MODELLING AND PROJECTING LAND-USE AND LAND-COVER CHANGES WITH A CELLULAR AUTOMATON IN CONSIDERING LANDSCAPE TRAJECTORIES: AN IMPROVEMENT FOR SIMULATION OF PLAUSIBLE FUTURE STATES

Thomas Houet and Laurence Hubert-Moy

Université de Rennes 2, Place du recteur Henri Le Moal, 35043 Rennes, and:
COSTEL, UMR CNRS LETG 6554 / IFR 90 CAREN; France; thomas.houet(at)uhb.fr

ABSTRACT

The modelling and projecting of land-use change is essential to the assessment of consequent environmental impacts. In agricultural landscapes, land-use patterns nearly always exhibit spatial autocorrelation, which is largely due to the clustered distribution of landscape features as hedgerows and wetlands and also to the spatial interactions between land-use types themselves. The importance of such structural spatial dependencies has to be taken into account while conducting land-use projections. Also, land-use simulations have to be based on land-use and land-cover trends for two reasons: to identify the land-use and land-cover change processes and to be logical with the land-use and land-cover temporal dynamic. The objective of this work is to improve land-use projections in considering the influences of landscape features on land-use and land-cover change and in using long/short series of past observations in the modelling process.

Cellular automata (CA) provide a powerful tool for the dynamic modelling of land-use change and are a common methodology used to take spatial interactions into consideration. They have been implemented in land-use models that are able to simulate multiple land-use types. This research adopts the spatial evolution concept embedded in CA and applies it to land-use and land-cover change study in one watershed. This watershed is characterised by a patchy landscape inserted in an intensive agricultural area in Central Brittany (France). Land-use and land-cover changes and agricultural practices have induced water pollution. A time-series of multi-scale and multi-temporal (including historical) satellite imagery and aerial photographs were used to determine both landscape features and the spatial characteristics and land-use and land-cover trends over the period from 1952 to 2003. Socio-economic and biophysical driving forces of observed changes have been established through a network of collaborating partners and agencies willing to share resources and eager to utilise developed techniques and model results. All these input data were compiled, analysed and assessed using spatial statistical techniques to quantify spatial dependencies. A summary of neighbourhood conditions of each target cell reveals the dynamic processes of land-use change constrained within the landscape frame and thus enhances the understanding of transition rules, which is the key element of a CA.

Cellular automaton modelling procedures were then applied to develop a spatially explicit model. Model performance was evaluated in comparing simulations where the influence of landscape features on land-use and land-cover change and have been considered insignificant and negligible. The influence of the duration of land-use and land-cover trends has been also tested on land-use and land-cover projections.

Results show that introducing landscape features and using a long-term land-use and land-cover trend improve simulations of the future states of land-use and land-cover and contribute to more plausible and realistic scenarios of future changes.

Keywords: Land-use, remote sensing, change detection, spatial modelling, Cellular Automata.

INTRODUCTION

Environmental impacts like water pollution have grown significantly during the past three decades in many regions. Water quality degradation is mainly caused by agricultural intensification and associated farming practices, including excessive use of nitrogen, pesticides and other soil amendments. In agricultural landscapes, management of landscape features, such as riparian wetlands or hedgerow systems, can contribute to the control of the non-point source pollution of surface and groundwater (T1). Their evolution, e.g. removal of hedges or wetlands drainage, depends on the spatial interactions between land-uses types themselves (2). Therefore, the importance of such structural spatial dependencies has to be taken into account while conducting land-use projections. The modelling and projecting of land-use change is crucial to the assessment of potential environmental impacts. Simulation of plausible human-influenced landscape change following different scenarios may reveal strategic policies that should be modified to improve environmental issues such as water quality.

Numerous methods are used to build scenarios of the future: narrative methods, models, hybrid methods using both qualitative and quantitative methods. The most frequently used models are based on logistic regression, multi-agents and cellular automaton. When they are used to simulate land-use / land-cover (LULC) changes, projections are produced without taking in account the influence of landscape structure on land-use distribution (3). The objective of this work is to improve land-use projections with a Markovian Cellular Automaton (M-CA) in considering landscape features in the modelling process. The simulations are done for a *current trends* scenario. A *current trends* scenario assumes that management policies will not evolve and sudden spatial management (epiphenomenon) will not occur. The reason for including such a scenario is to highlight the value made with a contrasted scenario with which a comparison can also be investigated.

Cellular Automaton (CA) provides a powerful tool for the dynamic modelling of land-use change, and is a common methodology used to take spatial interactions into account (4). Ulam and Von Neumann (1961) state that a CA is a cellular entity that independently varies its states based on its previous state and that of its immediate neighbours according to specific rules. It is a spaced dynamic system where the variable (e.g. land-cover), time and space are discrete. Ferber (5) considers CA a particular Multi-Agent System where agents are fixed and contiguous surface elements.

The Markov chain is a convenient tool for modelling land-use changes setting exploratory scenarios based on *current land-cover trends*. It uses evolution from t-1 to t to project probabilities of land-use changes for a future date t+1. However, a stochastic Markov model is not appropriate, because it does not consider spatial knowledge distribution within each category and transition probabilities are not constant among landscape states (6). A hybrid Markov-Cellular Automaton (M-CA) model is a suitable approach to modelling both spatial and temporal land changes:

(a) the Markov process controls temporal dynamic among the cover types through the use of transition probabilities

(b) spatial dynamics are controlled by local rules through a CA mechanism considering either neighbourhood configuration and transition probabilities (7)

(c) GIS and remotely sensed data can be used to define initial conditions, to parameterise the M-CA model, to calculate transition probabilities and determine the neighbourhood rules (8).

They are fittingly suitable when more than one processes interfere at different spatial and temporal scales. They were mostly used for urban growth simulation (8,9,10,11,12) for monitoring urban sprawls and preserving natural ecosystems. They were also used as a spatial support system to assess socio-economic and environmental policies at national scale (13) and/or regional scales (14).

Therefore, temporal dynamic is determined through a quantitative diachronic analysis which is a simple method compared to others (15). Moreover, land-cover changes may have various rates, magnitudes and directions (16). Thus, in an intensive agricultural context, what would be the influence on the projections in the use of a short-term LULC trend compared to a long-term LULC trend?

This study proposes to use this method in an agricultural context in which the temporal dimension (evolution of land-use/land-cover) is expressed by the Markovian process as a continuity of the current evolution and the spatial dimension (spatial modelling) considers the landscape structure to improve projected plausible future states in relation to water quality. First, this paper focuses on the influence of the landscape features to improve plausible future LULC state. Then, it shows how LULC trends from which the temporal dynamic is calculated could affect the simulations on a small patchy watershed.

