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The identification and simulation of an urban spatio-temporal dynamic: An approach based on a neural network and coupled map lattices

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Abstract

This paper presents a method for identifying and simulating an urban land-use dynamic. It has been tested on a real, rapid-growth situation: Abidjan, Cote d'Ivoire (CI). Residents and employees are classified per type and assigned to a raster GIS; these quantities are the variables of the model. The spatial relations among variables are identified by using a neural net approach; in turn, parameters controlling the dynamic are calibrated by using simulated annealing. The evolution of urban land-use in Abidjan is modeled by means of a discrete coupled map lattice based on parameters found in previous steps. Finally, results are presented of the simulated urban evolution, with and without the construction of two bridges, and differences are highlighted.

Introduction

The urban dynamic can be considered to be a spatio-temporal system (Tobler, 1970). For this reason, it can be simulated by using a coupled map lattice approach. Despite this advantage, the approach holds one inherent problem: difficulty in identifying rules capable of characterizing the dynamic when experimental data consists of a few temporal series or, in the worst case, only the initial and final pattern. The present paper focuses on this problem by presenting studies made for both the static and dynamic aspect using a neural network and simulated annealing, and by applying this method to development in Abidjan (CI). An earlier paper by Semboloni (1999) lay the groundwork for this problem and set out a detailed case study of the city. Therefore, the current paper reports only that information which is essential to the present study.

Land use and spatial structure of Abidjan

Abidjan is built around a lagoon that lies along the Gulf of Guinea. Over the years, the city took on the role as economic capital of the CI. In 1992, the population of Abidjan amounted to ca. 2.4 million inhabitants. Essentially, in Semboloni (1999), the statistics were based on data related to employment per sector and population per type of dwelling. This statistical information was displayed on a square grid containing 122x144 cells; each cell represented a square with sides of 250 meters. The data for population and economic activities served to differentiate each group of the population based on type of dwelling. For market purposes, housing was organized into four main types: high standard dwellings for the upper-classes; social housing built by public or private building companies; houses with a common, enclosed courtyard, and shanty-towns built by squatters on hazardous areas using precarious material. Economic activities were classified as formal (industry, transportation services, commercial services, and public administration) and informal (small business, retail activities, activities performed on the streets, and servants). In essence, the variables in each cell of the square grid were the following:

x_1: population living in high standard dwellings;
x_2: population living in social housing;
x_3: population living in courtyard houses;
x_4: population living in shanty towns;
x_5: employees in industry;
x_6: employees in transportation services;
x_7: employees in commercial services;
x_8: employees in public administration;
x_9: employees in small business;

x_{10}: employees in retail activities;
x_{11}: employees in street activities;
x_{12}: servants.

These variables were calculated in units representing residents or employees.

The neural network approach to the spatial analysis

In order to establish a spatial relationship between the 12 variables listed above, in the current study each cell has been surrounded by three annuli a^1, a^2 and a^3 (figure 1).

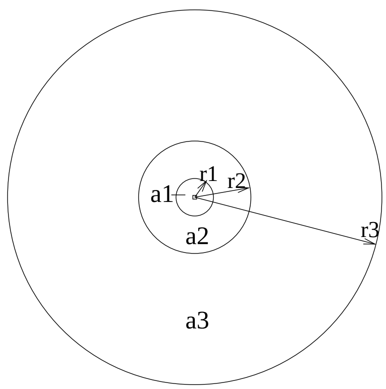

Figure 1: The three annuli that a^1, a^2 and a^3 surround the cell and the corresponding outer radii r^1, r^2, and r^3.

The centers of these annuli correspond to the center of the cell, and the annuli are characterized by an inner and outer radius. The inner radius r^{n-1} of the a^n annulus is the outer radius of the a^{n-1} annulus, as in figure 1. In order to exclude the central cell from the computation, the first annulus, a^1, has a fixed inner radius r^0 of 250 meters. The other two radii depend on the maximum measurement established for the outer radius of the more extended annulus, r^3. The formula used is: $r^1 = 0.1(r^3)$, and $r^2 = 0.3(r^3)$. To obtain the input for the neural network, a sum is made of variables located in cells and associated with a specific annulus. Normalization is obtained for the range $0 - 1$ as by taking the sum of an annulus and dividing it by the maximum attained:

$$A^n_{h,i} = \frac{\sum_{j \in a^n} x_{h,j}}{\max(\sum_{j \in a^n} x_{h,j})} \tag{1}$$

