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# SIMULATION AND PREDICTION OF URBAN LAND USE CHANGE AS A TOOL FOR BETTER PLANNING

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**ABSTRACT**

This scientific paper is committed with building up a methodological guideline for modelling urban land use change through GIS, Remote Sensing imagery and Bayesian probabilistic methods. A medium-size town in the west of São Paulo State, *Bauru*, was adopted as case study. Its urban structure was converted into a 100 x 100 (m) resolution grid, and transition probabilities were calculated for each grid cell by means of the "weights of evidence" statistical method and upon basis of the information related to the technical and social infrastructure of the town. The probabilities therefrom obtained fed a cellular automaton (CA) simulation model – DINAMICA- conceived by the Centre for Remote Sensing of the Federal University of Minas Gerais (CSR-UFMG), based on a multiscale vicinity approach and stochastic transition algorithms. Different simulation outputs for the case study town in the period 1979-1988 were generated, and statistical validation tests were then conducted for the best results, employing a multiple resolution fitting procedure.

This modelling experiment revealed the plausibility of adopting Bayesian empirical methods based on the available infrastructure knowledge to simulate urban land use change, what implies their possible further applicability for generating forecasts of growth trends both for Brazilian and worldwide cities.

*Keywords: Urban Modelling, Cellular Automata, Town Planning, Land Use Change, Bayesian Methods*

## 1. INTRODUCTION

Recent generation models of urban dynamics have been dealing with diverse themes. According to Batty (2000), there are currently some twenty or more applications of CA to cities, such as the diffusion or migration of resident populations (Portugali et al., 1997), the competitive location of economic activities (Benati, 1997), the joint expansion of urban surface and traffic network (Batty and Xie, 1997), the generic urban growth

(Clarke et al., 1997), the urban land use dynamics (Deadman et al., 1993; Batty and Xie, 1994; Phipps and Langlois, 1997; White and Engelen, 1997; White et al., 1998) , and so forth.

Specifically regarding urban land use dynamics, it is possible to identify basically three main trends of CA models in respect to their balance between stochasticity and determinism. A first one concerns the predominantly deterministic models, whose most evident representative is the urban growth study for the San Francisco Bay area, conducted by Clarke et al. (1997). Although this model incorporates a certain randomness in selecting the cells for urban growth and in promoting the spread of growth seeds, its transition rules, which can be spontaneous, diffusive, organic or road-influenced, are fundamentally deterministic in the sense that the cell suitability for being urbanised is not dependent upon probabilistic methods.

A second trend relates to the stochastic models with both deterministic estimations of area for land use transition and deterministic transition algorithms. A good example of this category of models is the SIMLUCIA, conceived by White et al. (1998), which is an integrated model of natural and human systems operating at several spatial scales, and was aimed at providing the officials of the Caribbean Island of Santa Lucia with a tool to explore possible environmental, social, and economic consequences of hypothesised climate changes.

In this model, a sophisticated set of equations taking into account aspects of the natural environment is formulated in order to estimate the impact of economic and demographic changes on land use. The stochasticity of this model is present in the calculation of the probabilities of land use transition for each cell, which is basically a function of the cell suitability for the new activity in question and its relative accessibility for such an activity. In the SIMLUCIA transition algorithm, cells are ranked by their highest potential, and cell transitions begin with the highest ranked cell and proceed deterministically downwards, until the number of cells demanded by the above-mentioned equations is reached.

A third trend concerns the stochastic CA models with both stochastic estimations of area for land use transition and stochastic transition algorithms. The modelling experiment presented in this paper integrates this third category, in which the transition rules are randomised, the cell transition probabilities are calculated through Bayesian probabilistic methods ("weights of evidence"), and the Markov chain is in principle utilised for the definition of the transition rates for each possible type of land use change. An overview of the "weights of evidence" statistical method as well as an explanation of how it can be applied to the modelling of urban land use dynamics are presented throughout the next section.

