricultural goods. To achieve this high production, vast vegetation areas (natural ecosystems) are changed into agriculture.

Some other changes are not related to the intensification of the landscape. For instance, a probability of change of 0.0673 was found between the class freshwater and the class vegetation. This change may be explained by natural drought periods that have reduced the extension of artificial lakes and rivers and/or by human land use activities that have alter the hydrological cycle in addition to this, the occurrence of some land abandonment can also be seen in this table because some changes from human LUs to vegetation are identified. Land abandonment is caused by changes in agricultural practices, food habits and rural exodus, with consequences on the structure and functioning of traditional landscapes as, loss of local crops varieties (Jongman, 2002;Vasconcelos et al., 2002), disappearance of cultural and natural diversity as well as impacts on non-agricultural ecosystems (Tilman, 1999;Jongman, 2002). In some cases, market conditions force the abandonment of greenhouses that have to be sell for the more profitable use of urban development. When this is not possible, old abandoned greenhouses would remain as natural vegetation until another commercial use is established.

In addition to the above mentioned changes, the matrix of probabilities of transition shows some changes that might be imputed to classification errors in the input datasets. This is the case of changes from greenhouses to agriculture that can be explained by the lack of a more realistic projection due to the recent greenhouse activity and missing more up-to-date data that hampers a more realistic projection. Changes from urban to agriculture cannot either be explained.

Table 4. Markov probability of LU change matrix from 1999 to 2007.

	Urban	Agriculture	Vegetation	Freshwater	Greenhouses
Urban	0.8927	0.0530	0.0286	0.0014	0.0243
Agriculture	0.0097	0.9085	0.0572	0.0021	0.0225
Vegetation	0.0064	0.0673	0.9050	0.0010	0.0203
Freshwater	0.0014	0.0100	0.0867	0.9018	0.0000
Greenhouses	0.0123	0.0916	0.0190	0.0003	0.8768

3.2. LU projections for management

In this section two LUC dimensions are presented: time and space. LUC in time is referred to the prediction to 2007 of LUs per LU class. And LUC in space are represented by a provincial map of LUC from 1991 to 2007.

LUs trends for 2007 and for each spatial study unit (province and regional ecosystems) were represented per use. The general LU trends that stand out in Fig.5 is a decrease on vegetation as human LUs increases. The main LU forces of change of Almería's province are agriculture and greenhouses. This confirms the findings of Mota el al. (1996), who already identified agriculture and greenhouses as main LUC drivers. From figure 5 urbanization is also seen as one of the LUC forces. The Environmental European Agency detected already that urban areas are being expanded and intensified in Almería (Environmental European Agency, 2005).

The regional ecosystem SAH presents the highest growth on agriculture, greenhouses and urban LUs (Fig. 5). In fact, most of the greenhouses and tourist facilities of the province are localized in this regional ecosystem. This situation is favoured because it is the most flat area of the province, it is located on the coast as well as it lacks organized territorial policies (Exceltur-Deloitte, 2005). For the regional ecosystem SAM, agriculture is the main LUC force of change. The class vegetation is less transformed than in other regional ecosystems because (i) the orography of this area is not well suited for human activities and (2) most of its area is a natural park

