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CELLULAR AUTOMATA AND NEURAL NETWORKS AS A MODELLING FRAMEWORK FOR THE SIMULATION OF URBAN LAND USE CHANGE

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Abstract. Empirical models designed to simulate and predict urban land use change are generally based on the utilisation of statistical techniques to reckon the land use change probabilities. In contrast to these methods, artificial neural networks arise as an alternative to assess such probabilities by means of non-parametric approaches. This work introduces a simulation experiment on urban land use change in which a supervised back-propagation neural network has been employed in the parameterisation of the simulation model. The thereof estimated spatial land use transition probabilities feed a cellular automaton (CA) simulation model, based on stochastic transition rules. The model has been tested in a medium-sized town in the midwest of São Paulo State, *Piracicaba*. A series of simulation outputs for the case study town in the period 1985-1999 were produced, and statistical validation tests were then conducted for the best results, upon basis of a multiple resolution fitting procedure.

Keywords: urban modelling, land use dynamics, neural networks, cellular automata, town planning.

1. Introduction

The concept of cellular automata arose in the very beginnings of the digital computation era, around the 1920s and 1930s, when two mathematicians - Alan Turing and John von Neumann - pursued the idea that machines would be self-reproducible, i.e. they would be able to generate an infinity of diverse patterns that could be indefinitely perpetuated (Batty et al., 1997).

Cellular automata (CA) models consist of a simulation environment represented by a gridded space (raster), in which a set of transition rules determine the attribute of each given cell taking into account the attributes of cells in its vicinities. These models have been very successful in view of their operationality, simplicity and ability to embody both logics- and mathematics-based transition rules. It is thus evident that even in the simplest CA, complex global patterns can emerge directly from the application of local rules, and it is precisely this property of emergent complexity that makes CA so fascinating and their usage so appealing.

The usage of CA extend over a wide realm of scientific fields, including thermodynamics, deforestation processes, epidemics spread, behavioral biology, hydrology, oceanography, climatology, traffic engineering and control, amongst others.

Cellular automata models faced an extensive application in the field of urban studies, particularly since the end of the 1980s, impelled by the parallel development in computer graphics and in theoretical branches of the complexity sciences. The 1990s experienced successive improvements in urban CA models, which started to incorporate environmental, socioeconomic and political dimensions, and were finally able to articulate analyses factors of spatial micro and macroscale (White and Engelen, 1997).

Urban CA models may regard both theoretical and practical applications, where the formers concern abstract exercises, and the latter ones, experiments dealing with real case studies. There are now some twenty or more applications of CA to cities, including a vast repertoire at both thematic and methodologic levels.

The first CA models applied to urban studies were commonly based on very simple methodological procedures, such as the usage of neighborhood coherence constraints or Boolean rules (Couclelis, 1985) for the transition functions. These functions have been further improved by the incorporation of dynamic transition rules (Deadman et al., 1993), heuristics and fuzzy sets theory (Wu, 1996) as well as multicriteria evaluation techniques (Wu and Webster, 1998).

Theoretical progresses in the fields of complex systems have been also added to cellular automata through the seminal work of Wolfram (1984) and these themes became recurrent within the CA scientific community (Portugali et al., 1999). Top-edge advances in the broader discipline of artificial intelligence, such as expert systems, artificial neural networks and evolutionary computation, have been lately included in the scope of CA simulations (Papini et al., 1998).

Works associating artificial neural networks (ANN) to CA models for urban analysis are quite few. Li and Yeh (2001) conducted a simulation of land use change for a cluster of cities in southern China, using ANN embedded in a CA model upon a binary state basis (urban/non urban use). They further refined this model dealing with multiple regional land uses (Li and Yeh, 2002) and simulations for alternative development scenarios (Yeh and Li, 2003), but their investigations did not ever scale down at the intra-urban level.