## 2. METHODS: A BAYESIAN METHOD-BASED CELLULAR AUTOMATON MODEL

### 2.1 GENERALISATION PROCEDURES APPLIED TO THE LAND USE MAPS

Initially, the following procedures were applied to the initial (1979) and final (1988) land use maps (Figure 1) used in the simulation experiment so as to render them workable by the computational model and coherent to the reality they are related to:

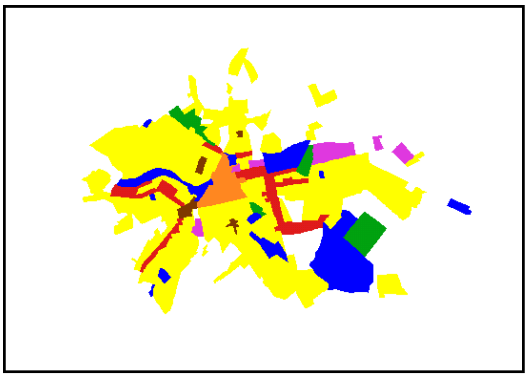
(i) reclassification of the zones initially assigned by the Bauru local authorities according to their dominant and effectively existent use with the help of satellite imagery;

(ii) reclassification of similar zones shown on official maps to only one category, e.g.: residential zones of different densities are all reclassified to residential zones only; special use zones and social infrastructure equipments zones are reclassified to institutional zones only, and so on;

(iii) adoption of eight land use zone categories: residential, commercial, industrial, services, institutional, mixed use zone, leisure/recreation, and non-urban zone;

(iv) exclusion of districts segregated from the main urban agglomeration, i.e. those which are located above 10 km from the official urban boundary;

(v) disregard of the traffic network and minor non-occupied areas in the simulations.



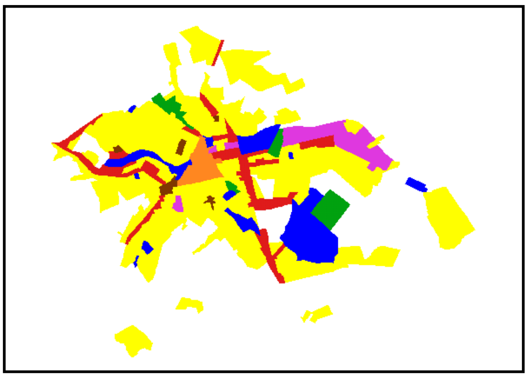


Fig. 1 – Official Bauru land use maps for the years 1979 (left) and 1988 (right).

The land use maps on Figure 1 are the results of the application of the generalisation procedures listed above on the official city maps. The yellow colour represents the residential use; the orange, the commercial use; the purple relates to the industrial use; the blue refers to the institutional use; the red corresponds to the services use zones and corridors; the brown is related to the mixed use zones; the green represents the leisure and recreation use; and the white refers to the non-urban use.

### 2.2 EXPLORATORY ANALYSIS AND SELECTION OF VARIABLES

Some of the maps of explaining variables related to the technical and social infrastructure of Bauru and employed in the modelling analysis are presented below. Initially, these maps were scanned in the hollandaise OCE scanner (model G6035S) and digitised in AutoCad release 14. These maps were then exported as files with extension DXF to the Geographic Information System (GIS) termed SPRING, conceived by the Division for Image Processing of the Brazilian National Institute for Space Research (DPI-INPE). It is worth mentioning that these procedures were also adopted for the production of the Bauru land use maps presented in Figure 1. In SPRING, the maps of variables were then subjected to a preliminary processing, including vector edition, polygons identification, elaboration of distance maps and spatial statistical analysis maps like the Kernel points density estimator, etc. (Figure 2).

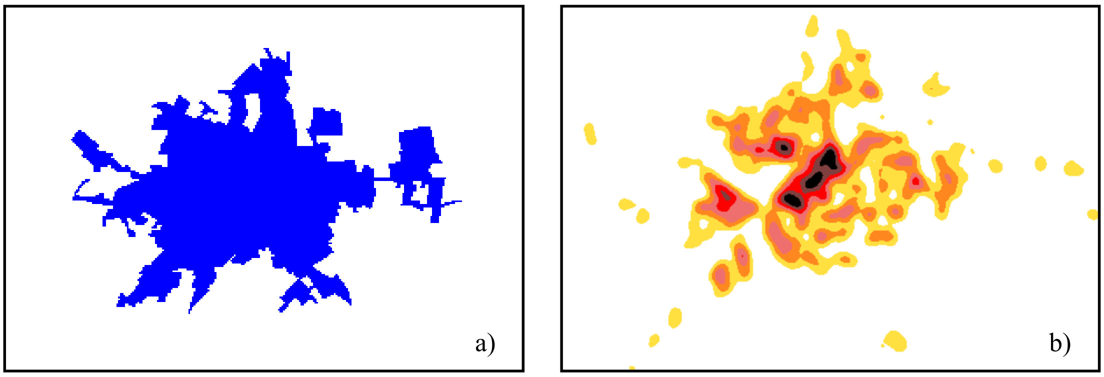



Figure 2 – Examples of maps of variables: (a) area served by water supply in Bauru, 1979; (b) Kernel estimator for the density of commercial establishments in Bauru, 1979.