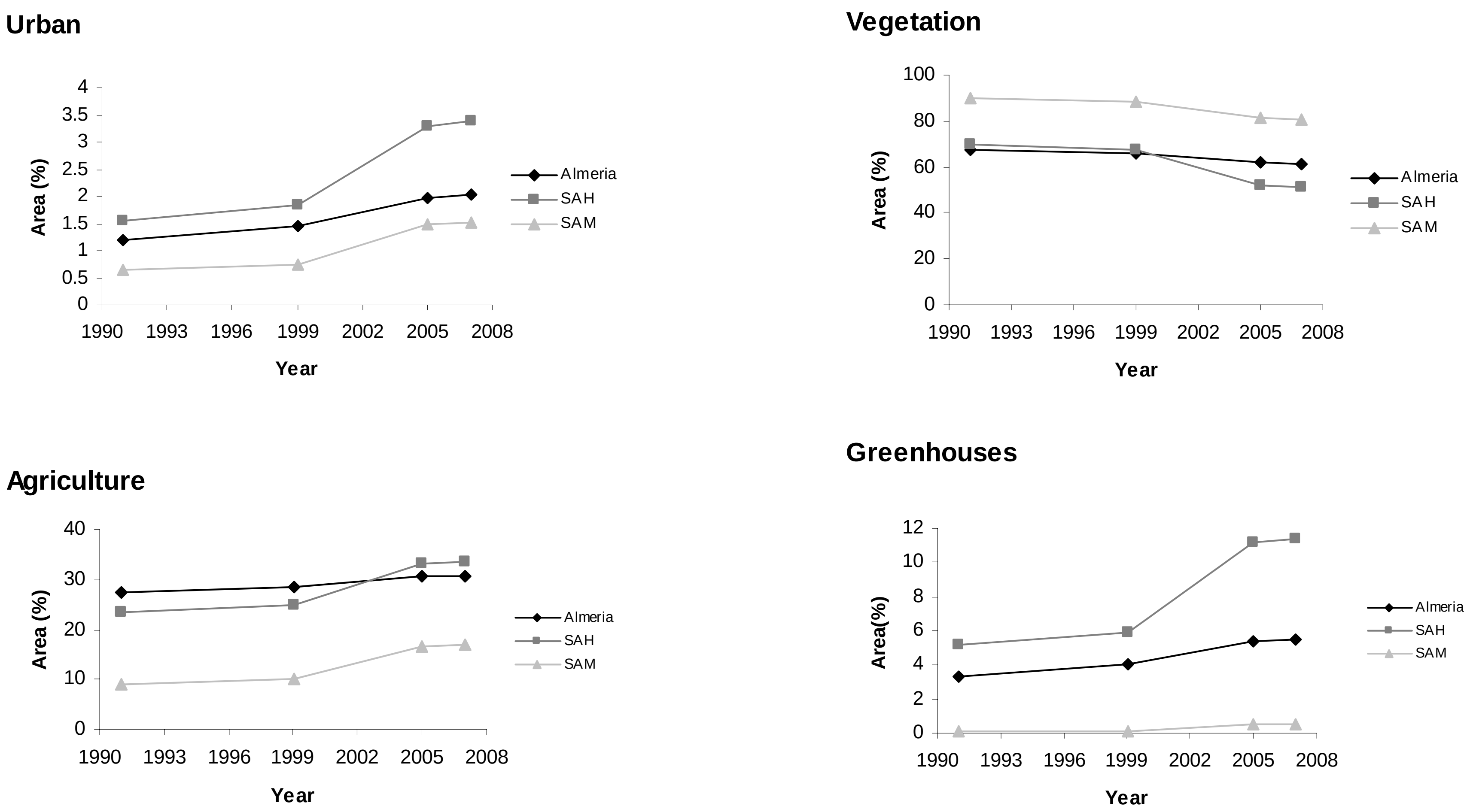

Figure 5. Historic and future LU changes in Almería province. LU with changes lower then 1%, were not presented since they are not consider relevant ,i.e. freshwater.

inside the RENPA. In general, it is well known that remote places and not accessible areas are less exploited by humans and the mountains are one of these cases .

Figure 6 shows the distribution of LU types in 200 and the LUC between 1991 and 2007. Displayed changes are: vegetation loss, vegetation gain, no-change, and other changes. According to the results, 91.2% of the total area did not experience any LU change, 0.6% is vegetation gained due mainly to land abandonment and 1.0% suffered other changes. This means that 7.2 % of the natural cover in the province was lost in the past fifteen years. Looking to the Fig 6.b, we can detect five areas where the vegetation is being lost and there is where we suggest more conservation efforts and efficient territorial planning should be focus. These areas (in black), which are mainly located in semi-arid ecosystems, and their main economic activities are:

- El Campo de Dalías: in the south west of the semiarid Hollows is well-known for its expansion on greenhouses,
- Campos de Nijar: in the southeast of the semiarid Hollows is the new location for the development of intensive agriculture,
- Corridor Tabernas-Sorbas: placed in one of the driest zone of the province (middle-south of semiarid hollows), know as the semi-desert of Almería, agriculture is developing fast,
- Almanzora River Basin (high, medium, low): located in the east of the semiarid hollows crossing some of the semiarid mountains. The high basin is characterized by its growing agriculture practices meanwhile the low basin with urban developments,
- Watercourse of Chirivel: The mid-west of the province containing Betic mountains are characterized by irrigational agricultural practices and mining activities.