STUDY AREA

The study area is located in Central Brittany, France (Figure 1). The watershed of the Coët-Dan River (1,200 ha) is characterised by intensive agricultural activities and thus favours an elevated prevalence of environmental exposures such as important non-point source water pollution by nitrates. Agriculture intensification led to important land-use changes as well as to modifications of landscape features, for example removal of hedgerows and drainage of riparian zones.

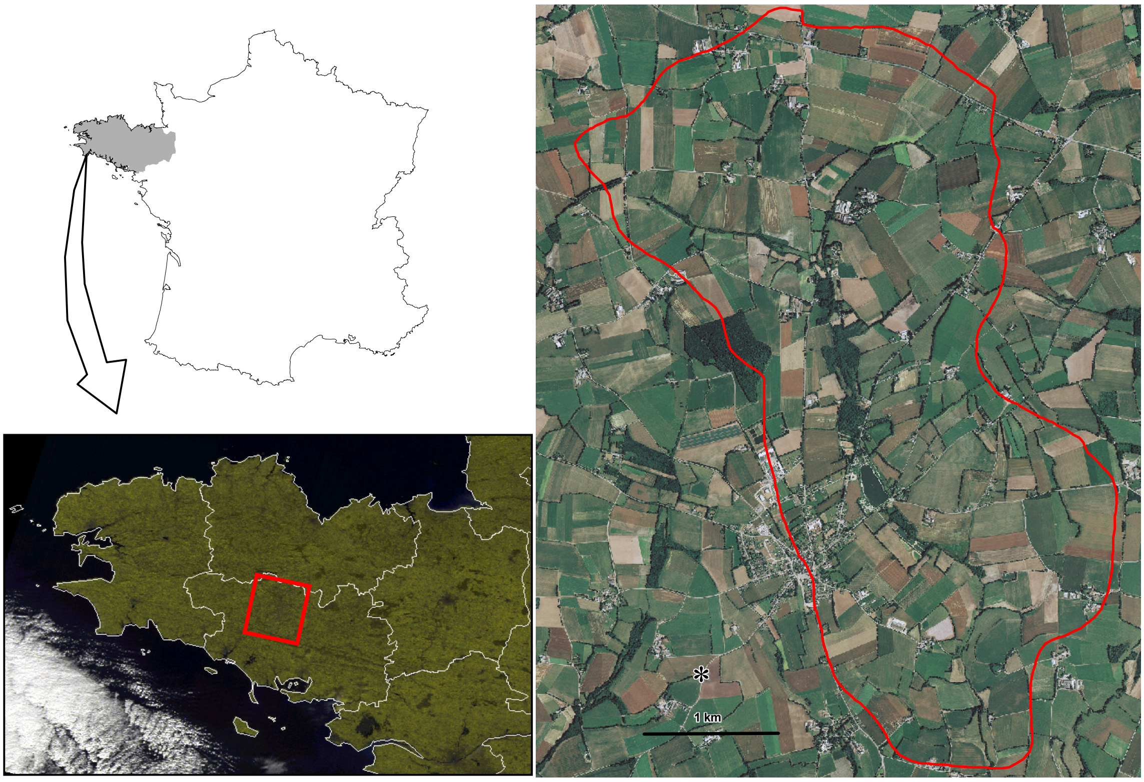


Figure 1: Location of the study area, the Coët-Dan watershed, Central Brittany, France. © Eurimage IRS-WiFS 2000/01/20 RGB composite (NIR, NIR, R), © IGN BD Ortho.

Land-use / land-cover trends

Multi-scale and multi-temporal time series - including historical satellite imagery and aerial photographs - were used to determine both landscape features and land-use/ land-cover changes over the study period between 1952 and 2003 (Figure 2).

Until the sixties, agriculture had many aspects of a self-sufficient system where crops (cereals, potatoes) were dominant products. During the seventies, the watershed of the Coët-Dan river followed changes that occurred in regional agriculture. Milk production increased dramatically extending grassland to feed cattle (200 ha in 1960, 394 ha in 1972). From the end of the seventies until the beginning of the eighties, intensified milk production may explain the growth of grassland proportions (454 ha in 1981), however, at the same time several farmers began to partially or entirely change their production for mixed milk/pork or pork production. This kind of production required more crops such as maize and cereals to feed the animals. Then, the national restriction of milk production (1982/83) had stopped grassland trends and also converted more farmers to an intensive pork production. The 1992 reform of the Common Agricultural Policy (CAP) of the European Economic Community (EEC) caused crops to increase, resulting in a reduction of grasslands (305 ha in 1999). In 2003, the watershed of the river Coët-Dan represents a highly agricultural area with a domination of pork and milk production. Between 1952 and 2003, agriculture changes (intensification of productions) are described as the change “from the farm to the firm” (17). Land-cover trends show variations in the rates and direction of change due to shifts in agricultural polices.

A synthesis of the evolution of the different land-cover classes identified from remote sensing data is shown in Table 1.