This paper is concerned with the simulation of multiple intra-urban land uses (e.g. residential, commercial, industrial, etc.) by means of ANN-based CA modelling. The following section approaches the study area and pre-processing techniques. The third section introduces the intervening factors in urban land use change. In the forth section, a theoretical overview on artificial neural networks is provided. Section five discusses questions related to model implementation and explains how it is conceived for determining transition probabilities governing changes in land use as functions of a variety of socio-economic and infrastructural factors. In section six, the simulation results are presented and explained in the context of urban land use dynamics. Finally, section seven is reserved for final comments and directions for future work.

2. The Study Area

This simulation model is developed for the city of Piracicaba, located in the midwest of São Paulo State, which in 2000 had a population of 319,104 people. The period for which the model is fitted is from 1985 to 1999, when the population grew from 198,407 to 309,531 inhabitants.

The city maps provided by the Piracicaba local authorities presented inconsistencies due to the fact that illegal settlements are not shown on the official maps, and not all of the legally approved settlements drawn have been in fact implemented. Moreover, some urban zones refer to areas which are not yet occupied, and some other zones categories do not correspond to the prevailing use indeed encountered within their limits, reflecting just the local officials´ intention for their future use. In this way, satellite imagery arise as a feasible solution for the identification of urban settlements actually existent, as well as for the delineation of the true urban occupation boundaries of the case study town.

In this way, the initial (1985) and final (1999) land use maps were subjected to a reclassification of zones according to their dominant effective use; residential zones of different densities were all reclassified to simply residential, and special use and social infrastructure were reclassified to institutional. Eight land use zone categories were adopted. Districts segregated from the main urban agglomeration by more than 10 km were judged outside the simulation area, and the traffic network was not considered to be at a fine enough scale to be represented as a land use.

The land use maps for the two time slices are shown in **Figure 1 (a)** and **(b)**. The changes between 1985 and 1999 are shown in **Figure 2 (a)** with the most significant land use change – from non-urban to residential use – shown in **Figure 2 (b)**. All data used in this experiment were represented at 50 m x 50 m grid square, pre-processed using the SPRING GIS (from the Division for Image Processing of the Brazilian National Institute for Space Research – DPI-INPE) and IDRISI (from Clark University).

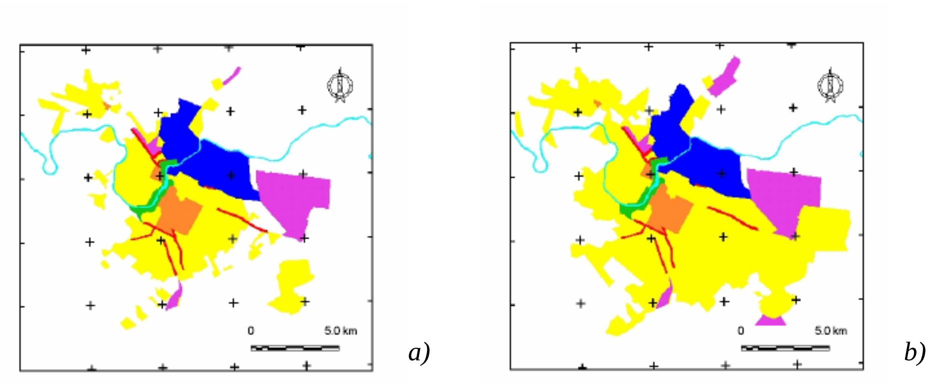


Figure 1. (a) Land use in Piracicaba in 1985 and (b) Land use in Piracicaba in 1999. Residential use is yellow, commercial use is orange, water streams are light blue, institutional use is dark blue, industrial use is purple, services corridors are red, leisure/recreation is green, and non-urban use is white.