Since the "weights of evidence" statistical method (to be employed in the calculation of the cells transition probabilities) is based on the "Bayes theorem of conditional probability", the selection of variables for the modelling analysis should take into account the checking of independence amongst pairs of variables chosen to explain the same category of land use change. For this end, two methods were used: the Cramers Coefficient ($V$) and the Joint Information Uncertainty ($U$). For further details of these two indexes, see Bonham-Carter (1994). In both cases, it is necessary to obtain values from an area cross-tabulation between pairs of maps of variables under analysis. For the Cramers Coefficient, the empirically established threshold was ***0.45***, and for the Joint Information Uncertainty, ***0.35***. As none of the association measure values surpassed the thresholds, no variables preliminarily selected for modelling have been discarded from the analysis.

### 2.3 ESTIMATION OF TRANSITION RATES

For the specific case study town in question – Bauru – in the period 1979-1988, five types of land use change were detected (Table 1). In order to calculate land use transition rates for the period 1979-1988, the initial and final land use maps were converted to raster files with extension TIFF and resolution 100 x 100 (m), and then exported to the IDRISI Geographic Information System. In IDRISI, a cross-tabulation operation was made between both land use maps (See Figure 1) so as to generate transition percentages for the five existent types of land use change.

**TABLE 1 - IDENTIFIED TYPES OF LAND USE CHANGE FOR THE CITY OF BAURU, IN THE PERIOD 1979-1988, AND RESPECTIVE CODES**

| ***Code*** | ***Type of Land Use Change*** |
|---|---|

| | |
|---|---|
| NU_RES | *Non-Urban to Residential* |
| NU_IND | *Non-Urban to Industrial* |
| NU_SERV | *Non-Urban to Services* |
| RES_SERV | *Residential to Services* |
| RES_MIX | *Residential to Mixed Use* |

Due to the stochastic structure of the DINAMICA transition algorithms, envisaged transition rates established through cross-tabulation are not always reached.

For the estimation of land use percentages in the case of modelling land use change forecasts through DINAMICA, the Markov chain is to be employed. This chain is a mathematical model designed to describe a certain type of process that moves in a sequence of steps through a set of states, whose formula is defined as:

$$\Pi(t+1) = P.\ \Pi(t), \tag{1}$$

where $\Pi(t)$ is a column vector, with $n$ elements, that represents the system condition in a certain time $t$ (e.g. area percentages for each $n_i$ land use category or state); $\Pi(t+1)$ is the vector representing the occupation of $n$ states in a given future time $t+1$; and $P$ is the transition probabilities matrix or the table for land use transition rates.

An important constraint of the Markov model lies on the fact that, in principle, it supposes that transition probabilities do not change over time (stationary process). Moreover, given its stochastic nature, the Markov chain masks the causative variables. It is not an explanatory model, and is thus of no use in understanding the causes and driving factors of land use transition processes. On the other hand, the Markov chain analysis has the great advantage of presenting a mathematical and operational simplicity. Simple trend projection involves no more than matrix multiplication, and the only data requirement is for current land use information (JRC and ESA, 1994).

### 2.4 RECKONING OF THE CELLS LAND USE TRANSITION PROBABILITIES

As previously said, the "weights of evidence" statistical method, employed in the calculation of the cells transition probabilities, is based on the "Bayes theorem of conditional probability". Basically, this theorem concerns the favourability to detect a certain event, which can be in the current case a given category of land use change (e.g. non-urban use to residential use), provided that an evidence (e.g. water supply area), also called explaining variable, has already happened. The evidences or explaining variables in the experiment presented in this paper mainly refer to the technical and social infrastructure of the case study town, Bauru.

The favourability to find the event (change from non-urban to residential use) $R$ given the presence of the evidence (water supply) $S$ can be expressed by:

$$P\{R/S\} = \frac{P\{R \cap S\}}{P\{S\}} \tag{2}$$

where $P\{R/S\}$ is the conditional probability of occurring the event $R$ given the presence of the explaining variable $S$. The equations of the Bayes theorem can be expressed in an *odds* form. ***Odds*** are defined as a ratio of the probability that an event will occur to the probability that it will not occur. The weights of evidence method uses the natural logarithm of *odds*, known as *log odds* or ***logits***. In this way, through some algebraic manipulations, the following expression is obtained:

$$O\{R/S\} = O\{R\}\ .\ \frac{P\{S/R\}}{P\{S/\overline{R}\}} \tag{3}$$

where $O\{R/S\}$ is the conditional (*posterior*) odds of $R$ given $S$, $O\{R\}$ is the *prior odds* of $R$ and $P\{S/R\}/P\{S/\overline{R}\}$ is known as the *sufficiency ratio* ($LS$). In weights of evidence, the natural logarithm of both sides of Equation *3* are taken, and $log_e\ LS$ is the *positive weight of evidence* $W^+$, which is calculated from the data. Then:

$$logit\{R/S\} = logit\{R\} + W^+ \tag{4}$$

Similarly, the *logits* expression for the conditional probability of $R$ given the absence of the evidence $S$, will provide the *negative weight of evidence* $W^-$:

$$logit\{R/\overline{S}\} = logit\{R\} + W^- \tag{5}$$

If the evidence is uncorrelated with the events, then $LS$=$LN$=1, and the *posterior* probability equals the *prior* probability, and the probability of an event would be unaffected by the presence or absence of a certain evidence. In this sense, $W^+$ is positive, and $W^-$ is negative, due to the positive correlation between the evidences and the events. Conversely $W^+$ would be negative and $W^-$ positive for the case where a very limited part of the event occur on the evidence area than would be expected due to chance. If the events are independent of whether the evidence is present or not, then $W^+ = W^- = 0$ (Bonham-Carter, 1994). In the particular case of the DINAMICA simulation model, adopted for the modelling experiment being considered, the cells transition probabilities are calculated through a formula which converts *logit* into conventional probability, as follows:

$$P = \frac{O(R) \; . \; e^{\sum_{i=1}^{n} W^+}}{1 + O(R) \; . \; e^{\sum_{i=1}^{n} W^+}} \tag{7}$$

This formula shows a clear similarity with the one employed for the calculation of probability in the logistic regression method (also known as logistic function), which obviously does not include *odds*. In the above case, the sum of the positive weights of evidence ($W^+$) corresponds to the product of the linear regression coefficients by the independent variables adopted in the regression analysis.

The first step in the very process of calculating the cells transition probabilities using DINAMICA is to obtain a cross-tabulation map (Figure 3) between the initial and final land use maps elaborated for the city of Bauru, respectively for the years 1979 and 1988, both previously presented in Figure1.

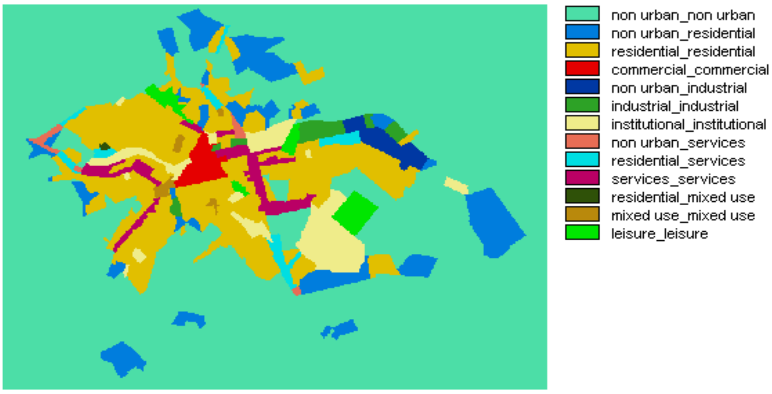



Fig. 3 – Cross-tabulation map between the initial (1979) and final (1988) land use maps elaborated for the city of Bauru. Types of land use permanence as well as transition are listed on the legend.

In IDRISI, the land use cross-tabulation map of Bauru (1979-1988) was used to generate land use transition maps (Figure 4) for each of the five possible types of land use change presented in Table 1. This was done through reclassification tables ("edit" command), on which three basic rules were observed. First, all raster values corresponding to classes of land use permanence or transition whose initial land use was different from the initial land use category in the considered type of land use change were assigned value 0 (***black colour***). This reclassification to value 0 is automatic for raster values not included in the "edit" table. Second, all raster values corresponding to classes of land use transition whose initial and final land use categories were equal to the initial and final categories of the land use change at issue were assigned value 2 (***blue colour***). Third, all other remaining classes of land use permanence or transition were assigned value 1 (***green colour***).


Fig. 4 – Example of the non-urban_residential land use transition map for Bauru in the period 1979-1988.

Once all the possible types of land use transition maps were elaborated (nu_res; nu_ind; nu_serv; res_serv; res_mix), they were then subjected to partial cross-tabulations with selected explaining variables (evidences) maps according to an apparent interdependence between a certain type of land use transition and a given explaining variable. The evidences maps, pre-processed in the SPRING Geographic Information System, were in the same manner as the initial and final land use maps converted to raster files with extension TIFF and resolution 100 x 100 (m), and then exported to IDRISI. The partial cross-tabulations disregard the raster values 0 (black colour) in the land use transition maps and are accomplished through the "ermatt" command of IDRISI.