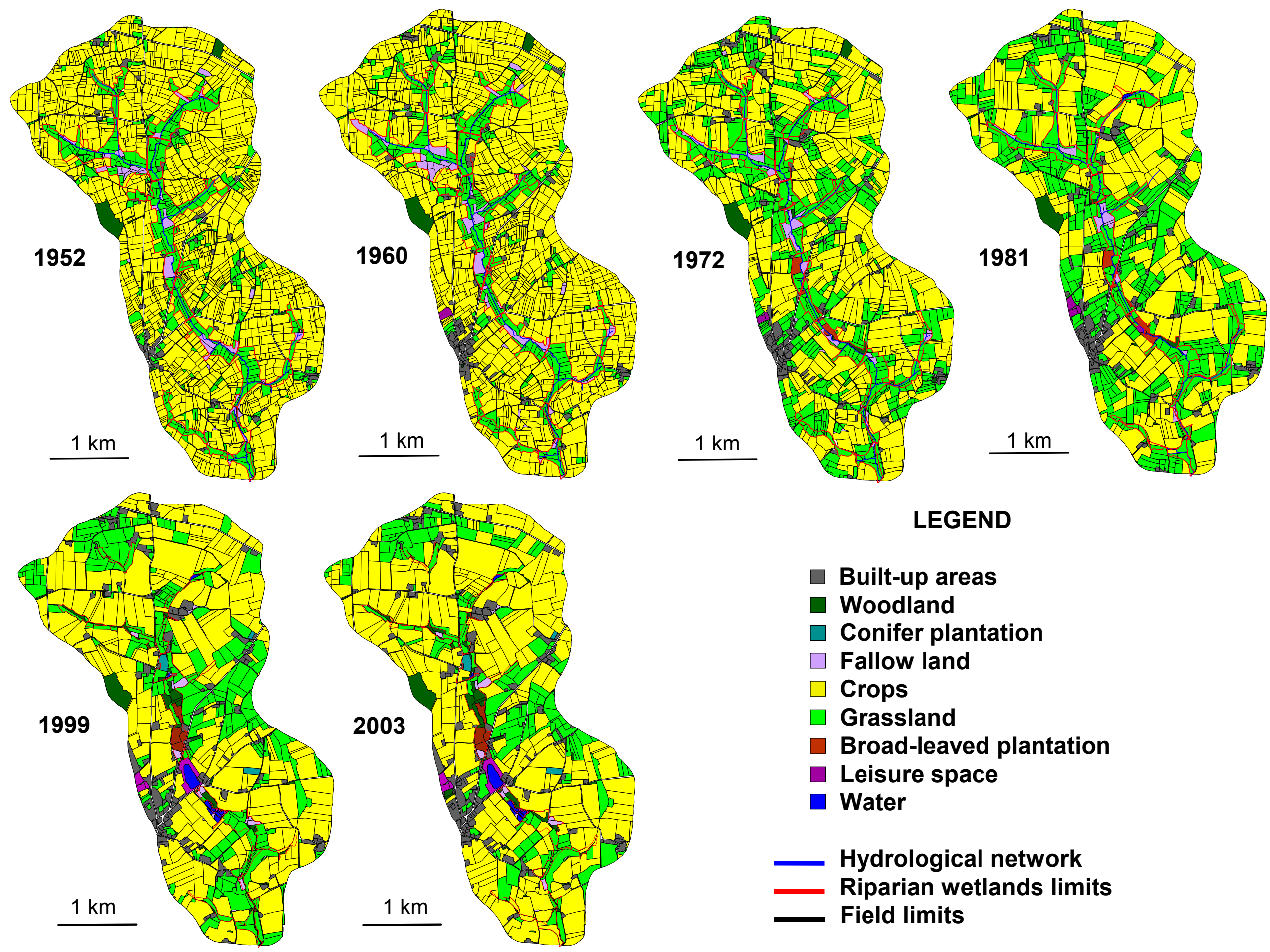


Figure 2: Land-use and land-cover changes (1952-2003).

Table 1: Changes in land-use and land-cover classes between 1952 and 2003 (hectares).

Years	Roads	Built-up areas	Wood-land	Fallow-land	Crops	Grass-land	Leisure space	Water
1952	40.5	26.1	14	26.6	877.6	220.4	0	0
1960	40.1	40.1	12.7	37.6	874.7	198.1	1.7	0
1972	40.5	49.2	21.8	19.9	676.4	395.6	1.3	0
1981	35.8	59.3	22	10.2	616.6	457.1	3.3	0.4
1999	35.1	76.2	36.8	7.7	730	304.8	7.8	6.2
2003	35.1	81.6	42.1	7.7	791.7	232.6	7.8	6.2

Throughout a similar observational period (1952-2003) riparian wetlands and hedgerows had declined considerably (Table 2). Also spatial dependencies between LULC and landscape features have considerably evolved during this period. During the fifties and sixties, grasslands were essentially located in riparian wetland areas because of the hydromorphic constraints for crop production. With the intensification of agriculture, grasslands located in riparian zones were less managed and exploited by farmers thus leading to fallow land and woodland expansion in these areas.

Table 2: Evolution of landscapes features (riparian wetlands, hedgerow density) between 1952 and 1999.

Years	Riparian wetlands area / ha	% of riparian wetlands to total area	Hedgerow density / m/ha
1952	177.2	14.8	159.3
1960	173.7	14.5	154.3
1972	137.3	11.4	122.9
1981	105.9	8.8	60.0
1999	74.8	6.2	53.7

During the seventies and eighties, both local planning authorities and individual initiatives led to the process of grouping land areas together and thus explain the removal of hedgerow networks, especially those located along crop fields distant from the farmstead. Thus, processes have induced a dramatic enlargement of field sizes within 30 years. However, planning policies changed during the nineties, when the effects of landscape features on water quality and erosion were highlighted, leading to preservation and restoration program actions. The influence of landscape features on the LULC distribution is noticeable (18). For example, riparian zones are less extensively used by farmers (2) and woodland areas have become dominant; small fields are often covered with grassland (63% of fields less than 1ha or greater when the field is surrounded by hedgerows). Most of the significant changes in the landscape occurred prior to 1981, and only slight modifications have been observed in the riparian wetlands since then, which are still decreasing, but at a slower rate.

THE M-CA BASED MODEL

The LULC change model used spatial knowledge (GIS / remotely sensed data), temporal data (a transition probabilities matrix and a transition area matrix) and considers spatial interactions through the definition of the transition rules. MARKOV and CA_MARKOV functions available in the IDRISI Kilimanjaro software were used in this case.

Transition probabilities matrix / Transition area matrix

The M-CA based model is processed for two dates and produces:

- A transition probabilities matrix. It determines the likelihood for a cell or pixel to change from a land-use class to every other category from date 1 to date 2. This matrix is the result of cross tabulation of the two images adjusted by the proportional error. It produces a set of probability images, one for each land-use class.
- A transition area matrix which records the number of cells or pixels that are expected to change from each land-use class to each other land-use class over the next time period. This matrix is produced by the multiplication of each column in the transition probability matrix by the number of cells of corresponding land-use in the later image.

This Markovian model also outputs a set of conditional probability images. Taken from the transition probability matrix, the images report the probability that each land-use class would be found at each location in the next step, as a projection from the later of the two land-use/land-cover images (19).

Projection of land-use and land-cover is carried out for 2015 and 2030 using a short-term trend and a long-term LULC trend (1999-2003 and 1981-1999, respectively). These two trends are considered to evaluate the influence of the trend duration in LULC projections. In the case of the long-term LULC trend, the 2015 and 2030 transition probabilities tables are constructed from the LULC images of 1981 and 1999, as far as the entire period is characterised with the same farming production system, involving the spatial dependencies within the landscape features in a similar way (Tables 3 and 4). For the short-term LULC trend, the 2015 and 2030 transition probabilities matrix are derived from the LULC images of 1999 and 2003.

Table 3: Transition probabilities matrix used for the land-use and land-cover changes projection for 2015 considering the long-term trend (1981-1999).