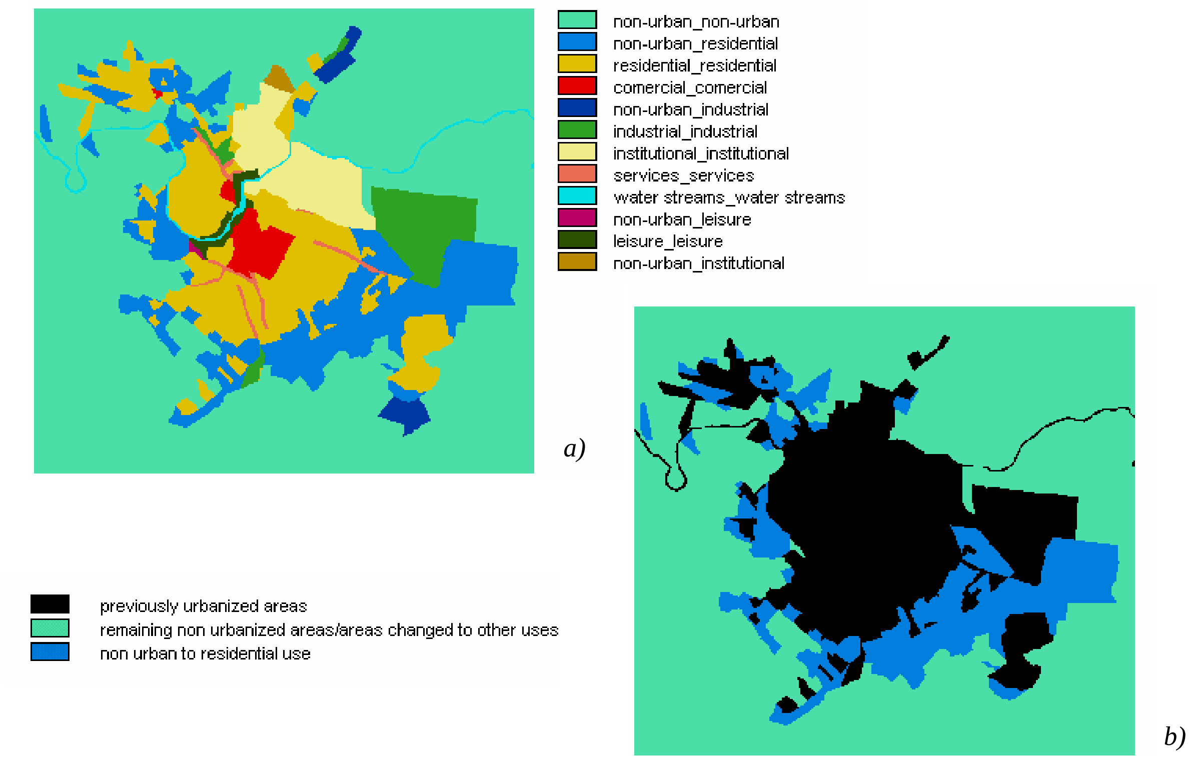


Figure 2. (a) Land use change from 1985 to 1999 (top left) and (b) Map of land use transition for the case “non-urban to residential use” during the period 1985-1999 (bottom right).

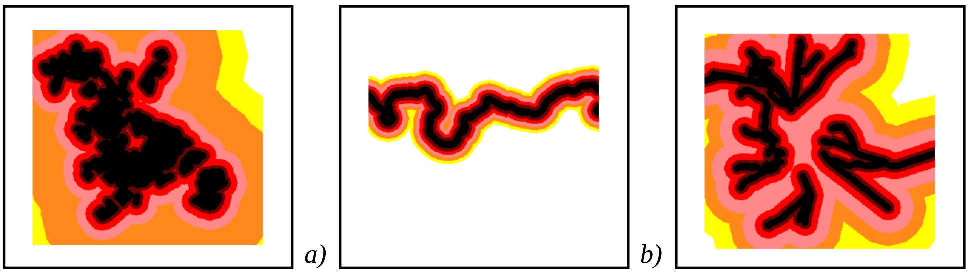
3. Variables Governing Land Use Change

From the map of land use changes from 1985 to 1999, shown in Figure 2 (a), obtained through a cross-tabulation operation between the initial and final land use maps shown in Figure 1, four types of transitions were observed and are listed in **Table 1**.

