Prospective GIS modelling of land cover in Mediterranean mountain regions

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Proceedings of the 6th AGILE
April 24th-26th, 2003 – Lyon, France

PROSPECTIVE GIS MODELLING OF LAND COVER IN MEDITERRANEAN MOUNTAIN REGIONS

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1. INTRODUCTION

Geographic information systems includes among the variety of analytical functions those intended to spatial-temporal modelling and decision support. This paper focus on GIS methods and results of prospective land cover modelling applied to a mountain basin in Eastern Pyrenees (France). This research is a part of an international project1 involving four research centres in France and Spain focussing on development, validation and comparison of three different methods for environmental modelling (statistical approach by non linear parametric model, mathematical approach by neuronal network and geographic approach by using GIS functions).

French Mediterranean mountains are going throw a deep social and economic restructuring visible by landscape changes. The reorganization of these mountain systems begun in the first part of XIXth century by the decline of the traditional agro pastoral economic showing an important rural exodus and a major landscape changing. To analyse these dynamics, we consider land cover as an appropriate indicator for use and activities sprat out in space by societies and responding with inertia to their changing. The knowledge of past dynamics is considered as a fundamental aspect to apprehend future evolution and prospective simulation [1, 2].

2. TEST AREA

Garrotxes, a catchment basin of 8 750 ha, is located in a region named “Haut Conflent”, part of the Eastern Pyrenees (France). The difference of height between the major summit at the north extremity (Madrès, 2469m) and the confluence of the Cabrils, draining the basin, with the value of Têt river (650 m) on the SE limit is important. On the right side, characterized by a ponderous geomorphologic relief based on granite, are situated quasi all earlier terrace cultivations and coniferous forests (Pinus uncinata) – a space characterized by a fast dynamic of vegetation. The left bank forms a large, steep and south facing side on schist used as pasture. The demographic maximum (1820/30) meant intensive use of all natural resources. 1826 25% of the whole area were developed as crop terraces (Napoleon cadastre of 1826). The population pull down from 1832 habitants in 1826 to 92 habitants in 1999. Crop terraces were transformed to pastures and became, later, bushy or forests. Actually crops are completely marginal and the near future probably depends on pasture management which will determinate maintain of pasture of spontaneous forest spreading.

3. GIS DATA BASE

The GIS data base includes a lot of land cover maps and layers of relevant environmental and social factors. The choice of vector or raster representation is function of

1 Project supported by CNRS –PEVS (program environment, life and societies)

planned data processing: the essential analysis steps lends better to raster approach while attribute data query is easier to implement onto vector layer with associated database.

Land cover maps have the same resolution (pixel size about 18 m) but different origins and captions: the first land cover map (1826) stem from the Napoleon cadastre allowing to distinguish forest, pasture, grassland, agriculture and urban use. First aerial photographs (1942) allows to insert a category between pasture and forest : scrubs. The land cover map of 1962 has the same captions, while scale and quality of later aerial photographs allows to distinguish deciduous from coniferous forests and broom lands from grass-based pastures (1980, 1989). Actual land cover map (2000) exists in two formats: one with the same captions, another, based on terrain, with 20 captions.

Land cover evolution about almost two centuries is dramatic as shown in fig. 1.