	Roads	Built-up area	Wood-land	Fallow land	Crops	Grass-land	Leisure space	Water
Roads	0.855	0.027	0.002	0.002	0.066	0.044	0.002	0.000
Built-up area	0.021	0.869	0.000	0.000	0.047	0.058	0.004	0.000
Woodland	0.008	0.016	0.721	0.004	0.046	0.092	0.058	0.057
Fallow land	0.001	0.000	0.615	0.121	0.000	0.263	0.000	0.000
Crops	0.002	0.008	0.001	0.001	0.748	0.237	0.002	0.001
Grassland	0.002	0.035	0.027	0.014	0.539	0.370	0.005	0.008
Leisure space	0.002	0.012	0.021	0.000	0.000	0.000	0.823	0.141
Water	0.000	0.013	0.258	0.036	0.129	0.346	0.015	0.203

Table 4: Transition probabilities matrix used for the land-use and land-cover changes projection for 2030 considering the long-term trend (1981-1999).

	Roads	Built-up area	Wood-land	Fallow land	Crops	Grass-land	Leisure space	Water
Roads	0.776	0.042	0.005	0.003	0.111	0.060	0.003	0.001
Built-up area	0.030	0.802	0.002	0.001	0.089	0.070	0.005	0.001
Woodland	0.013	0.029	0.572	0.007	0.113	0.125	0.082	0.058
Fallow land	0.006	0.015	0.565	0.021	0.149	0.185	0.027	0.030
Crops	0.003	0.020	0.007	0.004	0.691	0.268	0.004	0.003
Grassland	0.004	0.050	0.048	0.008	0.628	0.254	0.009	0.007
Leisure space	0.003	0.021	0.061	0.004	0.012	0.037	0.722	0.141
Water	0.002	0.029	0.282	0.019	0.311	0.266	0.029	0.061

Transition rules: the suitability maps

The transition rules result from socioeconomic-biophysical factors and spatial dependencies (e.g. distance of a field from the farmstead) that contribute to LULC changes.

Socio-economic and biophysical driving forces have been determined through a network of collaborating partners and agencies. Interrelations between factors of change as well as spatial dependencies between land-use types and landscape features have been identified and quantified. Factors of change used in the land-use change model vary for each land-use class. For agricultural land-use, e.g., driving forces of land-cover change may depend on the type of system of production and the characteristics of the fields of a farm (size, distance from the farmstead, level of hydromorphy, slope).

Transition rules are produced for each land-cover class through a suitability map built from spatial dependency and driving forces of change. Suitability maps represent the probability (range from 0 to 255) of a pixel or a cell to belong to the corresponding land-use type. Each suitability map highlights where changes are plausible for one land-use category in the future. Change scenarios cannot occur in some specific areas (e.g. urban areas cannot become crops) or where land-cover classes are not expected to change in a *current trends* scenario (e.g. water areas).

Thus, the set of all suitability maps used to project and model future scenarios integrates transition rules and spatial knowledge. Driving forces of change for each land-use class are specified in the description of each suitability map.

Suitability maps of land-use /land-cover classes

Suitability maps correspond to boolean images where land-cover will not change (Figure 3). White areas (value = 255) in Figure 3 represent the (a) roads, (b) leisure space and (c) water LULC classes. These classes will not change over the time. The value represents the probability (range from 0 to 255) of a pixel or a field to belong to the corresponding LULC class.

(a) (b) (c)

Figure 3: Suitability maps of (a) Roads, (b) Leisure space, (c) Water.

Woodland, fallow land, built-up areas, crops and grassland may evolve in the future. Their projection is processed considering specific spatial rules (driving factors of changes and their respective weight) except for some areas where constraints are set.

(1) The built-up area suitability map (Figure 4a) constrains future *urban* development anywhere except on actual roads, leisure space, water surfaces, woodland and within a 50 m buffer zone around the hydrographic network. The most important driving force that contributes to the expansion of built-up areas is the proximity to the village. It is combined with three other equally weighted factors (proximity to main roads, proximity to existing built-up areas and field size).

(2) The woodland suitability map (Figure 4b) considers that woodland will preferentially progress to the detriment of fallow land and grassland and beside existing woodland.

(3) The fallow land suitability map (Figure 4c) is processed with factors that influence the distribution of fallow lands: field size, presence of grassland and fallow land, proximity of woodland and the soil hydromorphy.

(4) The crop and grassland suitability maps (Figures 4d,e) allow of crop extension except on existing roads, leisure space, water surfaces and built-up areas. The most important factor of change is the type of production (milk production, pork production, etc.). For each system of production, the probability of change is determined (i) at the farm scale according to the type of production, the distance of each field from the farmstead; and (ii) at the field scale according to the size of fields, the soil hydromorphy and the field's slope. Due to non-exhaustive farmer / field affiliation data, a mean value corresponding to the overall land-cover class change probability is attributed to the fields where data are missing.