where $A^n_{h,i}$ is the normalized value resulting from the sum of variable x_h located in annulus a^n. These normalized values serve to relate the value of a variable located in the central cell with values of other variables located in the surrounding cells. In addition, spatial autocorrelation of a variable is evaluated by using a special type of annulus a^4 which includes only the eight bordering cells. In this case, instead of considering the sum for each variable, the maximum value is considered. This value is normalized in the range $0-1$ by dividing it by the maximum attained, as in the following equation:

$$A^4_{h,i} = \frac{\max_{j\in a^4}(x_{h,j})}{\max[\max_{j\in a^4}(x_{h,j})]} \tag{2}$$

To reiterate, first four annuli having a common center in the cell are defined, then the values of the normalized variables are utilized as input for a neural network. Using this information, calculations can be made for the variables located in the central cell. By adopting this 12x4 method, it is possible to define 48 input variables $X_{k,i}$ for the neural net; these are numbered from 1 to 48 by setting $X_{k,i} = A^n_{h,i}$ where $k = n + 4(h-1)$. In addition, two input variables are defined for each cell: one, $X_{49,i}$, related to a measurement associated with land quality and one, $X_{50,i}$, for bias. It may be assumed that land quality is dependent on two factors: accessibility and slope, as in the following equation:

$$Q_i = \frac{(1/s_i)\sum_{h=7,8}\sum_j x_{h,j}exp(-\beta d_{i,j})}{\max[(1/s_i)\sum_{h=7,8}\sum_j x_{h,j}exp(-\beta d_{i,j})]} \tag{3}$$

where Q_i represents land quality, whose value is normalized in the range $0-1$ as for the previous input variables, s_i is an index related to the ground slope, and $d_{i,j}$ is the distance between cell i and cell j . In essence Q_i is a proxy for land rent. It is measured with accessibility to variables x_7, and x_8, i.e., employees in commercial services and in public administration divided by the index of ground slope, which is considered to be a negative aspect of a cell. The input variable $X_{49,i}$ is set as being equal to the negative of the quality of land. The reasons will be explained in the following sections. The last input variable $X_{50,i}$ represents the bias and is set as being equal to -1.

For each variable, and in each cell, the expected value $y_{h,i}$, ranging from 0 to 1, is calculated by using the following equation:

$$y_{h,i} = \Phi\left(\sum_k W_{k,h}X_{k,i}\right) \tag{4}$$

where Φ is a sigmoid function and $W_{k,h}$ are the weights calculated by using a neural network method (see figure 2). In fact these weights are calculated by using back-propagation. The network is trained by using the 1988 spatial pattern. Weights are constrained to be positive and some of them are set as being equal to zero if considered meaningless. In addition pruning is utilized in order to cut all the connections having a weight outside the desired value. In other words it is supposed that each activity is attracted by the other activities located in the annuli surrounding the central cell and that land rent and threshold, set at a negative value, must be overcome.

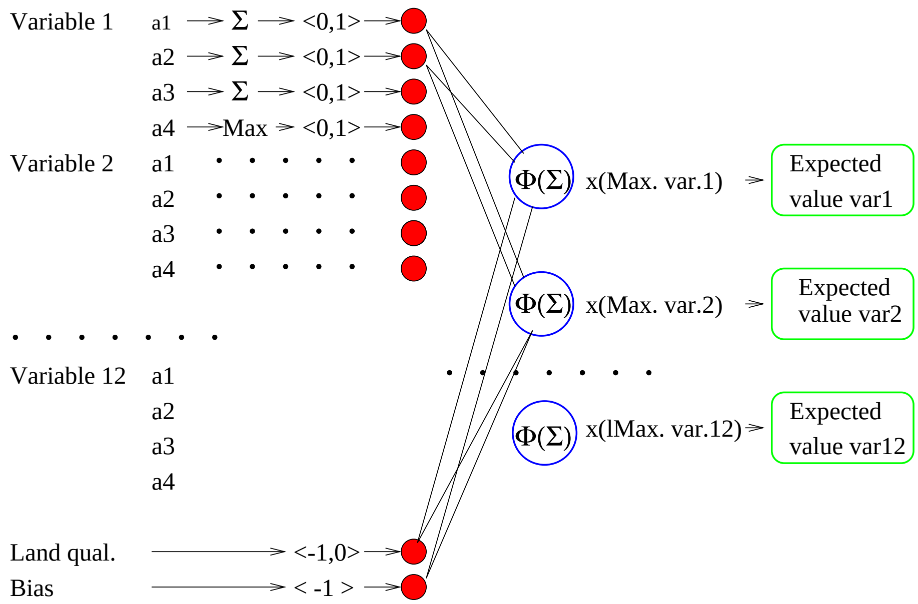

Figure 2: The structure of the neural network.