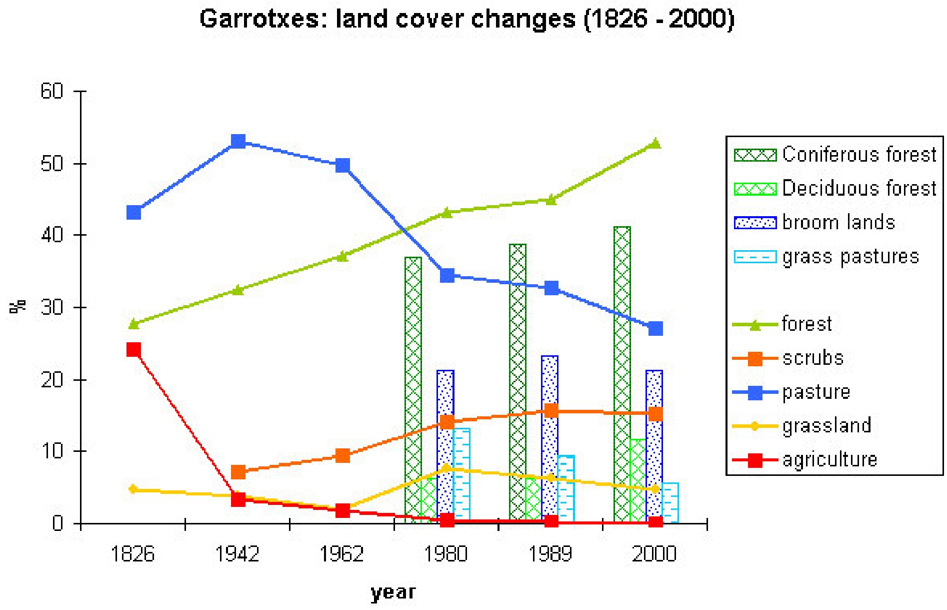

Fig. 1 Land cover changes in Garrotxes (Eastern Pyrenees, France) : 1826 - 2000

It appears clearly that crops (terrace cultivating), occupying 25% of space in 1826, quasi disappeared in the early 1980. Terraces became first pastures, then also forests. Because the social, economic and technical environment changed completely in two centuries, only the three later dates will be used in GIS modelling to predict future land cover.

Other GIS layer maps land cover relevant factors: altitude (DEM), slope, orientation, distance to roads and villages completed by a accessibility map (cost-distance), pasture management (pasture units, land property and pasture associations, cattle, …), administrative limits, hydrographs and particular status of areas: public forests, military area.

4. GIS METHODS APPLIED TO PROSPECTIVE LAND COVER MODELLING

The problem issue is time extrapolation applied to complex open social and environmental system. If geostatistical methods, offering improved tools for interpolation and extrapolation in space, are commonly implemented in GIS, tools to time modelling and decision support only appeared in GIS in the last years and should be considered on an experimental basis.

The GIS implementation (Idrisi 32 release 2) calls on a chain of different tools: Markov chains (time transition probabilities), multi-criteria evaluation (relationship between land cover changes and a lot of criteria able to explain or describe theses changes), multi objective evaluation (integration of the different suitability maps) and an cellular automate (introduction of the spatial neighbourhood).

4.1 Multi-criteria evaluation (MCE)

Our GIS approach is based on a knowledge database about land cover dynamics in time and space related to criteria which are considered responsible for the observed changes. Criteria might be split up into Boolean constraints (occurrence possible or not) and factors which express a suitability variable in space. Constraints will simply mask space while factors may be weighted and allowed to tradeoff each other.

Used constraints may be the same for all land cover captions (exclusion of villages which do not change at the employed scale) or specific to a land cover caption (f. i. altitude limits for forests, distance to roads for crops, accessibility level for grassland or masking of public woods for pasture suitability).

The rules of behaviour in time and space for each land cover type are carried out, on the one hand, from an analysis of the chronological set of land cover maps and, on the other hand, by evaluation of geographical roughness by noting significant differences between reel land cover location and a theoretic distribution (isotropic and homogeny space). This geographic roughness, or friction, is formed by a set of known and mapped variables (altitude, slope, orientation, cost-distance accessibility, proximity to land cover categories, particular status like domain forest, pastoral management, …) on a scale compatible with the resolution of the set of chronological land cover maps.

Some criteria, like proximity to existing land cover, is analysed in terms of probability that a type of land cover may occur (for instance forest spreading on the edges). Analysis of recent dynamics gives an idea about the model (linear, sigmoid, etc.) to employ and the parameters in terms of suitability / probability.

The factors, once calculated and standardized, are weighted by pairs using the Saaty matrix [3] to calculate the eigenvector of each factor.

Finally, six factors (altitude, slope, orientation, accessibility, probability of land cover caption change, proximity to existing land cover features) are used in multi-criteria evaluation. The nature and number of constraints are land cover caption specific.