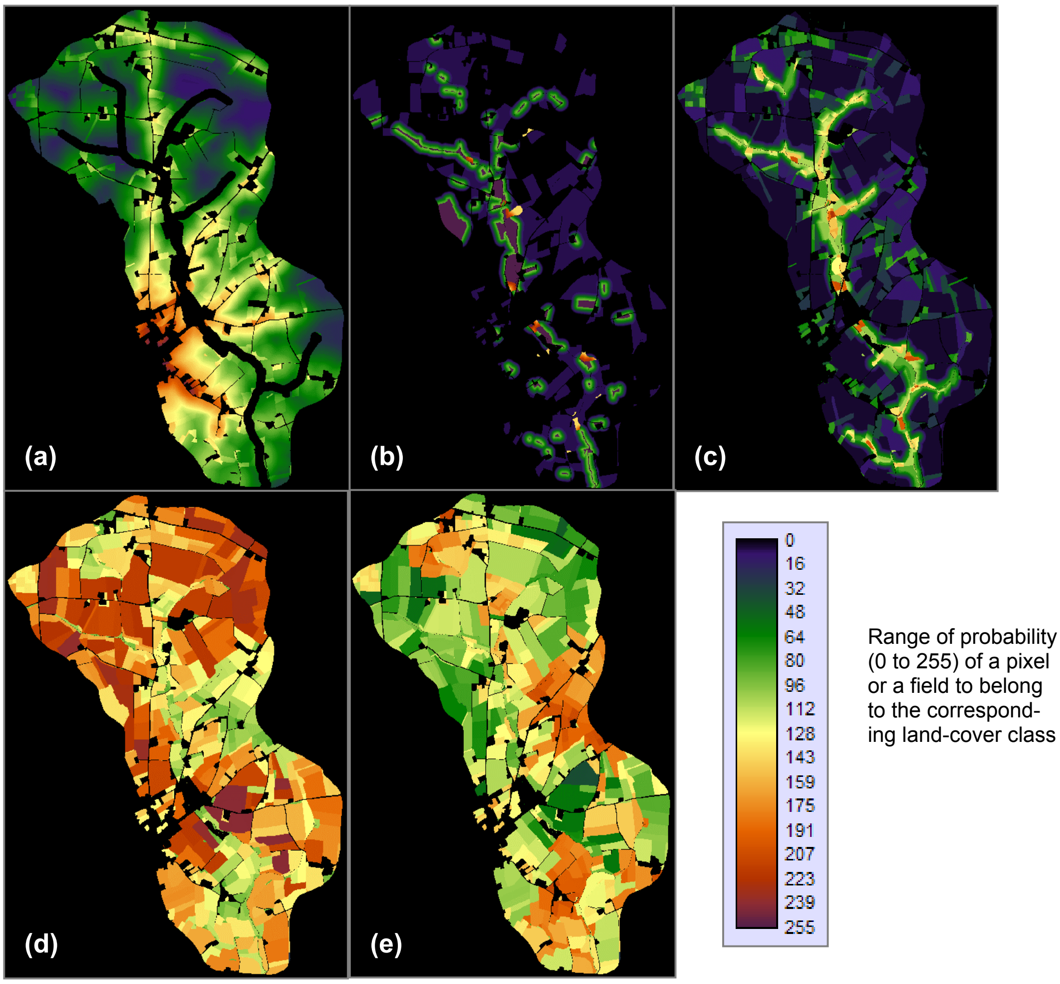


Figure 4: Suitability maps for (a) built-up areas, (b) woodland, (c) fallow land, (d) crops and (e) grassland land-use / land-cover classes.

Suitability maps considering landscape features influence on land-use / land-cover spatial allocation

Landscape features such as riparian wetlands can influence LULC changes at a local scale due to spatial factors (e.g. distance) constraining their usage (2), which varies with the production system adopted. Suitability maps for roads, leisure space and water surfaces do not differ from the suitability maps shown in Figure 3. The built-up area suitability map (Figure 5a) takes into account riparian wetlands as non possible extension areas.

Other suitability maps (Figures 5b-e) integrate the observed differences in LULC changes inside and outside the riparian zones. For example, the woodland suitability map considers land-use change from fallow land to woodland between 1981 and 1999 occurring exclusively inside the riparian zones; the fallow land suitability map also integrates changes from grassland and cultures to fallow land inside the riparian wetlands. It permits, when data are missing, to determine finer probability values for grassland and culture suitability maps for fields located inside and outside the riparian zone.

Thenail and Baudry (18) have shown that hedgerow networks also need to be taken into account when projecting land-use and land-cover changes. A field surrounded by a "woody perimeter" (part of the perimeter occupied by a woody hedgerow) is more likely to be covered by grassland.

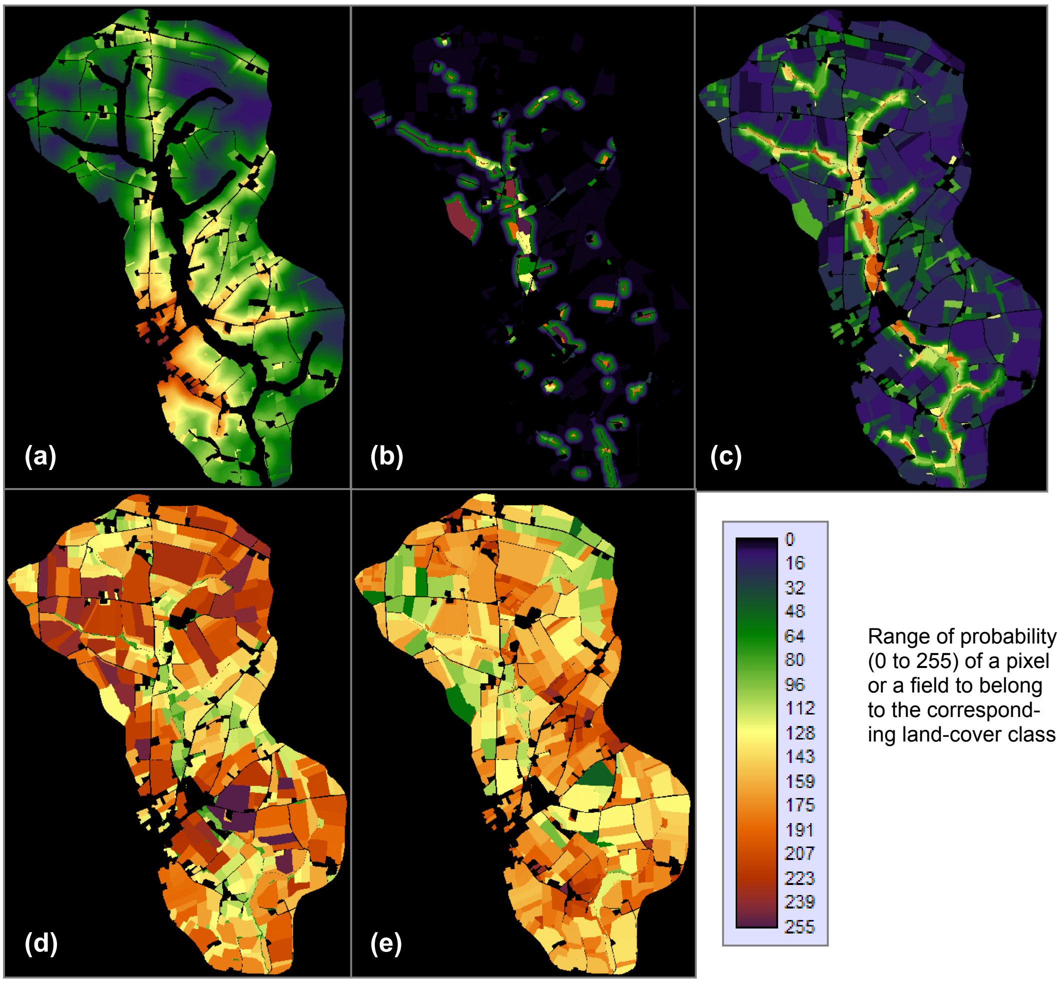


Figure 5: Suitability maps of (a) built-up areas, (b) woodland, (c) fallow land, (d) crops and (e) grassland land-use / land-cover classes considering landscape features.