The numerical values of cells proportions existing in the absence/presence of a binary evidence (e.g. water supply) or in the different ranges of distances maps and found to be overlying on either class 1 (green colour) or 2 (blue colour) of the land use transition maps are (for each cross-tabulation table) selectively transferred to EXCELL files specially created for the calculation of the weights of evidence (See Equations *3* and *4*).

Using the values for the positive weights of evidence $W^{+}$ concerning the several evidences maps employed in the analysis of each category of land use change, the DINAMICA simulation model will then calculate the cells transition probabilities (See Equation *7*) for the five types of land use transition. By means of the cells transition probabilities, DINAMICA will then generate the respective transition probabilities maps (Figures 5 to 7) for each of the five types of land use change existing in Bauru from 1979 to 1988. These maps are seen in ERMAPPER, a GIS employed by DINAMICA for visualisation purposes.

It is worth remarking the good ability of these probabilities maps to detect the transition areas (blue colour) in the corresponding land use transition maps, for all the reddish regions in the probabilities maps relate to the very areas owning the highest transition probabilities rates. Some examples of probabilities maps are shown in the sequence.

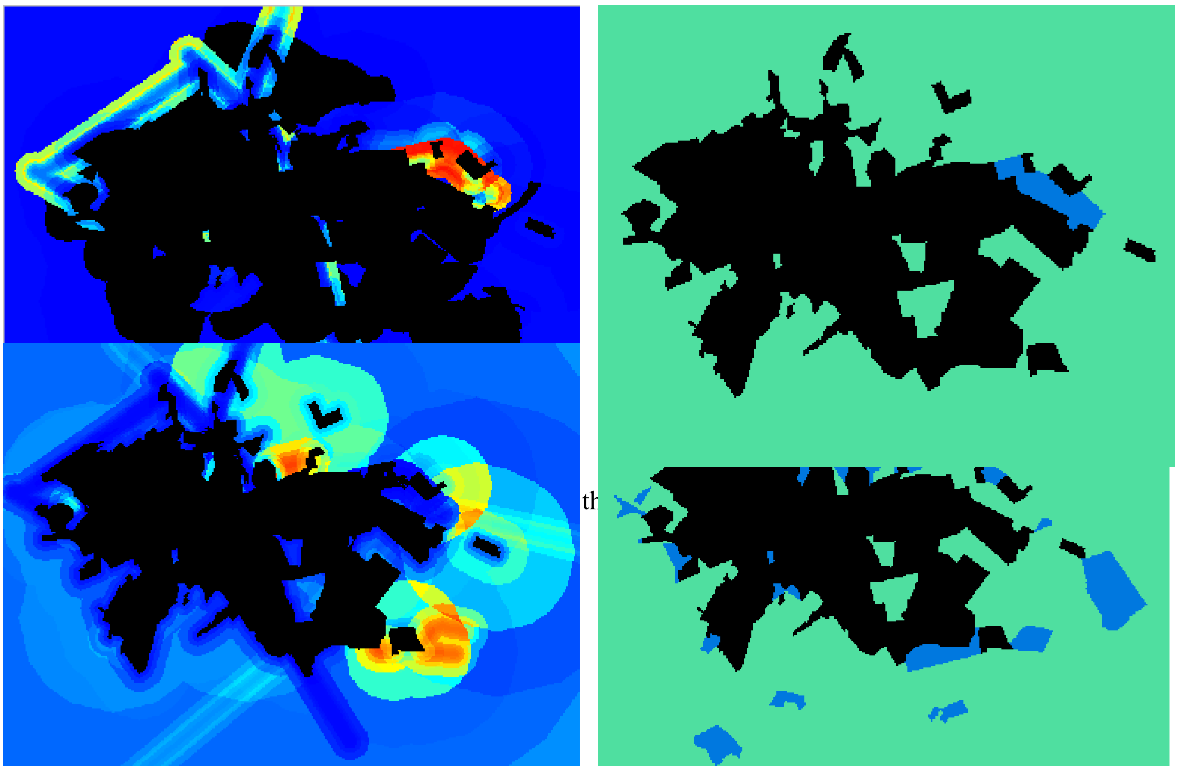


Fig. 6 - Map of cells transition probabilities, on the left, and map of land use transition “non-urban – residential” (nu_res), on the right.