The weights obtained by the training of the neural net, using observed data of 1988, are presented in table 1.

Thus, as demonstrated above, static analysis concerns the variation of variables in space. In contrast, the temporal variation of each variable in each cell is established by focusing on the dynamic of the system. This aspect will be explained in the next section.

The dynamic of the system and the competition for land use

The dynamic of the system includes the diffusion of variables and the competition for land use. Diffusion is obtained by using results from the neural net analysis, by increasing the maximum radius r^3, and by applying, at each step, a variation rate to each variable. In turn, competition is based on a set of 12 parameters representing the available income for land rent of each variable. In order to consider this point, a land market model is used to evaluate desirability. Thus, an offer per land unit surface in relation to each variable is calculated as follows:

$$O_{h,i} = \frac{y_{h,i} I_h}{S_{h,i}} \tag{5}$$

In other words offer, $O_{h,i}$, of the variable, x_h, for one unit of space in cell i will be dependent on the expected value of the variable in the cell $y_{h,i}$, ranging from 0 to 1, and on the maximum available income I_h to be utilized for land rent per unit of the variable; this is divided by the quantity of ground space $S_{h,i}$ utilized by a unit of the variable x_h. This quantity, $S_{h,i}$, ranges from a minimum, in cases of high-quality land, to a maximum, in cases of low-quality land (see figure 3).

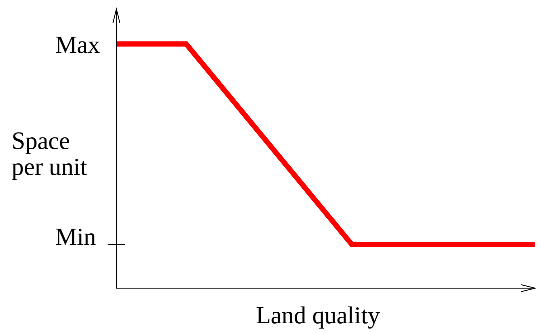

Figure 3: The relation between the increase of land quality, Q_i, and the decrease of requested space per unit, $S_{h,i}$.

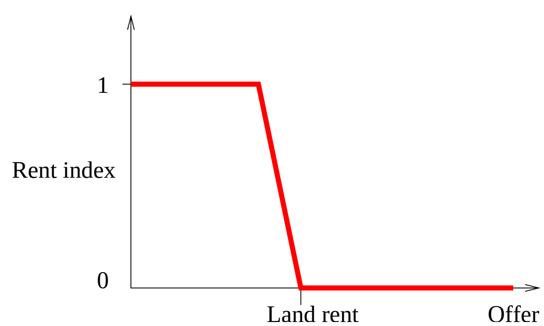

Figure 4: The relation between the land rent, R_i, and the variation of the related rent index, I_i^R.

Land rent in a cell, R_i, is calculated by using the mean of the offers; it is weighted by utilizing surface occupied by each variable in the a^1 annulus, as in the following equation:

$$R_i = \frac{\sum_h O_{h,i} A^1_{h,i} S_{h,i}}{\sum_h A^1_{h,i} S_{h,i}} \tag{6}$$

On the basis of land rent, an index, $I_i^R = f(R_i)$, ranging from 0 to 1 is calculated (see figure 4). When the offer overcomes the land rent this index, I_i^R, decreases, otherwise it increases. The variation of a variable is influenced three indexes: the rent index, I_i^R, and by two other indexes related to the saturation of space and to the maximum admitted value of a variable in a cell. In fact each cell has a surface of 250^2 meters; the saturation index, I_i^S, is calculated as follows:

$$I_i^S = \frac{\sum_h x_{h,i} S_{h,i}}{250^2} \tag{7}$$

The third index, I_i^M, is related to the maximum and is calculated in a similar way. Thus, by using observed data for each cell, it is possible to calculate the relation between the total value of a variable and its maximum value. The general equation is:

$$M_h = a - b\left(e^{-\beta \sum_i x_{h,i}}\right) \tag{8}$$

where a, b, and β are parameters which have been estimated by using observed data. The index, I_i^M, is calculated as follows:

$$I_i^M = \frac{x_{h,i}}{M_h} \tag{9}$$

The variation rate of the variable, x_h, in time, t, $g_h(t)$, is calculated by using the total existing value of a variable in relation to the exogenously established value. The desired value of variable, $Y_{h,i}$, in cell i is calculated by multiplying the expected value, $y_{h,i}$, obtained with the neural network and ranging from 0 to 1, by the maximum attained by the variable, and by the variation rate, g_h, as follows:

$$Y_{h,i}(t) = \max[x_h(t)][1 + g_h(t)]y_{h,i}(t) \tag{10}$$

The expected variation for the variable, x_h, is calculated by comparing the desired value, $Y_{h,i}$, with the existent value, $x_{h,i}$. The difference between the two values is divided by N_s, that is the number of steps needed for a complete adjustment of the existent value in relation to the desired value, as in the following equation:

$$\Delta x_{h,i}(t) = \frac{Y_{h,i}(t) - x_{h,i}(t))}{N_s} \tag{11}$$

The expected variation is summed up to the existent value in step t in order to obtain the value in step $t+1$. But expected variation is modified by the three above mentioned indexes. These three indexes have a diametrically opposed effect when the expected variation is positive or negative. In fact in case $\Delta x_{h,i}(t) > 0$ the value in step $t+1$ is calculated as follows:

$$x_{h,i}(t+1) = x_{h,i}(t) + [\Delta x_{h,i}(t)](1 - I_i^R)(1 - I_i^S)(1 - I_i^M) \tag{12}$$

It is clear that growth is reduced when indexes attain the maximum, such as in logistic growth. In turn, case $\Delta x_{h,i}(t) < 0$ shows that

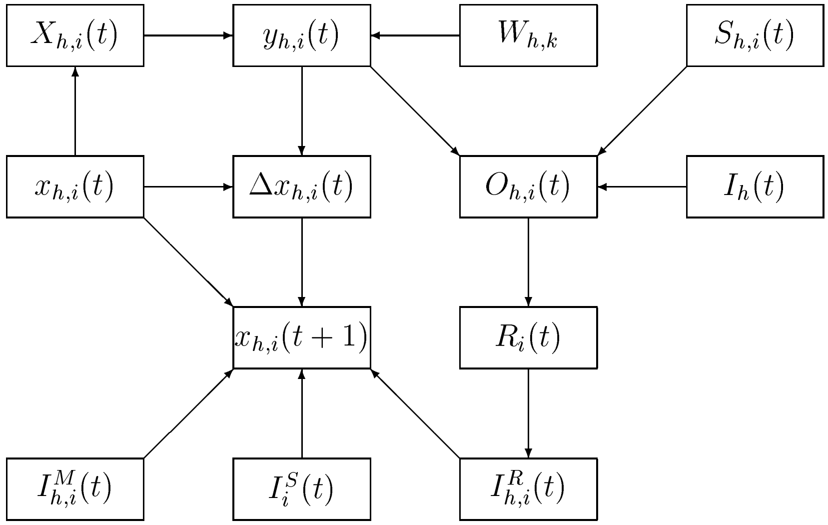

Figure 5: The relations among the main variables and parameters.

the decrease is reduced when indexes attain the minimum, as in the following equation.

$$x_{h,i}(t+1) = x_{h,i}(t) + [\Delta x_{h,i}(t)](I_i^R)(I_i^S)(I_i^M) \tag{13}$$

The relations among the main variables and parameters included in equations 1-13 are synthesized in figure 5. The main set of parameters included in these equations is the available income, I_h, for land rent. These parameters have been calibrated by using simulated annealing. The model has been tested utilizing data from surveys: the 1963 information is used to simulate the evolution of the city up to 1974. The ratio has been calculated using the variance between observed and simulated data and variance of observed data in the spatial distribution of each variable has been calculated. The sum of these ratios calculated in relation to each variable has been considered as the energy to be minimized. The values of the parameter obtained by using simulated annealing are presented in table 2.

The major problem associated with calculating variable variation is that it is necessary to maintain the total value of a variable as being equal to that established exogenously. This aspect of the problem will be explained in the next section.