Table 1
Observed land use transitions

Notation	Land Use Transition
NU_RES	Non-Urban to Residential
NU_IND	Non-Urban to Industrial
NU_INST	Non-Urban to Institutional
NU_LEIS	Non-Urban to Leisure

To explain each of the four existent land use transitions, eight variables were selected from an initial bunch of almost twenty variables regarding infrastructural and socio-economic aspects of Piracicaba. Examples of maps of independent variables are shown in **Figures 3 (a)**, **(b)** and **(c)**.



a) *b)* *c)*

Figure 3. (a) Distances to main paved and non-paved urban and interurban roads; (b) Distances to rivers and (c) Distances to residential zones.

These variables refer to site attributes and they regard several types of proximity attractiveness (Wu and Webster, 1998). Empirical procedures were used for the pre-selection of variables, like the visualization of distinct variables superimposed on the final land use map, what aimed at sorting out the set of those ones more meaningful to explain the four different types of land use change. These spatial variables, previously pre-processed in SPRING, were used as inputs to the neural network for urban simulation.

4. Artificial Neural Networks (ANN)

Artificial Neural Networks attempt to simulate human reasoning offering fault-tolerant solutions. They can be used either for pattern recognition or classification, and in many disciplines with a high degree of difficulty, they have been extensively and successfully applied. As stated by Fischer and Abrahart (2000), these mechanisms are able to learn from and make decisions based on incomplete, noisy and fuzzy information, and that is the reason why they can be easily suitable to handle spatial problems. Li and Yeh (2002, apud Openshaw and Openshaw, 1997, and Openshaw, 1998) identify a series of ANN advantages:

(a) The structure of algorithms enables neural networks to be robust and noise resistant regardless of poor data.
(b) They can solve highly nonlinear problems in complex systems.

(c) The method is rather simple because no exact questions or expressions are required.
(d) The best level of performance can be obtained.
(e) There are no restrictions about using nonnumeric data.
(f) They adapt to nonnormal frequency distribution.
(g) Mixtures of measurement types can be used.
(h) They can use many variables, some of which may be redundant.

Neural networks consist of processing units, the so-called neurons or nodes, which are organized in a couple of layers. Commonly, a neural network has a threefold design: one input layer, one output layer and no or some hidden layers inbetween, whose nodes report to those of contiguous layers by means of connections designed to assess weights and signals. All the neurons, except those in the input layer, perform two simple processing functions – collecting the activation of the neurons in the previous layer and generating an activation as the input to the next layer. The neurons in the input layer only send signals to the next layer.

Very simple functions establish the interactions between neurons. If p equals a sender neuron in the input layer and q is a receiver neuron in the next layer, the collection function is given as

$$net_q = \sum_p w_{pq} I_p \quad , \tag{1}$$

where I_p is the signal from neuron p of the sender layer, net_q is the collection signal for receiver neuron q in the next layer, and w_{pq} is the parameter or weight to sum the signals from different input nodes. The receiver neuron creates activation in response to the signal net_q. The activation will become the input for its next layer, and such activation is usually created in the form of a sigmoid function (Yeh and Li, 2003):

$$\frac{1}{1 + net_q} \quad . \tag{2}$$

The activation will be passed to the next layer as the input signal, and Equations *(1)* and *(2)* will be used to process the signal again. These routines remain until the final signals are obtained by the output layer.

Parameters (weights) are decisive to define the final signals. In this particular case, a back-propagation learning algorithm (Rumelhart et al., 1986) has been adopted. The algorithm involves an iterative procedure for minimization of an error function, in which the weights continuously undergo adjustments by means of comparison between the calculated and desired outputs, these latter extracted from a training data set. In this type of neural network, the weights are first initially set in a random way, and the errors, computed as the difference between calculated and desired activation for the output neuron, are propagated backwards through the network and used to refine the weights. In sum, this process of adjusting weights according to the errors will be repeated as many iterations as necessary in order to render the errors compatible with acceptable thresholds.

In a general way, the overall output error is defined as half the overall sum-of-the-squares of the output errors, which, for the k^{th} training pattern, is

$$Ek = 0.5 \sum_{q=1}^{m} (O_{kq} - D_{kq})^2, \tag{3}$$

where O_{kq} is the calculated network output, D_{kq} is the desired output for neuron q, and m is the number of neurons in the output layer of the network.