The chosen multi-criteria evaluation [4] include, finally, a lot of order weights (ordered weighted averaging) allowing choice of level of risk and tradeoff. The number of order weights is equal to the number of factors; the weights sum to 1.0. Order weights are calculated for each pixel. The first order weight is assigned to the factor of which suitability is the lowest in the weighted factor set; the last order weight is assigned to the highest suitability among the weighted factors for the considered pixel.

Allowing entire weight to the first order weight means a risk adverse decision without factor tradeoff, while the opposite means a high risk strategy (picking only the factor the highest suitability and not consider the other), also without tradeoff [5].

The used approach may be considered as low risk taking with some tradeoff as shown in figure 2.

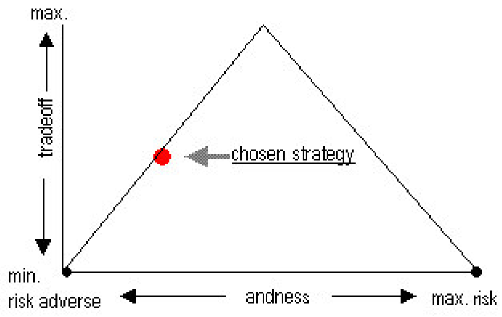

Fig. 2 Decision strategy space and chosen approach into multi-criteria evaluation (ordered weighted averaging); Idrisi 32 release 2. Used order weights: 0.45, 0.20, 0.15, 0.10, 0.07, 0.03

This knowledge of these “rules” of time and space behaviour, specific for each land cover caption, is the basis to calculate a lot of suitability (in this instance they express rather occurrence probability for a land cover caption than suitability) land cover maps using multi-criteria evaluation with ordered weighted averaging (MCE-OWA)2.

4.2 Markov chain analysis (MCA)

The next modelling step is a Markov chain analysis, a discrete process with discrete time which values at instance t_{+1} depends on values at instances t_0 and t_{-1} (Markov order 2). The prediction is given as estimation of transition probabilities.

In order to test the method, Markov chain analysis, like the other modelling steps, will first be applied to simulate land cover in 2000 (t_{+1}), based on land cover maps in 1980 (t_{-1}) and 1989 (t_0). Results are expressed as transition probability matrix and Markovian probability maps for each land cover caption. The set of Markovian probability maps may be integrated in a single map by stochastic choice [6]. The algorithm evaluate the conditional probabilities of each land cover for each pixel against a random probability distribution; the land cover caption exceeding random threshold is assigned to the evaluated pixel [7].

4.3 Integrating MCE, MCA and cellular automata

The integrating step, combining knowledge about likely spatial distribution (MCE), time transition probabilities (MCA) as well as multi-objective land allocation, is performed in the chosen software by CA_Markov, an aggregated module. It performs a spatial distribution, based on MCE results, of transition probabilities, computed by MCA, for each land cover. A multi-objective evaluation (MOE) then integrates the set of predicted land cover maps in an only one. The land cover prediction procedure finally adds an element of spatial contiguity. The applied cellular automata is based on a standard contiguity 5 x 5 filter. The algorithm is iterative so to match with time distance t_{-1} - t_0 and t_0 - t_{+1}.

The inputs are: land cover maps at instances t_{-1} (1980) and t_0 (1989), land cover probability (suitability) maps resulting from multi-criteria evaluation and area transition probabilities (Markovian output). The output is a prospective modelled land cover map for instance t_{+1} (2000 test the method by comparison with mapped reality).

The entire modelling steps are resumed in figure 3.