The functioning of the model

As stated above, this model is limited to the calculation of spatial distribution of the variable; therefore, as stated above, global quantities are established exogenously. In fact, the global quantity of each variable is used to dynamically calibrate parameters g_h; this has been estimated by utilizing survey data and by establishing a

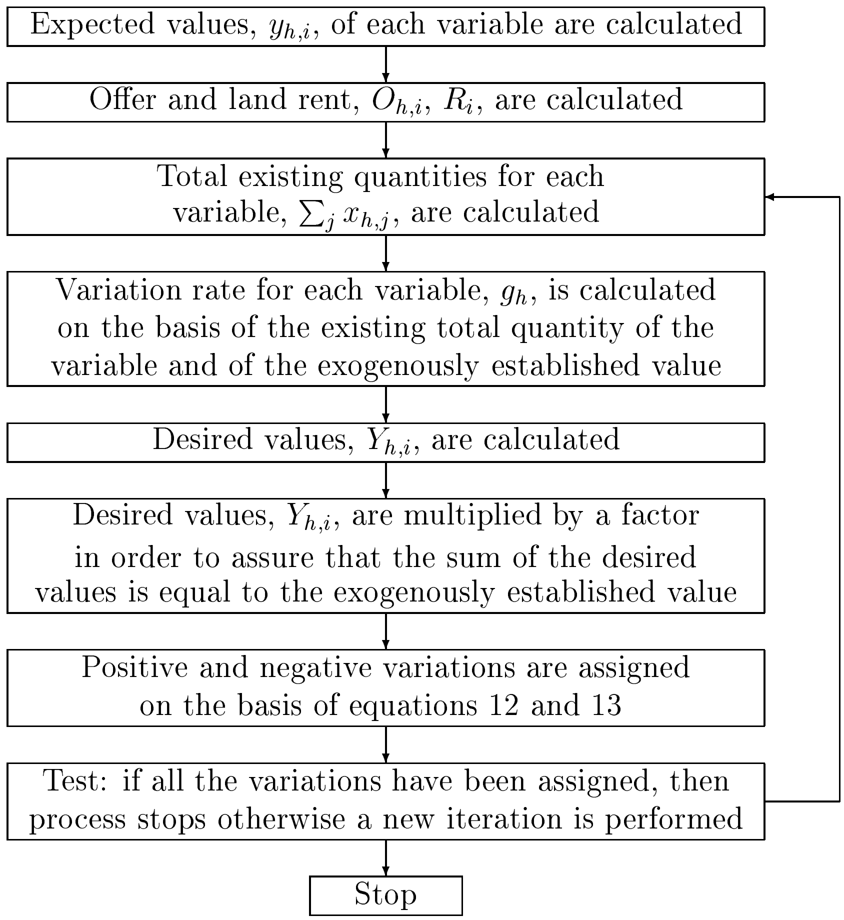

Figure 6: The phases for calculations of variable from step t to step $t+1$.

trend of evolution on the basis of the past trend. In addition, during the simulation the parameter responsible for the maximum admitted distance, r^3, is changed as a function of the total population. (Semboloni, 1999). Obviously, distances are calculated by using the main roads network.

The model calculates the location of variables at step $t+1$ on the basis of the location of variable at time t and on the basis of the total established value for each variable at time $t+1$. Each step covers a period equal to one quarter of a year. The phases for calculations are shown in figure 6.

Maps representing the simulated pattern in 1974 and the real pattern in 1974 are presented in figures 8 and 9. In addition a 3-D representation of the total number of population and employees in 1974 is shown in figures 10 (simulated) and 11 (observed). Macro-cells of 2.5 km per side, which contain 100 individual cells, have been utilized to show the fit of the model with the observed values.

Figure 7 shows the simulated and observed data for all variables summed up by using these macro-cells. Correlation coefficient is equal to 0.75.

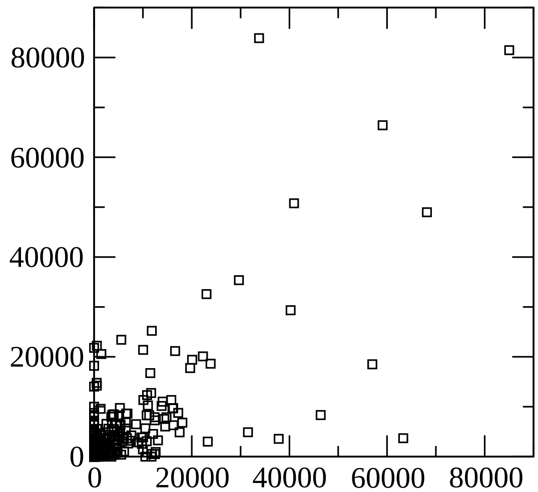

Figure 7: X axis, observed data in macro-cells in 1974. Y axis, simulated.