The M-CA process

The M-CA model uses an iterative process of land-cover allocation until the total areas predicted by the Markovian chain analysis are identified. The predicting LULC process specifications are:

- The number of iteration (n) is determined by the projection in the future (number of years).
- The model uses a contiguity filter to develop a spatially explicit contiguity-weighting factor to change the cells based on their previous states and those of their neighbours (16). This is a mean filter pool with a Boolean mask filter that is multiplied by the suitability map of the land-use class considered. By default, the filter size is a 5×5 kernel. The purpose of this filter is to down-weight the suitabilities of pixels far from existing areas of that class, thus giving preference to contiguous suitable areas.
- Within each time step, the re-weighted suitability maps are run through a multi-objective land allocation (MOLA) process to allocate 1/n of the total of land-cover predicted to change from one land-use/land-cover class to another. MOLA process resolves land allocation conflicts by allocating the cell to the objective for which its weighted suitability is highest, thus reducing

the amount of area to be assigned to each land-cover class. As a result, any particular objectives (competing land-use/land-cover types) will lose some conflict cases and will thus need to accept cells of lower suitability weight (16). In the M-CA process, each land-cover is considered in turn as a host category and all other land-use/land-cover classes act as claimant classes and compete with the host class for land. At the end of an iteration, a new land-cover map is built overlaying all results of the MOLA operation.

- The next iteration uses the new land-cover map as the input on which the CA component will pass to allocate another 1/*n* predicted total area expected to change.

RESULTS

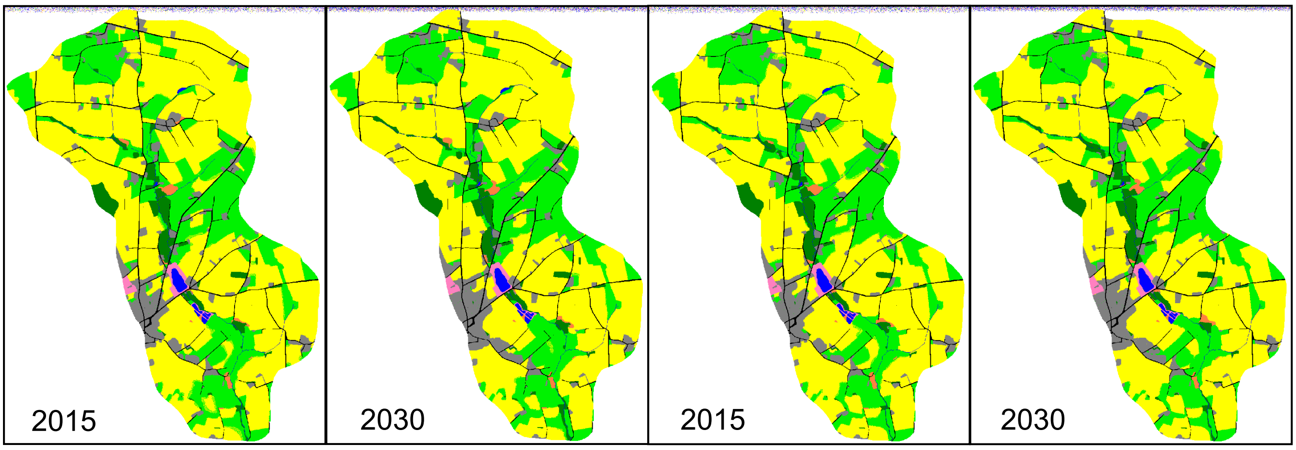
Validation of the projected land-use and land-cover states for 2015 and 2030 is an important but difficult stage. A precise evaluation of the projected images over decades is obviously not possible. The purpose of this work is to highlight the influence of landscape features and land cover trends in simulating plausible future LULC states.

Influence of landscape features

Figure 6 depicts the results of the modelling M-CA process with and without integration of the landscape features, i.e. the riparian wetlands and hedgerows.

Firstly, these results highlight the good representation of the agricultural landscape pattern, respecting the field geometry (Figure 6). Modelling the transition rules at the field scale through suitability maps which integrate both local spatial dependencies (e.g. field size) and driving factors at a larger scale (e.g. farm production), is necessary to restitute the landscape pattern in the projection maps with a M-CA model based on contiguity relations.

No influence of landscape features *Considering landscape features influence*



■ Roads ■ Built-up areas ■ Woodland □ Fallow land □ Crops ■ Grassland □ Leisure space ■ Water

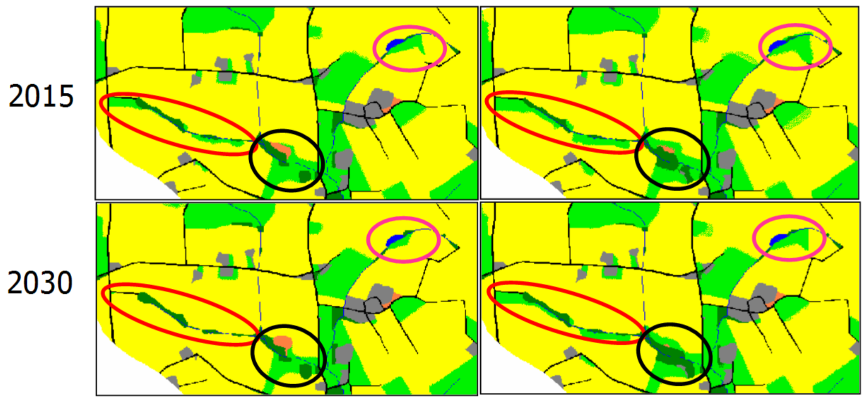
(a) (b)

Figure 6: Projections of land-use and land-cover in 2015 and 2030 using the long-term LULC trend (1981-1999), in case of (a) no influence of landscape features or (b) influence of landscape features on LULC changes.

Secondly, the two maps of possible future states in 2015 show very little spatial changes. This is most likely due to the M-CA process that respects the predicted changes; the grassland and crops amount to 301 ha and 721 ha, respectively for both scenarios of *no influence of landscape features* and *influence of landscape features*. Compared to the LULC state in 1999 (Figure 2), these maps illustrate the LULC trends: (i) the closing up of riparian areas by woodland and fallow land; (ii) the grassland concentration around farmsteads. In 2030, the closing up of riparian zones is observed to increase slightly. An important result concerns the LULC modelling inside and adjacent to the riparian zone. Without considering the influence of landscape features, the northern riparian zones are contiguous to cropland. However, if the influence of landscape features is taken into consideration in the modelling process, fields of grassland are surrounding them (Figure 7, red and black circles). Considering the influence of landscape features (riparian wetlands) provides more plausible results, because actual policies provide meadows along the river network in order to prevent surface runoff and soil erosion as existing in 2030 (Figure 7).