The predictions of the LUC could be extended in time reaching an stable state of the landscape. That could lead to the detection of potential areas threatened by human LUs. Taken into account the presented model predictions, the landscape of Almería would reach LU stability (steady state) by the year 2223 (Eq. 9, Fig. 7). If the current management policy continues, in 2034, natural protected areas belonging to Natura 2000 Network will enclose all the remaining natural vegetation of the province. This isolation of natural ecosystems will harm biodiversity conservation as ecosystem fragmentation will prevent population connexions (Saunders et al., 1999). Therefore, a sustainable management outside protected areas, especially in the SAH, is needed

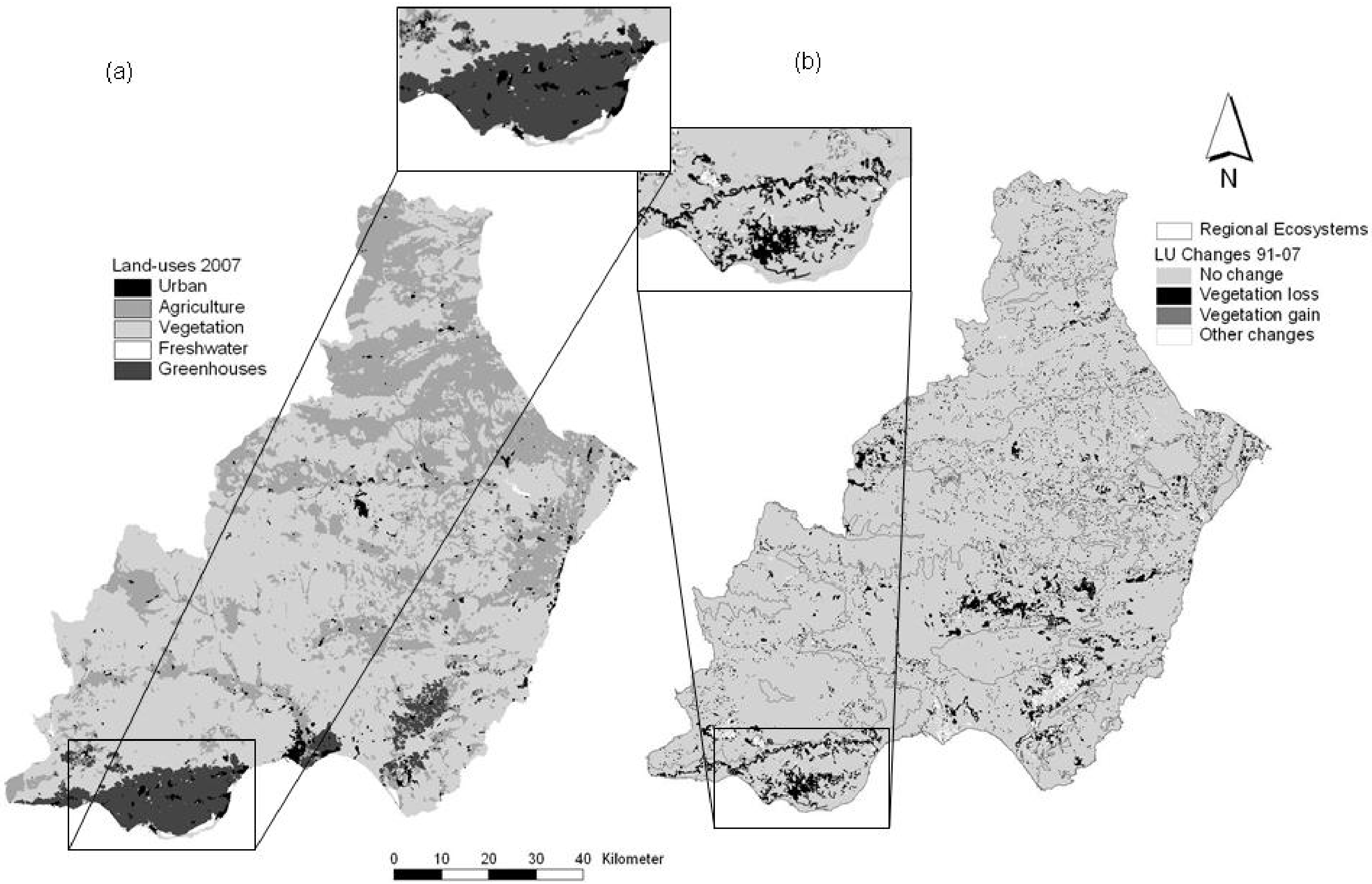

Figure 6. Spatial LU projection to 2007 from 1999 (a) and spatial LUs changes from 1991 to 2007 (b). Detail of one of the biggest greenhouse concentration in the province, Campo de Dalías (El Ejido).

since conservation based only in protected areas is not enough for maintaining biodiversity (Diezt and Adger, 2003).

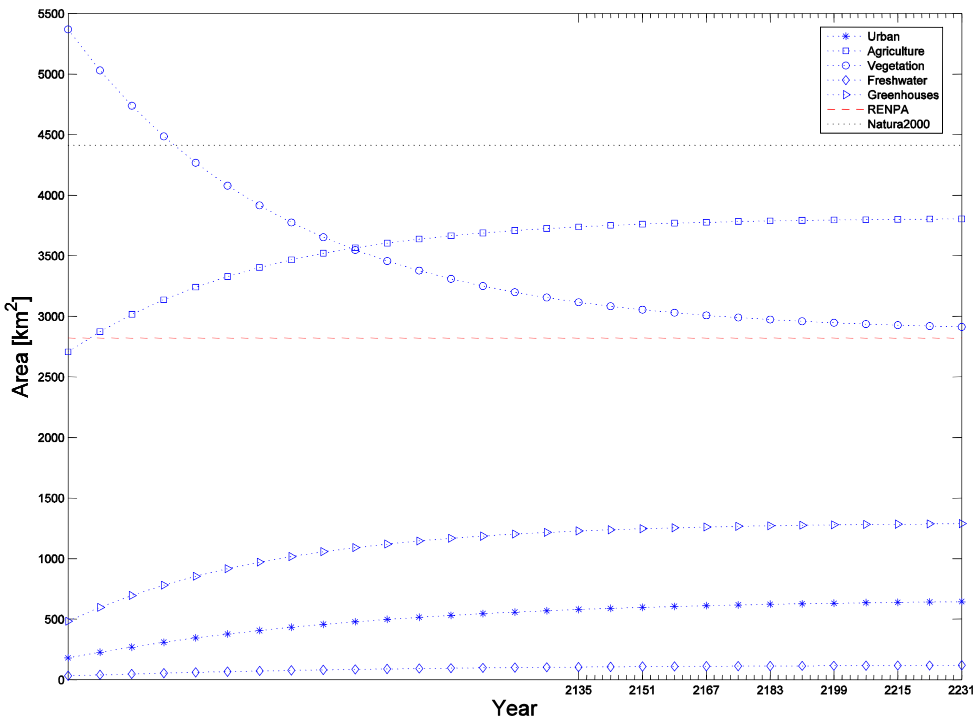

Figure 7. Land-use area for the provincial stable state of the landscape.