2 All modelling steps are implemented with Idrisi 32, release 2

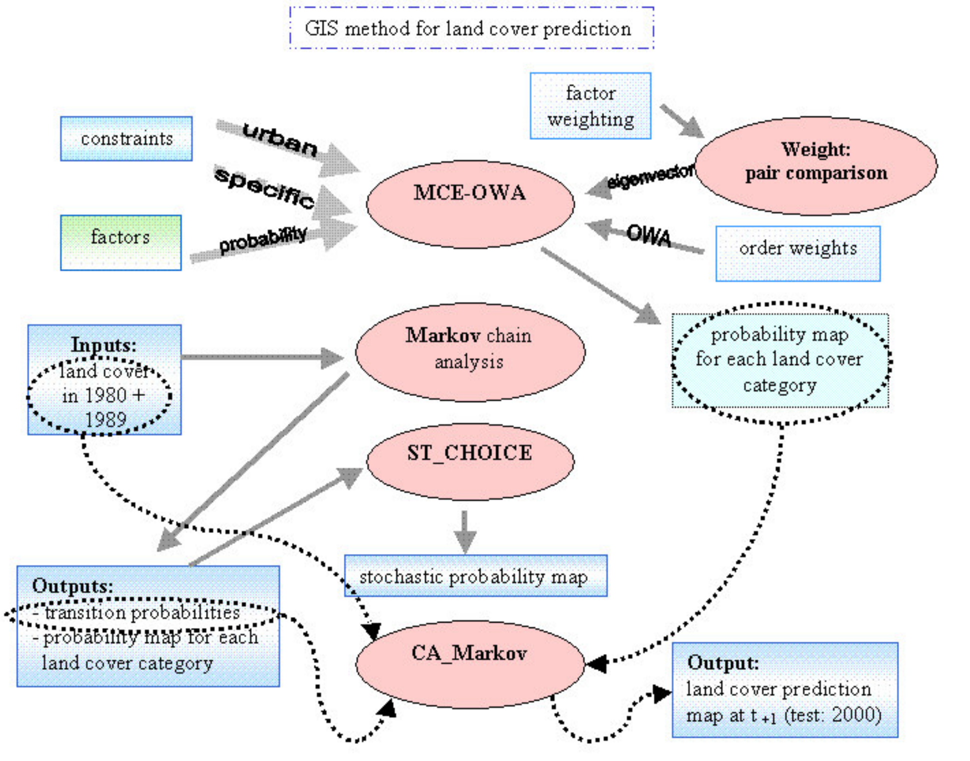

Fig. 3 Overview of methodological steps to prospective land cover modelling

5. RESULTS

To validate the land cover prediction model, we first applied it to predict known land cover (2000) based on information about 1980 and 1989.

As described in the methodological part above, the resulting probability maps (MCE-OWA) give an idea of probability occurrence for each land cover. Figure 4 shows the probability map for coniferous forest. Black bordered areas were really covered by coniferous forest in 1989 (t_0) matching well with computed suitability while entirely white areas corresponds to masked land by constraints (villages, altitudes lower then 1000 m and higher then 2400 m).

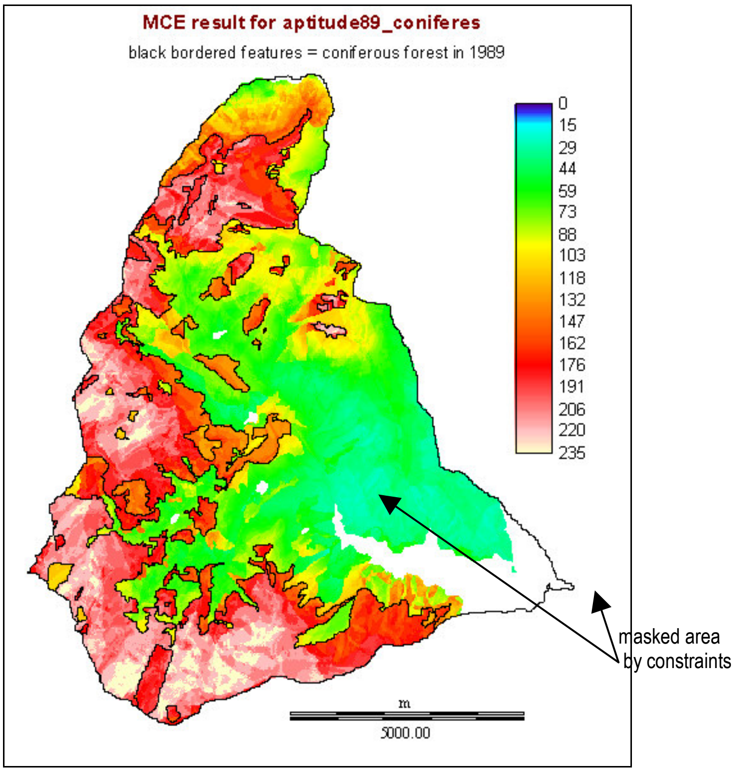

Fig. 4 MCE-OWA probability map for land to be covered by coniferous forest. Black outlined area shows coniferous forests in 1989