While hedgerow networks appear to have little influence on LULC modelling, the increase of cropland concentration highlights areas where a removal of hedges would accelerate soil erosion and surface runoff (Figure 7, pink circle). Since the mid-seventies important hedgerow removals have been done by farmers to increase the arable land. Projected LULC maps with existing hedgerow network distribution could emerge as useful tools for water quality preservation and/or restoration practices.

No influence of landscape features *Influence of landscape features*



■ Roads ■ Built-up areas ■ Woodland ■ Fallow land ■ Crops ■ Grassland ■ Leisure space ■ Water

Figure 7: Projected land-use and land-cover for 2015 and 2030 using the long-term LULC trend (1981-1999) inside and adjacent to the riparian zone. In red: Over-estimation of crops when the influence of landscape features on LULC change is not taken into account in the modelling process. In pink: Preservation of a more realistic landscape pattern when the influence of landscape features is considered due to the spatial configuration of the hedgerow network. In black: Considering the influence of landscape features on LULC changes produces a more plausible landscape pattern regarding the closing-up process in the riparian areas.

Influence of land-use and land-cover trends

A comparison of the simulations of land-use and land-cover in 2015 and 2030 using a short-term LULC trend and a long-term LULC trend has been performed considering landscape features in the modelling process.

For both trend durations, the two major land-use/land-cover classes (crops and grassland) demonstrate a reduced evolution and are almost stabilized during the last 25 years, even if the short-term trajectory is higher than the long-term trajectory (Figure 8). Similarly, woodland and urban areas increase significantly when considering the short-term LULC trend. Other LULC classes demonstrate little or no change.

The short-term LULC trend appears to be less adapted than the long-term LULC trend, because it considers inter-annual changes (due to crop successions) to project LULC changes over decades. Conversely, the long-term LULC trend considers general trends of LULC changes, that partially smooth changes from crop successions.

Therefore, LULC changes may be easily over-estimated or under-estimated using a short-term LULC trend. Thus, LULC change trend detections require standard conditions and similar methodologies. For example, climate hazard as a drought may induce significant changes in cultures/

grassland estimations from one year to the next. Such hazards may alter long-term LULC change trends, and thus should be taken into account in the modelling process.

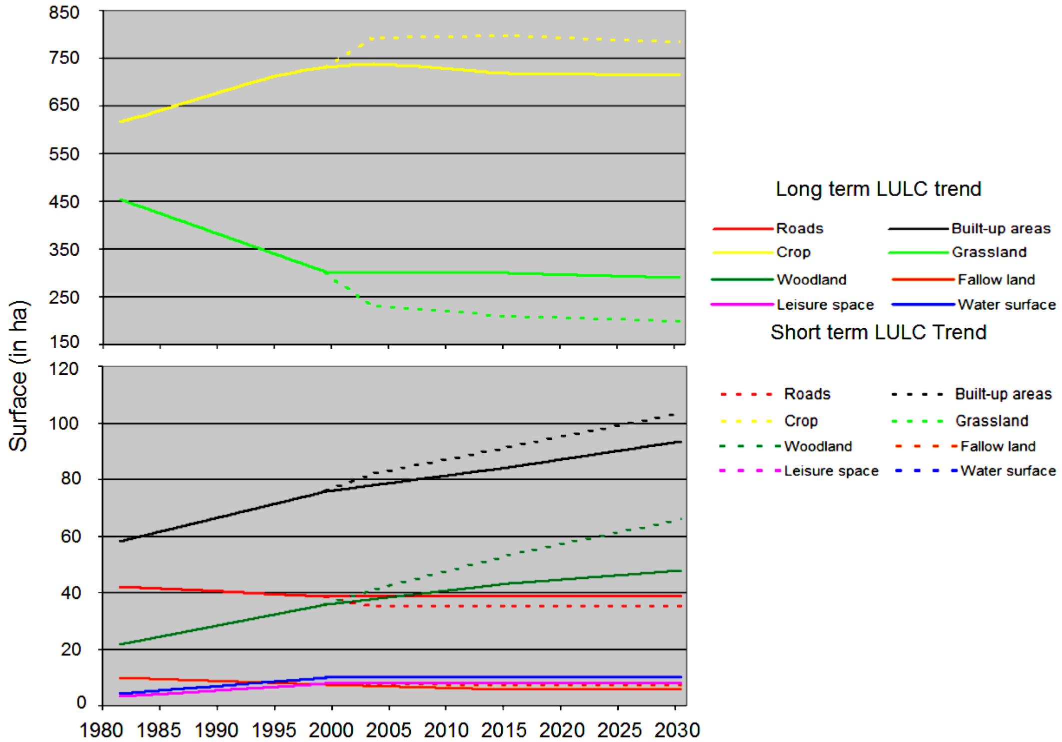


Figure 8: Influence of the duration of LULC trends on projections considering the influence of landscape features on LULC changes. The two graphs with two different Y-axis scales enhance both major and small LULC changes.

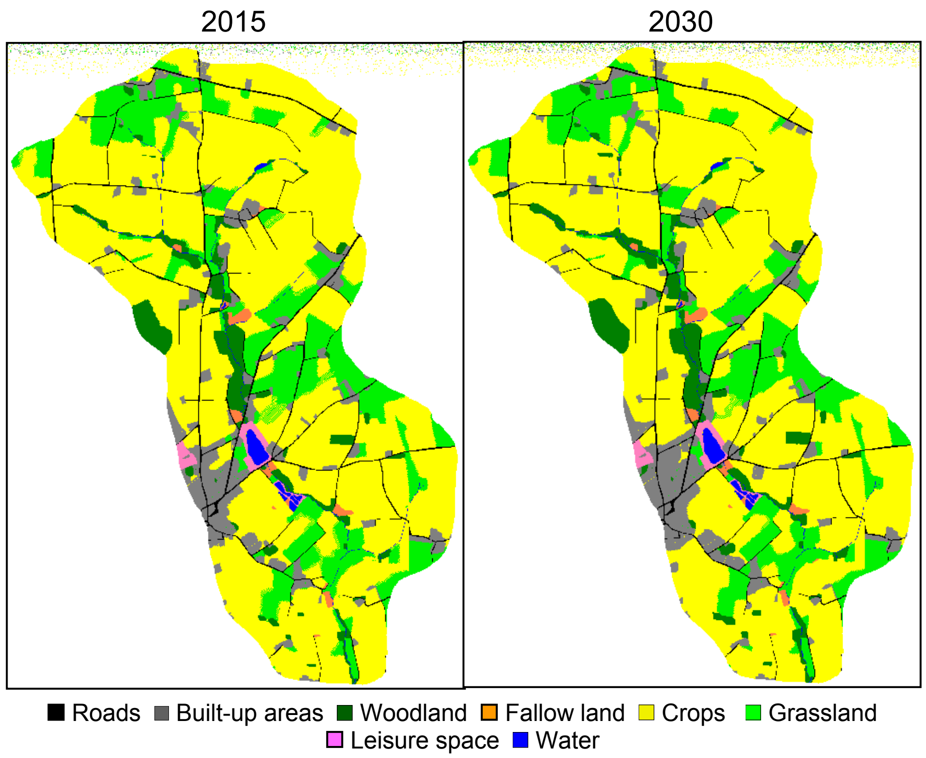


Figure 9: Projections of land-use and land-cover in 2015 and 2030 using the short-term LULC trend (1999-2003) and considering the influence of landscape features on LULC changes.