3.3 Validation

Overall per-pixel classification accuracies were calculated for the whole province of Almería and for the semiarid regional ecosystems using the projected LU for 2005 and the sample filed data of 2005. Results showed that mainly agriculture, vegetation and greenhouses kept overall accuracy values above 60% (Table 5). On the contrary, LU classes with little surface as urban or freshwater showed low accuracy or no accuracy data. The execution of the model for the whole province gave a kappa index of 0.6152, a 78.75% of overall accuracy and the highest accuracy per LU class. The overall accuracy value for SAH was of 60.29% with a kappa index of 0.4414. SAM showed a higher overall accuracy of 78.43% and a kappa index of 0.3647. According to the kappa classification system of Landis and Koch (Landis and Koch, 1977), the kappa index for SAH is consider to be moderate, for SAM fair and for the province was substantial.

These differences on classification accuracy and kappa index might indicate that the LUC dynamics of the whole province and the ones of the regional ecosystems are different. Nonetheless, these are only preliminary conclusions because the random field sampling resulted in different number of validation points per ecosystem and this might affect the validation results.

Table 5. Land-use Accuracy Assessment analysis´ results for 2005 for Almería province and semiarid ecosystems.

LU class	Almería		Semiarid Hollows		Semiarid mountains	
	Accuracy(1)	Reliability(2)	Accuracy	Reliability	Accuracy	Reliability
Urban	10	50	0	0	28.57	100
Agriculture	83.61	69.86	76.47	54.17	50	33.33
Vegetation	88.73	85.14	72	62.07	90	85.71
Freshwater	--	--	--	--	--	--
Greenhouses	62.5	66.67	71.43	76.92	--	--
Overall Accuracy	78.75%		60.29%		78.43%	
n (3)=	240		68		51	
Kappa Index	0.6152		0.4414		0.3647	

(1) Refered to Producer´s accuracy; (2) Refered to User´s accuracy, both are showed in %. (3) Number of sampled points in field.

Figure 8 illustrates the results of the indicator kriging that was done using the LU projections for the year 2005 (Fig.8a) and the 240 field samples that were collected that year. There were 189 points of the 240 sample points classified as correct (value1) while the rest were classified as incorrect (value 0). The krigging was adjusted by an spherical approach and anisotropy was set as a characteristic of the data. The amount of points that gave the best fit were: 25 neighbours as the maximum and 15 the minimum.

The error measures for the kriging were: mean -0.001776, root-mean-square 0.04029 (in the same range of the average standard error: 0.3922) and root-mean-square standardized of 1.025. These measures show the statistical reliability of the mathematical adjustment of the interpolation. A mean around zero indicates that the projection errors are unbiased. Similar values for root-mean-square and average standard error show no under or overestimation of the variability of the projections. And a root-mean-square standardized close to one confirms that the projections values are close to the field measurements (Johnston et al 2001).

In general, areas with a high density of samples presented higher accuracy values. Less-dynamic areas as mountains, protected areas or remote places had higher reliability values than the rest. The low accuracy in the right strip of the province (Fig. 8.b) can be due to a lower sampling effort or a high dynamicity that cannot be modelled by the CA Markov. One possibility leading to low accuracies in dynamic areas is the use of a not proper suitability map (section 2.3.1.). The suitability map generated by the CA Markov model distributes the LU equally in every landscape. The fact that it does not take into account the degree of LU change per use, difficults that the future map of LU reflects dynamics areas. Especially, two areas well sampled but with low reliability values were observed: one of them located in the middle south of the province, corresponding with Almería city and surroundings, and a second one in the east of the province, where most of the recent tourist development is taking place.

Although it does not exists yet any reference on the suitability of the goodness-of-fit of the validation results from a LUC model (Pontius, 2004), the results of the per-pixel classification accuracy and the kappa coefficient discussed above might, however, not be very appropriated to evaluate a LU model. The use of fuzzy similarity measures may be preferred because the use of per pixel validation techniques might be too strict when validating LU projections. (Hagen, 2003;Hagen-Zanker, 2005). Fuzzy measures can give different accuracy results more appropriate for the detection of broad areas where to focus conservation efforts.