To demonstrate a possible utilization of the model, it has been applied to a specific situation: the evolution of the city from 1988 to 1998. The first simulation uses the existing pattern of main roads; the second simulation assumes that the two planned bridges have already been built. The differences of the results after a ten year simulation can be evaluated by comparing figures 12 and 13.

Conclusions

This method addresses a crucial problem related to dynamic systems: the identification of the rules. If a spatio-temporal series is available, then it is possible to estimate parameters for computing a state at step $t+1$ from data at step t. But, if no spatio-temporal series are available, as is often the case in urban studies, or if the temporal lag is too extended in relationship to the lag utilized for temporal causation, then it is necessary to calibrate dynamic parameters, by using simulated annealing. However, as this method requires a longer computing time, it is necessary to limit the number of parameters to be calibrated. Finally, it should be stressed that the results of this model are dependent on the initial conditions. This dependency increases with the disaggregation of variables. Thus the problem is to choose between a finer disaggregation and a more limited temporal horizon for the forecasting, or a more aggregate variable and a longer forecasting time.

In conclusion, this paper has proposed a model of a dynamic urban system which includes a method for calibrating parameters.

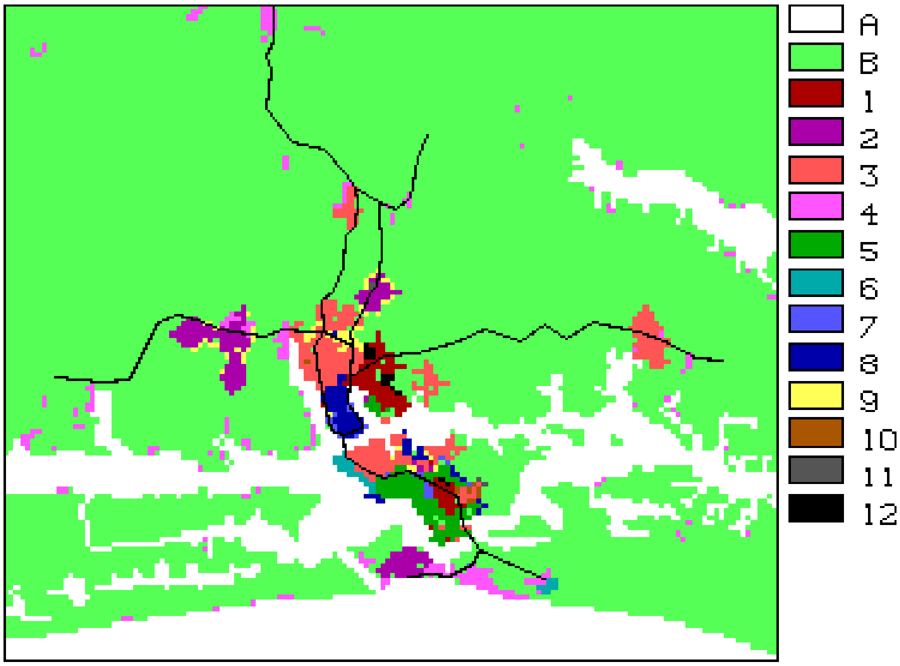

Figure 8: Variables with the maximum value in each cell. 1974, simulated. Legend: A, sea; B, open land; numbers refer to the variables. The main roads network is included.