Figure 9 represents LULC simulations obtained using the short-term LULC trend. The riparian zones are continuously covered by woodland and are under pressure of land-use associated with farming practices in upland areas. The salt and pepper effect located in the northern part of the maps highlights the inability of the M-CA model to allocate all the LULC proportions expected to change over the period. It proves an over-estimation of crops and grassland classes by the use of a short-term LULC trend.

CONCLUSIONS

The approach described in this paper shows the influence of spatial dependencies between landscape features and LULC change, which have to be taken into account in the modelling process to improve projections of plausible future states. Restoring water quality could be helped by the identification of areas potentially threatened by soil erosion and surface run off in long-term projections.

A first interest in using a CA to model LULC plausible states is the possibility of integrating multiscaled factors of landscape evolution. The two scales used in that case are the field scale and the farm scale. An intermediate scale, the islet scale (a cluster of adjacent fields of a farm), could be integrated in the elaboration of the suitability maps to improve the LULC projections, as it appears that change occurs at this scale (18).

Limitations of the M-CA model result from the fact that it is computationally exigent. Moreover, LULC changes need to consider cyclic changes coming from crop successions with an occurrence probability. Thus, the modelling is performed considering a probability matrix of plausible future states respecting a general trend for each LULC class. Taking into account crop successions in a new model -currently under development- may constitute a possible way to increase the accuracy of simulations in the long term but also to discriminate different types of crops. This model will also be able to consider exploratory scenarios but following different strategies and policies which is not possible with the M-CA model. *Current trends* scenarios are relatively easy to implement with an M-CA procedure and can be used as reference in comparison with contrasted scenarios.

ACKNOWLEDGEMENTS

We are thankful to the Region Bretagne, the SAGE Blavet Institution and the PEVS *Zone Atelier* Programme (Environment, Life and Societies Programme of the French National Centre of Scientific Research) that funded this work for their support and interest. We also acknowledge our partners from INRA-SAS and INRA-Sad Armorique for contributing data and methodology. We are grateful to collaborating partners and agencies for their participation in the determination of factors and driving forces of land-use and land-cover evolution.

The authors thank the anonymous reviewers for their comments and critical review of the manuscript.

We are very grateful to Christopher Barnes of USGS Eros Data Center / Landcover Institute for helping to improve the manuscript.

REFERENCES

1 Viaud V, P Merot & J Baudry, 2004. Hydrochemical buffer assessment in agricultural landscapes, from local to catchment scale. Environmental Management, 34(4): 559-573

2 Baudry J & C Thenail, 2004. Interaction between farming systems, riparian zones and landscape patterns: a case study in western France. Landscape and Urban Planning, 60: 121-129

3 Lay J G, 2000. A land use change study using Cellular Automata. In: 21st Asian Conference on Remote Sensing Proceedings (Teipei, Taiwan)

4 Wolfram S, 1986. Theory and Applications of Cellular Automata (World Scientific, Singapore) 560 pp.

5 Ferber J, 1997. Les Systèmes Multi-agents, vers une Intelligence Collective (InterEditions) 522 pp.

6 Boerner R E J, M N DeMers, J W Simpson, F A Artigas, A Silva & L A Berns, 1996. Markov Models of inertia and dynamic on two contiguous Ohio landscapes. Geographical Analysis, 28: 56-66

7 Sylvertown J, S Holtier, J Johnson & P Dale, 1992. Cellular automaton models of interspecific competition for space the effect of pattern on process. Journal of Ecology, 80: 527-534

8 Wang X & X Zhang, 2001. A dynamic modelling approach to simulating socioeconomic effects on landscape changes. Ecological Modelling, 140: 141-162

9 Goetz S, A Smith, C Jantz, R Wright, S Prince, M Mazzacato & B Melchior, 2003. Monitoring and predicting urban land use change: Applications of multi-resolution multi-temporal satellite data. In: IEEE International Geoscience And Remote Sensing Symposium 2003, (Toulouse, France) 1567-1569

10 Dubos-Paillard E, P Langlois & Y Guermond, 2003. Analyse de l'évolution urbaine par automate cellulaire. Le modèle Spacelle. L'Espace Géographique, 4: 357-378

11 White R & G Engelen, 2000. High-resolution integrated modelling of the spatial dynamics of urban and regional systems. Computers, Environment and Urban Systems, 24: 383-400

12 Batty M & Y Xie, 1994. From cells to cities. Environment and Planning, B21: 31-48

13 Engelen G, R White & A C M De Nijs, 2002. Environment explorer: spatial support system for the integrated assessment of socio-economic and environmental policies in the Netherlands. Integrated Assessment, 4(2): 97-105

14 Engelen G, S Geertman, P Smits & C Wessels, 1999. Dynamic GIS and strategic physical planning: a practical application, geographical information and planning. In: Advances in Spatial science, edited by J Stillwell, S Geertman & S Openshaw (Springer, Berlin) 87-111

15 Loveland T R, T L Sohl, S V Stehman, A L Gallant, K L Sayler & D E Napton, 2002. A strategy for estimating the rates of recent United States land-cover changes. Photogrammetric Engineering & Remote Sensing, 68(10): 1091-1099

16 Lambin E F, 1996. Change detection at multiple temporal scales: seasonal and annual variations in landscape variables. Photogrammetric Engineering & Remote Sensing, 62(8): 931-938

17 Canévet C, 1992. Le modèle Agricole Breton. Histoire et géographie d'une révolution agro-alimentaire (PUR Edition) 397pp.

18 Thenail C & J Baudry, 2004. Variation of farm spatial land use pattern according to the structure of the hedgerow network (bocage) landscape: a study case in northeast Brittany. Agriculture, Ecosystem and Environment, 101: 53-72

19 Eastman J R, 2003. Idrisi Kilimanjaro, Guide to GIS and Image Processing (Clark University Edition) 328pp.