Another component for the validation of the model was to compare the projected values (2005 and 2007) with the 1999 LU data in order to check the stability of the changes predicted by the model, the null model (Table 6). The disagreement due to quantity, i.e. differences between the study periods, shows that the anthropic classes resembles to each other more than the vegetation class. In general, similarities are high enough for stating that the LU in both periods (1999-2007, 1999-2005) cover similar areas. The disagreement due to location (overall accuracy and kappa) shows a high similarity among the validation for 1999-field data and 1999-projected data. The model, therefore, is projecting more stability than changes. Pontius (2004) previously detected this characteristic for the majority of the LUC models and argues that, as long as a LUC model is predicting the same change than the Null model, it is worth its use.

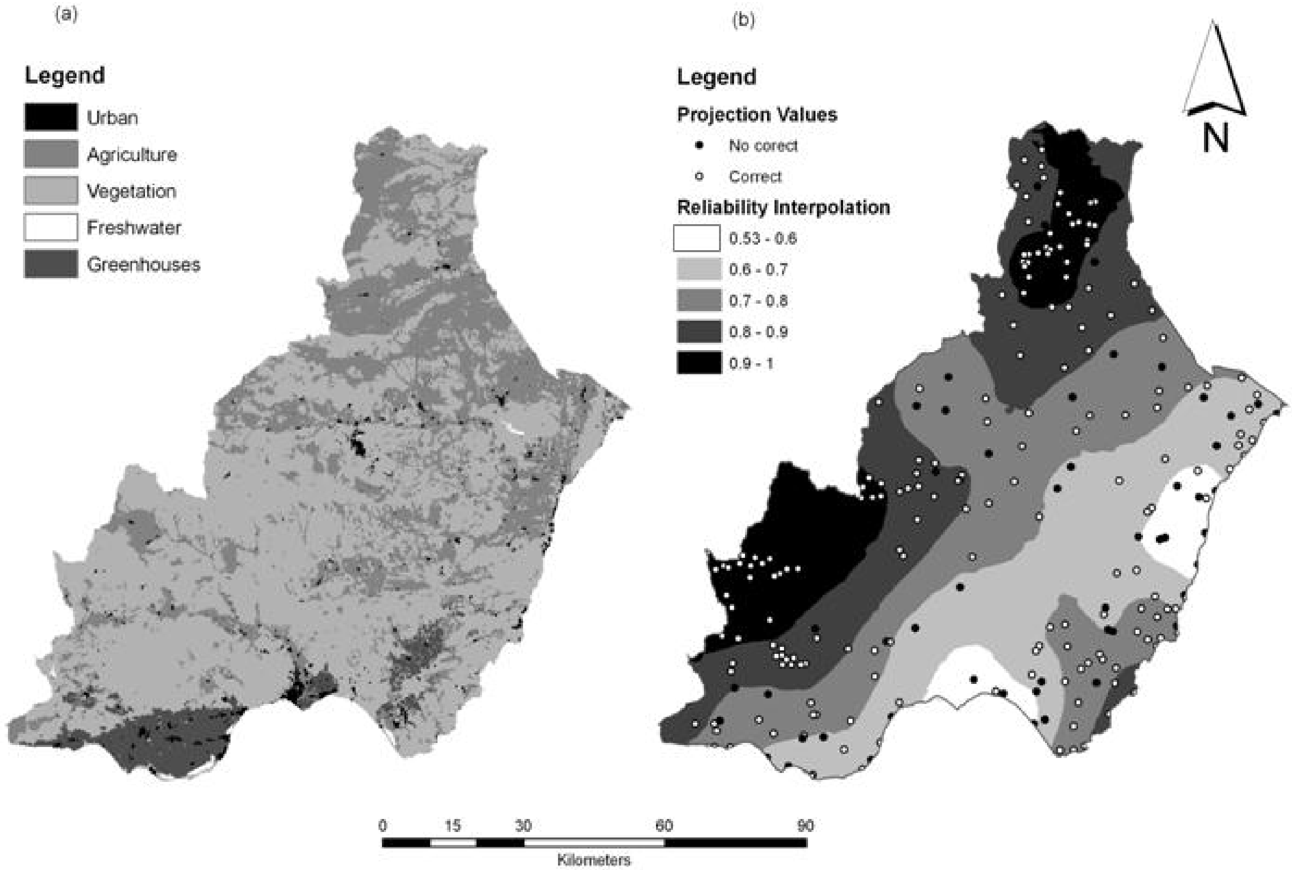

Figure 8. Spatial LU projection to 2005 from 1999 (a) and spatial reliability of the projections (b)

Table 6. Model disagreement due to quantity (area) and location (accuracies) for the province.