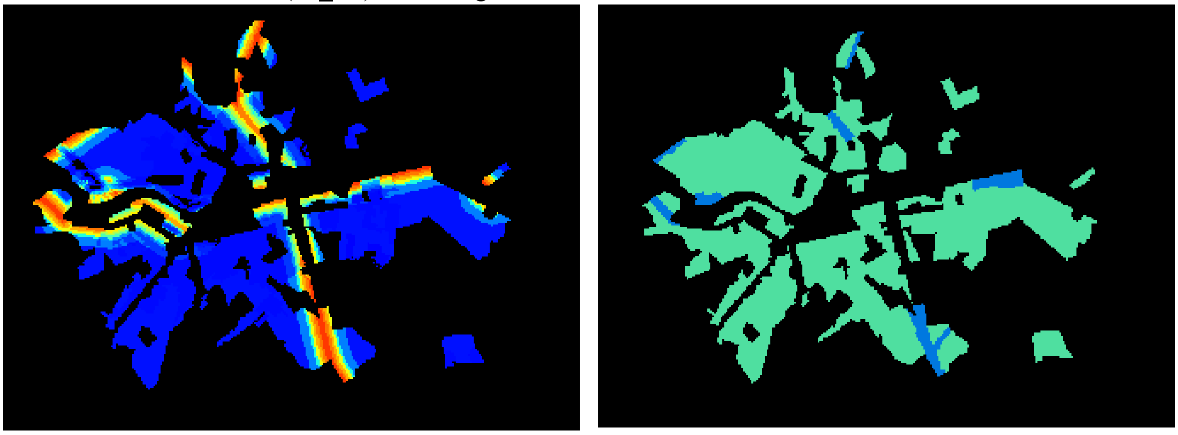


Fig. 7 - Map of cells transition probabilities, on the left, and map of land use transition “residential - services” (res_serv), on the right.

## 2.5 MODEL CALIBRATION

For the calibration of the model designed to emulate urban land use transition for the town of Bauru in the period 1979 – 1988, empirical procedures were adopted. They basically concern the visual comparative analysis, for each type of land use change, amongst the general trends of preliminary simulation results, the hints provided by both the transition probabilities map and the land use transition map, and the guideline information contained in the simultaneous overlay of different explaining variables maps upon the final land use map in vector format

The model calibration, on the other hand, is as well accomplished by the analysis of scatter plots relating subcategories of evidences (distances ranges), whenever they are available, with their respective positive weights of evidence. In a general manner, when the plots present a good fit of trendlines (which can assume different orders and types), i.e. when the lines do not demand very complex models for adjustment, the evidences to which they are associated are highly prone to be included in the model (Figure 8).

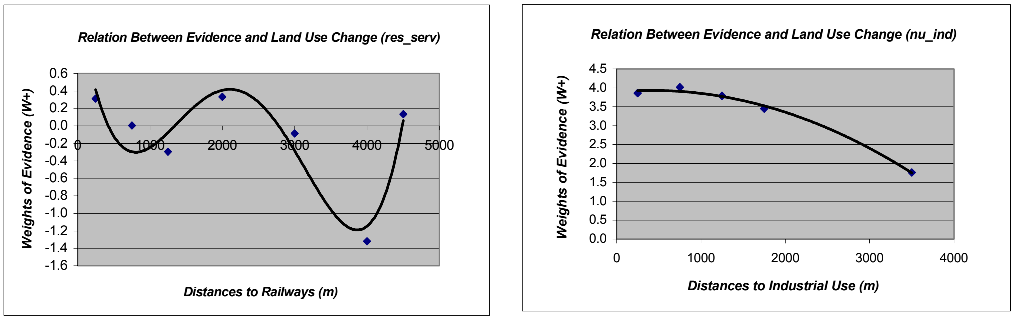



Fig. 8 – Examples of scatter plots and respective trendlines for the relations between subcategories of evidences (*X axis*) and their corresponding positive weights of evidence (*Y axis*), considering different types of land use change. The plot on the left show a typical case of poor fit, and hence, of evidence exclusion. On the contrary, the right plot presents a good adjustment of trendline, what implies the high probability of inclusion of such an evidence in the urban land use model.

The final decision towards the inclusion or exclusion of a given evidence will always rely upon a broad judgement, in which the environmental importance of the evidence and its coherence concerning the phenomenon (land use transition) being modelled are analysed. As stated by Couclelis (1997), to take full advantage of CA models as simulating (and forecasting) tools, planners and others need to rely as much on their right-brain powers of pattern recognition and relationship perception as on left-brain analyses of the inevitably innacurate quantitative outputs.