Suitability of coniferous forests, like most land cover types, is easy to model with available data. It is turned out that modelling spatial distribution and their dynamics squares lesser with reality for grassland (low score of explained variability by database layers) and cultivated land (to little area). Table 1 shows average and standard deviation of suitability scores for each land cover in comparison to the rest of the test area. Average suitability scores are higher and more homogeneous on area really covered by respective land cover.

Land cover	Average		Standard deviation	
Coniferous forest	191. 3	(68.0)	26.0	(42.3)
Deciduous forest	124.6	(56.9)	71.3	(80.5)
Scrubs	163.2	(94.1)	29.5	(35.4)
Broom land	172.8	(76.9)	28.5	(62.8)
Grass pasture	150.2	(87.3)	33.1	(50.4)
Grassland	117.3	(84.2)	73.0	(84.8)
Agriculture	148.2	(62.9)	60.9	(82.2)

Table 1 Multi-criteria evaluation performed average suitability scores and standard deviation for each land cover in 1989 (t_0) compared to the rest of the test area (data in brackets)

The Markovian prediction for Garrotxes to be covered by coniferous forest in 2000 and real distribution for this land cover is shown in figure 5.

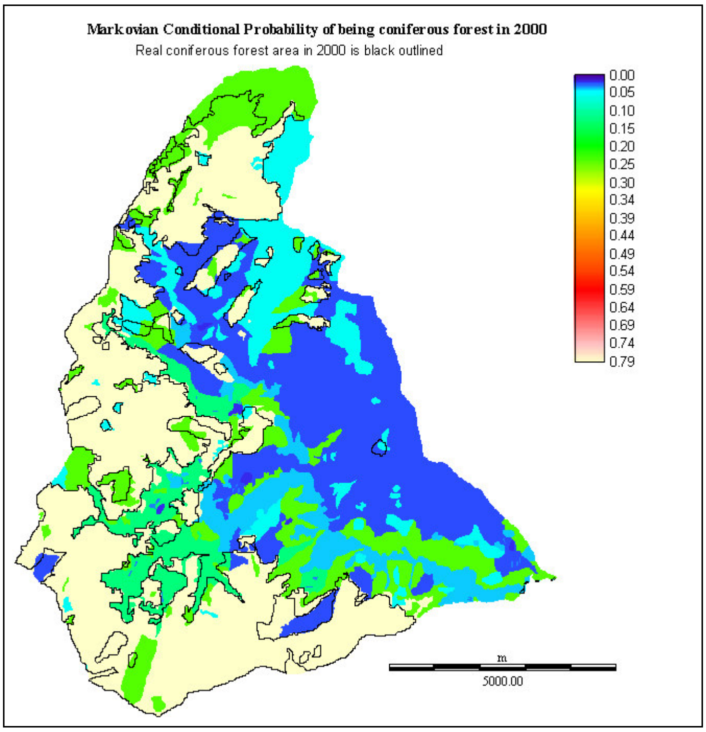

Fig. 5 Markovian predicted probability to be covered by coniferous forest in 2000 and real coniferous forest distribution (black outlined area)

Markovian probability scores are always distinctly higher on areas where prediction matches real land cover in 2000 but generally more variable as shown in table 2.

Land cover	Average		Standard deviation	
Coniferous forest	70.0	(12.7)	21.6	(18.5)
Deciduous forest	31.3	(2.7)	29.7	(4.7)
Scrubs	29.7	(19.3)	14.8	(10.1)
Broom land	54.5	(13.3)	11.2	(19.2)
Grass pasture	22.7	(7.6)	9.1	(7.9)
Grassland	46.6	(3.2)	19.6	(8.5)
Agriculture	0.8	(0.1)	0.4	(0.3)

Table 2 Markov chain analysis predicted average probability scores (%) and standard deviation for each land cover in 2000 (t_{+1}) compared to the rest of the test area (data in brackets)

Performing a predicted land cover map for 2000 by integration of the seven Markovian probability maps using only stochastic choice squares more or less with facts, depending on land cover. Table 3 shows Markovian predicted land cover area (%) for 2000 (t_{+1}) and their likeness to reality.