LU Area (%)	1999-2005 field	1999-2005 projected	1999-2007 projected
Urban	*	-0.521	-0.577
Agriculture	*	-1.918	-2.166
Vegetation	*	3.896	4.336
Freshwater	*	-0.087	-0.095
Greenhouses	*	-1.371	-1.498
Overall Accuracy	77.92	90.61	89.68
Kappa	0.59	0.92	0.91

3.4. Spatial Extent

Differences detected on accuracy measures (Table 5) when applying the model to different territorial extents (the whole province and regional ecosystems) shows the possible existence of a CA Markov dependency when applied to different spatial extents. In this section accuracy differences are quantified comparing differences in LU area covered by each use when applying provincial or regional ecosystem transition probabilities in the CA Markov model.

When the dynamics of the LU changes are different for two areas (e.g. province and regional ecosystem), the smaller the regional ecosystem the least contribution to the provincial transition probability. Therefore using the provincial transition matrix for calculating ecosystem LU changes will result in great errors as transition values are not representative for that ecosystem. In general, LUs in SAH are more similar to the provincial ones than SAM (Table 7). Those regional ecosystems with higher similarities to provincial LU trends will differ less in terms of area difference: Ap-Ae (Fig.9). For SAM, agriculture and urban uses are the classes with the greatest differences in spatial area analysis. Slight differences exist for vegetation and greenhouses in the SAH. Area overestimations or underestimations show the need of a more spatially detailed approach when the LUs of the study area differ from its surroundings. In these cases, a more spatially detailed approach than the provincial one, gives a more realistic projected area as the Markov probability matrix is calculated for a detailed extent, the regional ecosystem. However, geo-political limits do not correspond with regional ecosystems. Considering that landscape planning actions are decided at a provincial level, the provincial approach is appropriate for political management.

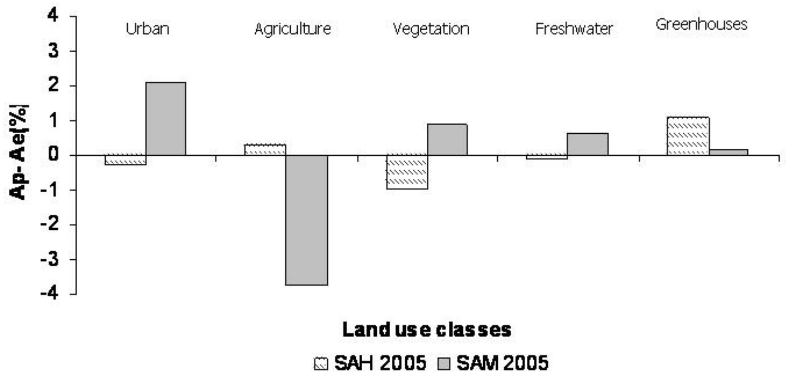

Figure 9. Spatial extent analysis: area difference between the application of Markov at provincial (Ap) and ecosystem (Ar) level. SAH are Semi-arid Hollows and SAM Semi-arid Mountains.

Table 7. Markov probability of LU change for 2005 Almería province and semiarid ecosystems.

	Urban	Agriculture	Vegetation	Freshwater	Greenhouses
	0.9052	0.0468	0.0252	0.0012	0.0216
Urban	0.9126	0.0388	0.0166	0.0003	0.0317
	0.8716	0.0682	0.0572	0.0029	0.0000
	0.0087	0.9171	0.0518	0.0019	0.0204
Agriculture	0.0104	0.9083	0.0489	0.0027	0.0297
	0.0155	0.9116	0.0590	0.0014	0.0125
	0.0058	0.0606	0.9145	0.0009	0.0183
Vegetation	0.0077	0.0681	0.8905	0.0012	0.0326
	0.0054	0.0673	0.9234	0.0005	0.0033
	0.0013	0.0087	0.0779	0.9122	0.0000
Freshwater	0.0005	0.0104	0.0740	0.9151	0.0000
	0.0075	0.0000	0.1430	0.8495	0.0000
	0.0107	0.0797	0.0162	0.0003	0.8930
Greenhouses	0.0110	0.0781	0.0160	0.0003	0.8947
	0.0000	0.4927	0.0688	0.0037	0.4348