## 3. RESULTS AND DISCUSSION

Upon basis of the carried out calibration process, it becomes evident that the probability of certain non-urban areas in the city of Bauru to shelter residential settlements ("nu_res" land use transition) largely depends on the previous existence of this type of settlements in their surroundings, on the greater proximity of these areas to commercial activities clusters as well as on the available accessibility to such areas.

As to the transition of non-urban areas to industrial use (nu_ind), there are two great driving forces: the nearness of such areas to the previously existent industrial use and the availability of road access. This can be explained by the fact that in the industrial production process, the output of certain industries represent the input of other ones, what raises the need of rationalisation and optimisation of costs by the clustering of plants interrelated in the same productive chain. Furthermore, plots in the vicinities of industrial areas are often prone to be devaluated for other uses, what makes them rather competitive for the industrial use.

Regarding the transition of non-urban areas to services use (nu_serv), three major factors are crucial: the proximity of these areas to clusters of commercial activities, their closeness to areas of residential use, and last but not least, their strategic location in relation to the N-S / E-W services axes of Bauru. The first factor accounts for the suppliers market (and in some cases also consumers market) of services; the second factor represents the consumers market itself; and the third and last factor corresponds to the accessibility for both markets related to the services use.

The transition "residential to services use" (res_serv) supposes the insertion of services into previously consolidated urban areas. In this way, since this transition type already takes place amid the suppliers and consumers markets, it will solely prioritise the strategic location in relation to the N-S / E-W services axes of Bauru, besides of course, the existence of water supply, which in the specific case of Bauru does not correspond to the whole urbanised area.

Finally, the last type of land use transition concerns the shift from residential use to mixed use (res_mix). The mixed use zones, which actually play the role of urban subcentres, constitute a sort of commercial centres consolidation, which at a later stage also start to attract services and social infrastructure equipments besides commercial activities themselves. Therefore, new mixed use zones arise in more peripheral areas, where a greater occupational gathering is at the same time assured. Thus, the decisive factors for this last type of land use change are:

- existence of medium-high density of occupation (higher density values only occur in the central commercial zone of the town or in the immediacies of already existent mixed use zones);
- presence or proximity of social housing settlements (for they shelter the greatest occupational densities in more peripheral areas, and hence, greater consumers markets);
- nearness to planned or peripheral roads, since new mixed use zones arise in farther areas of the town.

After the calibration of evidences maps sets is accomplished, a new calibration process concerning the script parameters of the DINAMICA simulation model takes place. Such parameters refer to the number of iterations (runs), proportion of cells transition by contiguity ("*expander*" operator) and by nucleation ("*patcher*" operator), average size and variance of patches to be generated either by the *expander* or *patcher* operators, etc.

The *expander* is an algorithm of the DINAMICA model which realises transitions from a state *i* to a state *j* only in the adjacent vicinities of cells with state *j*. The *patcher* operator, on its turn, is also an algorithm of the DINAMICA model, but which realises transitions from a state *i* to a state *j* only in the adjacent vicinities of cells with state other than *j*.

Due to the randomness of the DINAMICA transition algorithms, even though the same sets of evidences maps for each type of land use transition and the same script parameters are kept in different runs, distinct simulations results will be produced after each run of the model. In this way, the best urban land use simulation results for the city of Bauru in the period 1979–1988 are presented in Figure 9. The *patcher* algorithm proved to be of great suitability for the modelling of residential settlements disconnected from the main urban agglomeration. Nevertheless, the shapes of these settlements in the modelling results do not strictly coincide to those observed in reality. This happens because these contours are associated with the real state properties limits. Since legal actions for the merging or split of plots may occur at any time and drastically alter their form, such boundaries can be regarded as highly unstable factors, and thus, inappropriate for modelling.

The services corridors, in light brown, were well modelled in all simulations. The industrial use zone, in light green, was considerably well detected in all of the three simulations results, specially in S2 and S3. The leisure and recreation zones (yellowish green), the institutional zones (red) and the central commercial zone (light blue) did not suffer any transitions. The new mixed zone that arose in the north-western part of the town during the simulation period was rather well modelled, particularly in S1 and S3.