Real and predicted land cover area (%) in 2000			
Land cover	Real (R) land cover	Predicted (P) land cover	R - P
Coniferous forest	40.93	40.37	0.56
Deciduous forest	11.69	8.32	3.37
Scrubs	15.08	16.13	-1.05
Broom lands	21.61	23.56	-1.96
Grass pastures	5.65	6.24	-0.59
Grassland	4.80	5.12	-0.32
Agriculture	0.01	0.03	-0.02

Table 3 Comparison of real and by Markov chain analysis predicted land cover (% of area)

The final step consists in couple Markovian predicted land probabilities (2000) with known multi-criteria evaluation performed suitability (1989) intending to model a realistic land cover distribution in space. This process is supported by a cellular automata improving spatial contiguity. The resulting predicted land cover map, compared with real land cover in 2000, is shown in figure 6.

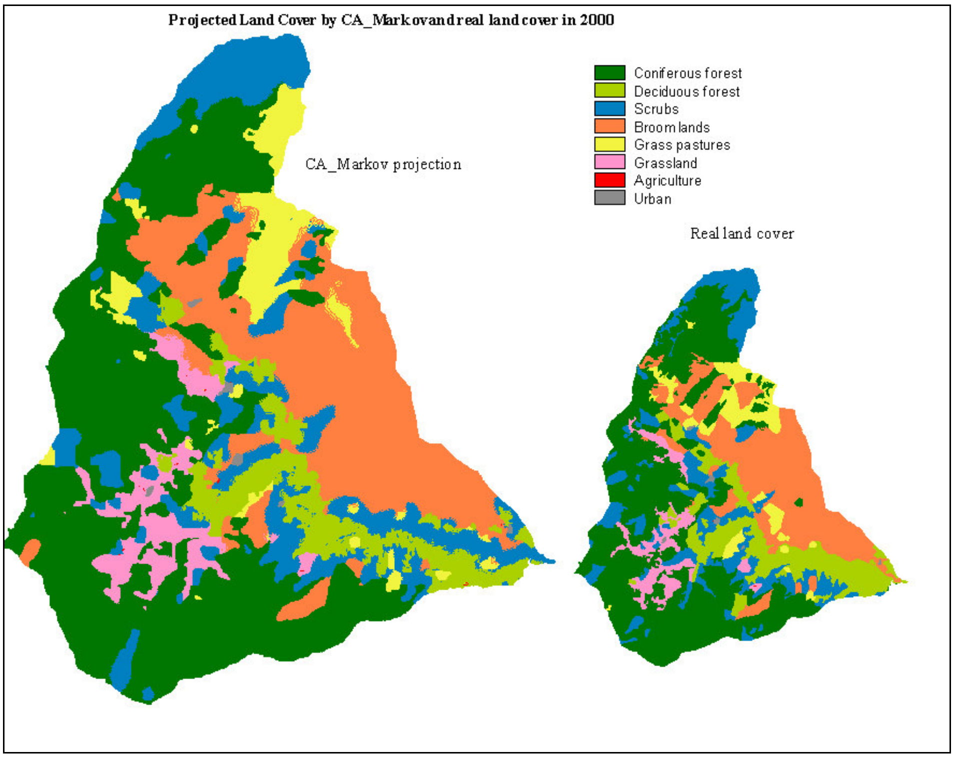

Fig. 6 CA_Markov predicted land cover and real land cover in 2000

The overall prediction rate is about 73 % but unequal distributed over land cover captions. The prediction fits to reality for land cover covering large areas like coniferous forests and broom lands but is low for other land cover like deciduous forest, scrubs, grass pastures and grassland and intends to zero for crops covering only 0.007 % of area (16 pixels) while prediction for villages (urban) corresponds, by definition (constrained area), to reality. Table 4 compares predicted and real land cover.