Upper row: Almería province; Medium row: Semi-arid Hollows, Lower row: Semi-arid Mountains

4. Conclusions

In this paper we have discussed the use of a cellular automata markov model for LU change detection to identify natural areas that can be affected by human LU activities. The low data requirements and easy performance of Markovian models facilitates its broad use to a wide range of users, from landscape managers to scientists, and for a great number of applications, i.e. agricultural, ecological or land-

use change (Brown et al., 2000;Schneider and Pontius, 2001;López et al., 2001;Luijten, 2003;Wootton, 2004;Paegelow and Camacho Olmedo, 2005).
However Markov probabilities reach an asymptotic stage that limits the model projections to a short time interval. Therefore this model can be easily applied for short term analysis of non-complex landscapes, where the main goal is the detection of environmentally vulnerable areas (Verburg and Veldkamp 2001). Markov transition probabilities of change lack spatial dependence. Therefore to overcome this weakness, a Cellular Automata Markov was selected for locating the land-use changes, bringing the visual help to the users and facilitating results interpretation. In contrary to uni-variate and non-spatially-explicit approaches, the Cellular Automata Markov approach offers the possibility to project all LU classes present in the landscape (Trani and Giles, 1999;Trejo and Dirzo, 2000;Pontius and Malanson, 2005), although does not take into account spatial dynamicity of the LUC.

Although it is a challenge to simulate landscape patterns using transition probability models (Turner, 1987), the selected model has been proved to be a simple but effective approach to model the evolution of LU patterns in areas with intense human activity and dynamicity. In the area of Almería the loss of natural ecosystems was analysed by means of the vegetation loss and its LUs. Semi-arid ecosystems (mountains and hollows) were selected as the most dynamic regional ecosystems of the province. Using as an input two LU maps from 1991 and 1999, the CA Markov module was used to project a LU map for the year 2007. The time step until when to project is in close relationship with the time step of the input data (see (López et al., 2001;Syphard et al., 2005;Paegelow and Camacho Olmedo, 2005). In this way, the time projection can be enlarged, when it will be interesting to predict further in time, by having more up-to-date disposal of data.

Results were validated comparing LU projections at 2005 with field sample points. The accuracy analysis showed that for the purpose of this analysis, results allow the detection of areas of LU change were to focus conservational efforts. The provincial LU projection showed reliable results for 2005 except for those very dynamic areas. Dynamic areas with lower accuracies can be due to the use of a suitability map locating the LUC that does not take into account the spatial degree of LUC. When the model was compared to a Null model it predicted more stability than change but this can be explain due to the quality of the inputs, the use of cell-to-cell accuracies measures instead of fuzzy ones (Hagen 2003) or can also be regarded as a normal characteristic of LU change models (Pontius 2004). The model showed spatial extent dependence when used to project at provincial and ecosystem level. The application of the ecosystem level approach is recommended when the study area is surrounded by a not similar landscape matrix than itself. However, the provincial approach is more appropriate since it fits within the geo-political units for management purposes.

For the province, the main LU forces of change detected were urban, agriculture and greenhouses. Semi-arid Hollows showed the most warning LU changes. In this ecosystem the rate of vegetation lost was especially high and its main forces of change were urban developments (tourism), agriculture and intensification of the agricultural practices (greenhouses). If current management policies persist, natural protected areas will enclose all the remaining natural vegetation surface of the province by the year 2034. This isolation of natural vegetation in protected areas will hamper the ecosystem conservation in the province what emphasizes the unavoidable need for conservation measures outside protected areas.

In general, the results are of suitable interest for landscape planning and the approach presented constitutes a fast and easy applicable tool that can be utilized for management purposes.

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