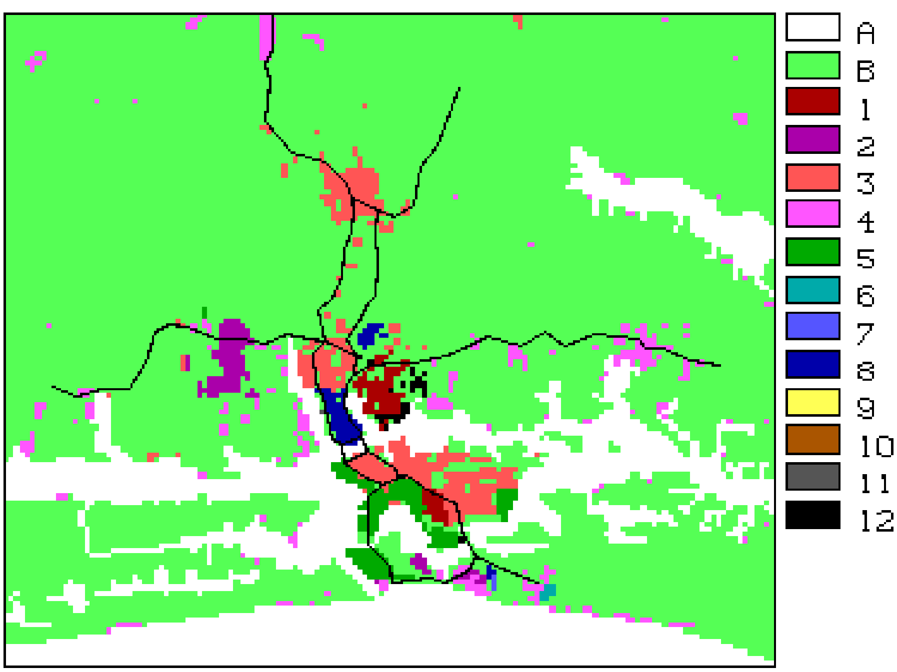

Figure 9: Variables with the maximum value in each cell. 1974, observed. Legend: A, sea; B, open land; numbers refer to the variables.

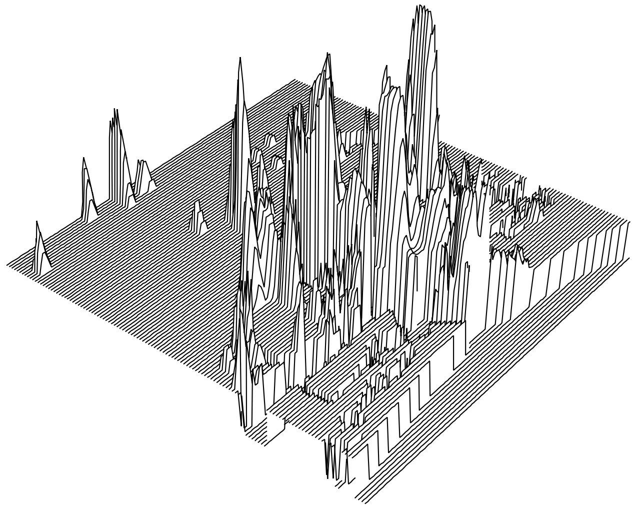

Figure 10: Total number of population and employees in 1974. Simulated

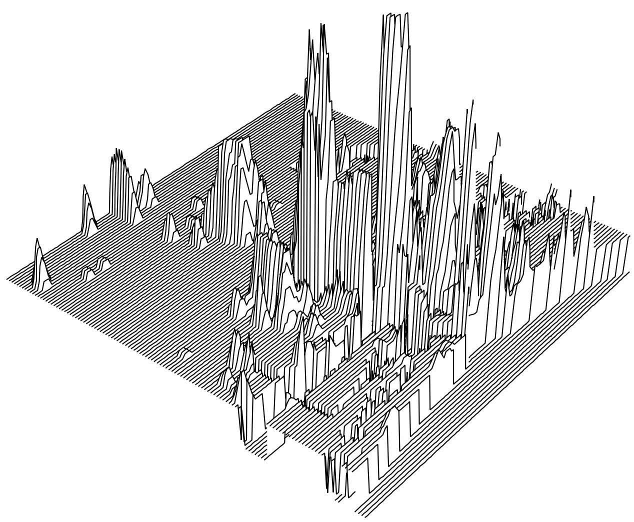

Figure 11: Total number of population and employees in 1974. Observed.

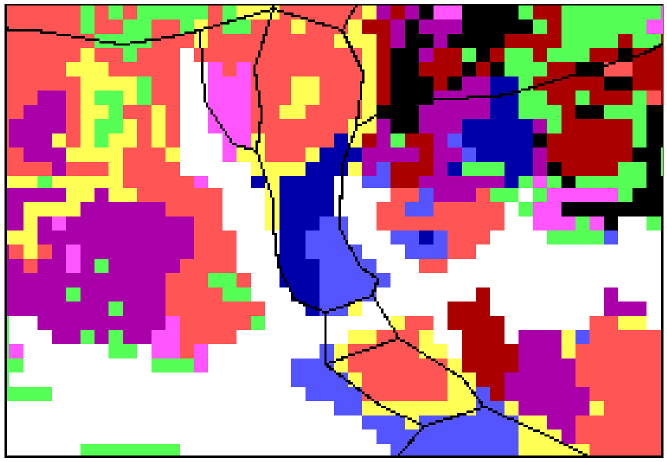

Figure 12: Variables with the maximum value in each cell. 1998, simulated by using 1988 data as initial pattern. Legend: A, sea; B, open land; numbers refer to the variables. The main roads network is included.