The accumulated error for all training patterns is

$$E = \sum_{k=1}^{l} E_k \quad , \tag{4}$$

where l is the total number of training patterns.

The learning process enables the neural networks to make predictions as close as possible to the desired values for a set of training data. Once the network has been properly trained, it is finally ready for conducting the simulations.

5. Model Implementation: Simulating Urban Land Use Change Using Neural Networks in a CA-Based Model

Each of the four types of land use transition identified in the city of Piracicaba during the period 1985-1999 were treated as a separate neural network. The platform used for training, simulation and validation of these four networks was the SNNS[1] package. This approach of dealing with the transitions independently is in accordance with the CA-based model employed in this experiment – DINAMICA[2] – which operates upon basis of transition probabilities maps for each type of land use change.

The architecture of the neural network should be conceived as simply as possible because the simulation contains many loops. In this study, the proposed neural networks have only three layers each – the input layer, a hidden layer and the output layer, as seen in **Figure 4 (a)**. Difficult learning tasks can sometimes be simplified by increasing the number of hidden layers, but according to Gong (1996), a three-layer network can form any decision boundaries. Each variable is associated with a neuron in the input layer. As these variables refer to various types of proximities, the ranges of distances were scaled according to an increasing rank of values departing from 0.1 and spaced also by 0.1, i.e. 0.1, 0.2, 0.3, …, 0.7. It is more appropriate to convert input data into the range of [0,1], since this scaling procedure makes the input values compatible with the sigmoid activation function that produces a value between 0 and 1 (Gong, 1996).

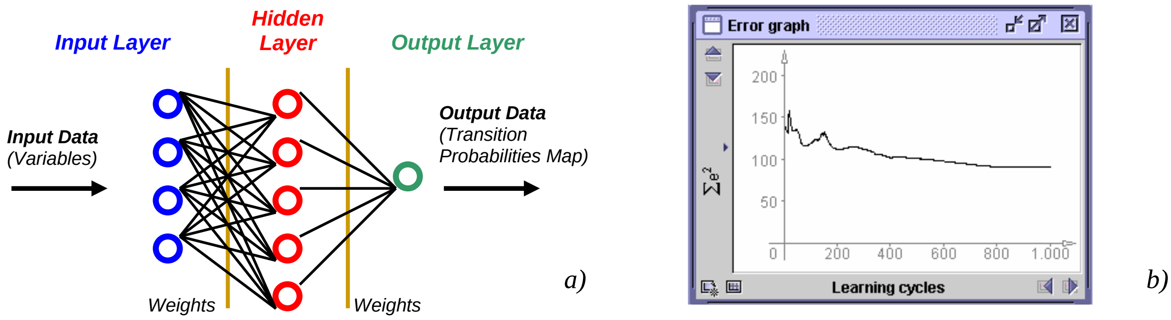


Figure 4. (a) Generic example of an artificial neural network structure with only a single output neuron (left) and (b) Example of a prediction error graphic, estimated for the transition "non-urban to institutional use" (right).

[1] SNNS (Stuttgart Neural Network Simulator) is a trademark of the Institute for Parallel and Distributed High Performance Systems of the University of Stuttgart (IPVR), Germany.
[2] DINAMICA is a trademark of the Centre for Remote Sensing of the Federal University of Minas Gerais (CSR-UFMG), Brazil.

The output layer, on its turn, has only one neuron that corresponds to the map of transition probabilities for the considered type of land use change. In the training data set, the desired (target) value in the output layer is recorded as 1 for a cell that underwent a change in its land use, and 0 for a cell that suffered no change. In the extraction of the training data set for each network, large rectangles were delimited within the study area containing representative samples of the existent ranges of distances (for the maps of variables) and of land use permanence and change (in the case of the maps of land use transition).