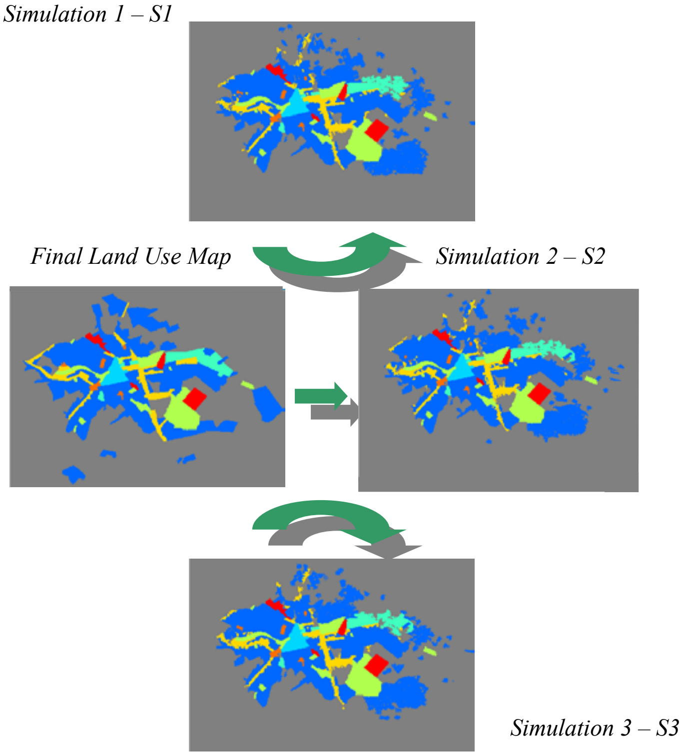



Fig. 9 – Bauru final land use map and simulations results for the period 1979-1988.

Lastly, the shifts from non-urban areas to residential use represented the most challenging category of land use transition in the modelling experiment at issue. The reasons for the difficulties in detecting their shapes have been previously commented in this paper. It is worth remarking that 65 % of this type of transitions occur through the *expander* algorithm. An evident shortcoming of this algorithm lies on the fact that, after the random selection of a seed cell for transition, neighbouring cells to it also undergo transitions though regardless of their transition probability values. The R & D team of CSR-UFMG, entrusted with the continuous upgrading programme of DINAMICA, is currently working to tackle this problem. Other enhancements such as the incorporation of fractal parameters in the transition algorithms as well as the possibility to define patches average sizes and variances for the *expander* and *patcher* algorithms separately are also envisaged.

To conclude, it is worth stressing here the wide feasibility (and the cells transition probability maps are a concrete prove) to optimise the simulations results by means of a model which embraces more refined algorithmic logics, suitable for the urban phenomena modelling under consideration.

## 4. STATISTICAL VALIDATION OF THE MODEL

With the purpose to conduct statistical tests for the spatial validation of models of land use dynamics, Constanza (1989) presents a procedure entitled "*Multiple Resolution Method*", in which a sampling window, that can assume different sizes, moves over the entire images considered, and the average fit between two given scenes (the real and the simulated one) for a particular window size is calculated. In this estimation, a comparative analysis is conducted between the absolute number of pixels belonging to the same classes existent on both scenes and found within a given window. This multiple resolution method was implemented in a UNIX environment programme named FIT, developed by CSR-UFMG. FIT was applied for the best simulation results presented in Figure 9, with sampling window sizes of 3x3, 5x5 and 10x10 (Table 2).

**TABLE 2 – TESTS OF THE MULTIPLE RESOLUTION GOODNESS OF FIT APPLIED TO THE BEST LAND USE SIMULATION RESULTS FOR THE CITY OF BAURU (1979-1988)**

| *SIMULATIONS* | *MULTIPLE RESOLUTION GOODNESS OF FIT (F)* |
|---|---|
| *S1* | *F = 0.902937* |

| | |
|---|---|
| ***S2*** | *F = 0.896092* |
| ***S3*** | *F = 0.901134* |

## 5. CONCLUSION

The urban land use dynamics models have proved to be useful for the identification of main urban growth vectors and their general land use tendencies, what enables local planning authorities to manage and reorganise (if it comes into question) city growth according to the environmental carrying capacity of concerned sites and to their present and envisaged (future investments) infrastructure availability.

The urban expansion forecasts provided by such models also help local authorities in general to establish investments goals in terms of technical and social infrastructure equipments. Decision makers from the private sphere can as well benefit from the modelling output data, since companies of transportation, conventional and mobile phones, cable TV and internet, and others will have subsidies for defining priorities as to where and how intense to invest. Also the organised civil society, either through NGOs or local associations, can profit from the modelling forecasts in order to enhance, by legal means, demanding social movements for the implementation of social and technical infrastructure, since their requests and respective arguments shall be based on realistic short- and medium-term urban growth trends.

Finally, it is worth reminding that the “weights of evidence” statistical method is not constrained by the straitjacket of rigid theories devices and does not either impose theoretical restraints to the modelling objects. Since this a wholly empirical approach, its applicability can be extended to further Brazilian and worldwide cities, provided that the minimum necessary sets of evidences maps are available.

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