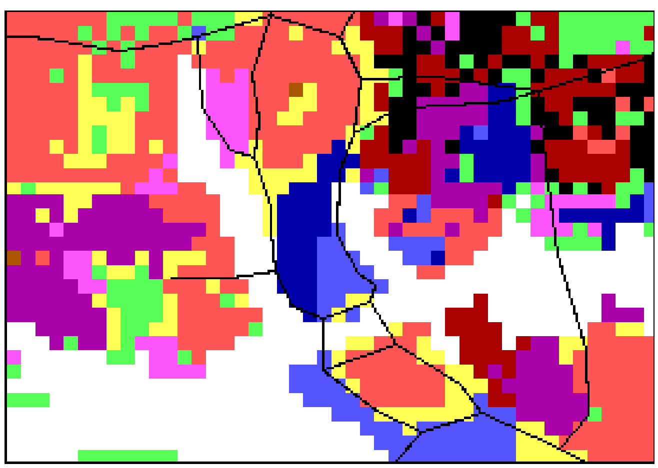

Figure 13: Variables with the maximum value in each cell. 1998, simulated by using 1988 data as initial pattern and by including into the main roads network two new bridges. Legend: A, sea; B, open land; numbers refer to the variables.

It can be used to produce scenarios for the future evolution of cities and, in particular, to estimate the consequences of plans for urban projects.

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Table 1: The weight obtained by the training of the neural net.

Var	1	2	3	4	5	6	7	8	9	10	11	12
1	-	-	-	-	-	-	-	-	-	-	-	5.23
	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	0.07	-	-	-	-	-
	4.42	-	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	1.34	1.23	-
	-	-	-	-	-	-	-	-	2.17	0.90	-	-
	-	-	-	-	-	-	-	-	-	-	-	-
	-	4.44	-	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	1.18	2.61	0.86	-
	-	-	-	-	-	-	-	-	0.32	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	3.82	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	4.83	-	-	-	-	-	-	-	-
5	0.49	-	-	0.41	-	1.37	0.44	-	0.40	-	0.21	-
	-	-	-	2.49	-	0.68	0.66	-	-	-	-	-
	-	0.58	-	1.82	-	-	-	1.78	-	-	-	-
	-	-	-	-	6.71	-	-	-	-	-	-	-
6	-	-	0.19	0.55	1.41	-	0.67	1.57	0.21	-	-	-
	-	-	-	-	1.16	-	-	-	-	-	-	-
	-	0.34	0.21	1.40	-	-	3.25	2.88	-	-	-	-
	-	-	-	-	-	5.38	-	-	-	-	-	-
7	1.32	-	-	-	1.22	-	-	2.50	1.08	-	1.53	-
	-	-	-	-	-	-	-	-	-	-	-	-
	1.70	-	-	0.13	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	4.39	-	-	-	-	-
8	0.24	-	-	-	-	1.47	0.23	-	1.00	-	1.52	-
	-	-	0.41	-	-	-	1.60	-	0.72	-	-	-
	0.75	0.70	0.66	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	2.69	-	-	-	-
9	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	0.48	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	2.60	-	-	-
10	-	1.23	2.37	-	-	-	-	-	-	-	-	-
	-	1.20	0.86	-	-	0.89	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	3.57	-	-
11	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	2.92	-
12	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-
Qual.	-	1.79	3.89	8.72	1.84	2.04	-	-	-	0.12	-	-
Bias	5.55	4.40	4.10	5.01	4.05	4.32	6.68	7.92	4.97	5.15	3.88	3.19

Table 2: The values of parameters I_h, S_h min, and S_h max.

Var	I_h	S_h min	S_h max
1	162.98	50	70
2	3.16	18	19
3	27.32	9	20
4	4.12	5	10
5	463.66	50	150
6	705.41	10	100
7	659.48	8	20
8	597.26	20	90
9	460.12	8	9
10	200.65	8	9
11	98.92	1	1
12	82.13	1	1