Diverging approaches rule the definition of the number of neurons in the hidden layer. According to Kolmogorov´s theorem (Yeh and Li, 2003), if n is the number of neurons in the input layer, the use of $2n + 1$ neurons can guarantee the perfect fit of any continuous functions, and reducing the number of neurons may lead to lesser accuracy. On the other hand, Wang states that $2n/3$ hidden neurons can produce results of almost similar accuracy but requires much less time to train (Wang, 1994 apud Yeh and Li, 2003). In all the four networks of this study, Kolmogorov´s premises have been observed, and the prediction error decreased considerably during the training, as shown in **Figure 4 (b)**. With the cells transition probabilities being defined by the ANN outputs, global transition probabilities were reckoned through a cross-tabulation operation between the initial and final land use maps shown in Figure 1. These probabilities are 0.1501 for the transition “nu_res”, 0.0113 for “nu_ind”, 0.0028 for “nu_inst”, and 0.0005 for the transition “nu_leis”.

6. Results and Discussion

Maps of transition probabilities were generated for the four types of land use change, where the learning parameter (η) was set to 0.2, the maximum distance to the error (d_{max}) was adjusted to 0.1, and the iteration cycles ranged from 800 to 1,000. Upon basis of the pruning algorithm, sets of variables have been selected to explain the land use transitions (**Table 2**).

Table 2
Selection of variables determining land use change

Independent Variables (Notation)	NU_RES	NU_IND	NU_INST	NU_LEIS
Distances to rivers (dist_riv)				♦
Distances to commercial zones (dist_com)		♦		
Distances to small-sized industrial zones (dist_ind)		♦		
Distances to institutional zones (dist_inst)			♦	
Distances to residential zones (dist_res)	♦	♦		♦
Distances to leisure/recreation zones (dist_leis)				♦
Distances to main interurban roads (int_rds)		♦	♦	
Distances to main paved and non-paved urban and interurban roads (main_rds)	♦			

The transition probabilities maps served as inputs to the CA simulation model – DINAMICA – which produced the land use change simulations, seen in **Figures 5 (a)**, **(b), (c)** and **(d)**.

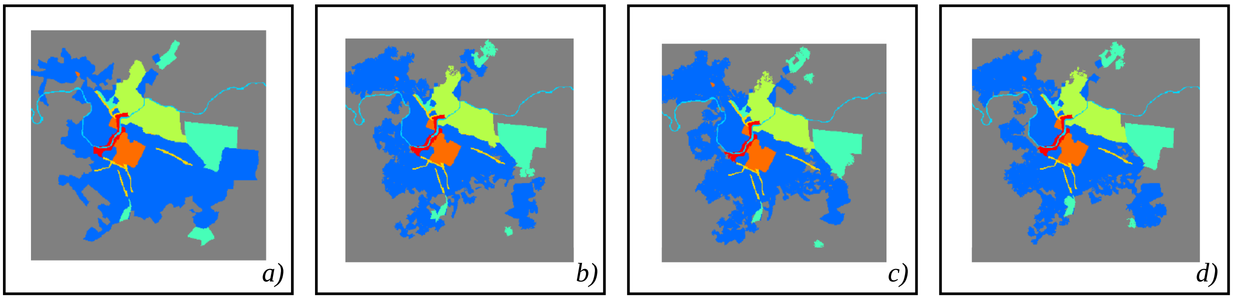


Figure 5. (a) Real land use in Piracicaba - 1999; (b) Land use simulation 1 – 1999; (c) Land use simulation 2 – 1999; and (d) Land use simulation 3 - 1999.

The land use change simulations were accomplished by two types of stochastic transition algorithms – "expander" and "patcher" – which operate changes through expansion and diffusion, respectively. These simulations were validated according to a multiple resolution fitting method (Constanza, 1989), and the values obtained for windows 3x3, 5x5 and 9x9 were 0.862682, 0.864872, and 0.864644, respectively for S1, S2, and S3. It is observable that the land use transitions comply with economic theories of urban growth and change, which maximize consumers´ and markets´ utilities in terms of real state prices and accessibility.

7. Conclusions

Cities are open and non-linear complex systems. ANN though proved to have the capability to model non-linear features and handle well the uncertainties of spatial data. ANN have two main disadvantages: they are black-box devises and the user´s intervention is still decisive for the results quality. Further studies are needed to assess the responsiveness of the simulation outputs in face of changes in the type, structure and internal parameters of the network.

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