CA_Markov land cover prediction 2000 % (area)

		Coniferous forest	Deciduous forest	Scrubs	Broom lands	Grass pastures	Grassland	Agriculture	Urban	Sum of real land cover
Land cover 2000 %(area)	Coniferous forest	35.81	0.12	3.47	0.63	0.43	0.47	0.00	0.00	40.93
	Deciduous forest	1.19	6.45	2.92	0.58	0.32	0.23	0.00	0.00	11.69
	Scrubs	2.28	1.26	6.87	1.70	1.82	1.13	0.01	0.00	15.08
	Broom lands	0.32	0.40	1.68	18.00	1.12	0.09	0.00	0.00	21.61
	Grass pastures	0.21	0.08	0.44	2.64	2.29	0.00	0.00	0.00	5.66
	Grassland	0.55	0.02	0.75	0.01	0.27	3.19	0.01	0.00	4.80
	Agriculture	0.00	0.00	0.00	0.00	0.00	0.005	0.00	0.00	0.01
	Urban	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.230	0.23
Sum	predicted land cover	40.37	8.33	16.13	23.56	6.24	5.12	0.03	0.23	100.00

Table 4 Matrix comparing real land cover in 2000 (rows) to predicted land cover in 2000 by CA_Markov (columns); data expressed in per cent of total area. Crosswise data means correct prediction. Data in the above right part of the matrix indicate a predicted landscape "opening" while data within the lower left triangle means a predicted landscape "closing".

Land cover captions are qualitative data but may be considered as order ranks on a landscape evolution scale. By this way, matrix of table 4 is mapped as the difference, expressed in distance of land cover captions (coniferous forest = 1, …, urban = 8) as shown in figure 7. Negative balance means a predicted landscape "opening" while positive balance express a predicted landscape "closing" that not happened.

Accurate prediction concerns 72.87 % of the Garrotxes, a prediction failure of only one land cover caption (for instance deciduous forest but scrubs predicted) sum to 12.9 % of the entire area.

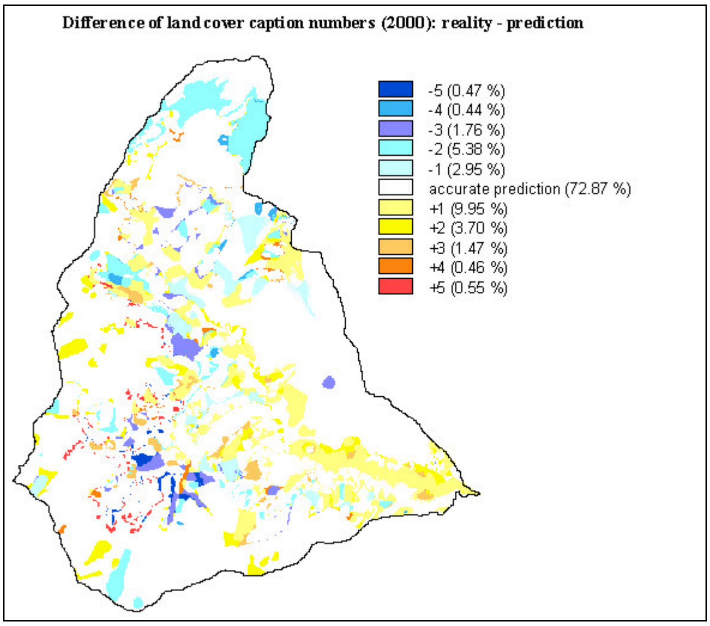

Fig. 7 Mapped difference (2000) of land cover caption ranks: real – predicted land cover

6. DISCUSSION OF RESULTS

First, it must be outlined that results not intend to predict (future) reality but they can help us to better understand environmental complex changes in time and space. Therefore interpretation of results must be done carefully; land cover modelling means simulation showing that would be can reality (scenario) in the frame of decision support.

Nevertheless obtained results not are very close to reality. Different parameters may explain the observed difference:

- number of land cover maps in the time series: only two land cover maps were used for this modelling test. The other, earlier, time series maps (1826, 1942, 1962) don't match with actual conditions;
- land cover changes occurred between 1989 and 2000 in earlier (1980 – 1989) stable areas: the area transition probabilities results entirely from Markovian chain analysis based on reality in 1980 and 1989. Multi-criteria evaluation, multi-objective land allocation and cellular automata only influence the spatial distribution of predicted transition probabilities. So it is logical that areas without land cover change in the reference period will be predicted stable;
- number of land cover captions: land cover maps as model for land cover reality are rather poor. The number of captions was intentionally limited to minimize interpretation failure rate (data origin is almost aerial panchromatic photographs). The disadvantage is a certain variability into each category. For instance, CA_Markov prediction shows in the SE part of Garrotxes (fig. 6) a large blue oblong area: scrubs (the same land cover as in 1980 and 1989). In reality this area changed by natural vegetation dynamics to deciduous forest and emphasize a general problem: intra-class changes. In the mentioned example scrubs became even compacter and higher, at the same time floristic composition changed and Quercus ilex got the upper hand;
- finally, each model may be affected by random side-effects like forest fire or windfall. These two random events only sum up to 0.86 % of whole area but the prediction failure is important : about 2 order ranks (+2).

7. OUTLOOK

Next steps will be comparison with results obtained by two other modelling approaches based on non linear parametric model [8, 9] and neuronal networks [10] before applying the model to future land cover predicting.

We intend also application and comparison to two other, comparable data sets focussing on a region on the south slope of Sierra Nevada (Alta Alpujarra Granadina, Spain) and a test area located in southern Alps (Lure mountain, France) in the frame of Mediterranean mountains. Finally it will be interesting to transfer the methodological approach to data sets of different nature: time series remote sensing images those values may be considered as quantitative, discontinuous data.

8. BIBLIOGRAPHICAL REFERENCES

[1] Paegelow, M., Camacho Olmedo, M.T., Menor Toribio, J., « Límites y aportaciones de los Sistemos de Información Geográfica para trazar la dinámica espacio-temporal del paisaje en áreas montañosas mediterráneas », *IX Congreso del Grupo de Métodos Cuantitativas, SIG y Teledetección. Asociación de Geógafos Españoles*. Universidad de Alcalá de Henares. 2000

[2] Paegelow, M., Camacho Olmedo, M.T., Menor Toribio, J., « Modelizacion prospectiva del paisaje mediante Sistemas de Informacion Geografica », *X Congreso de Metodos Quantitativos, Sistemas de Informacion Geografica y Teledeteccion. Asociación de Geógrafos Españoles*, Valladolid, 2002.

[3] Saaty, T.L., « A Scaling Method for Priorities in Hierarchical Structures », *J. Math. Psychology*, 15, 234-28, 1977.

[4] Eastman, J. R., Kyem, P. A. K., Toledano, J., Jin, W., *Explorations in Geographic Systems Technology Volume 4: GIS and Decision Making*, UNITAR, Geneva, 1993.

[5] Yager, R., R., « On Ordered Weighted Averaging aggregation operators in multicriteria decision making », *IEEE Transactions on Systems, Man, and Cybernetics*., 8(1), 183-190, 1988.

[6] Flamm, R.O. and Turner. M.G., « Alternative model formulations for stochastic simulation of landscape change », *Landscape Ecology*, 9(1), 37-44, 1994.

[7] Eastman, J.R., *Idrisi32 release 2 Tutorial*, Clarklabs, Worcester, 2001.

[8] Ferraty, F., Goia, A., Vieu, P., « Régression non-paramétrique pour des variables aléatoires fonctionnelles mélangeantes », *C. R. Acad. Sci. Paris*, Ser. I 334, 217-220, 2002.

[9] Ferraty, F., Goia, A., Vieu, P., « Functional Nonparametric Model for Time Series: A Fractal Approach for Dimension Reduction », *TEST*, to come out, 2002.

[10] Ferré, L., « Determining the Dimension in Sliced Inverse Regression and Related Methods », *Journal of the American Statistical Society*, vol.93 n°441, 1998.