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The urban sprawl dynamics: does a Neural Network understand the spatial logic better than a Cellular Automata?

Lidia Diappi, Paola Bolchi, Lorena Franzini *
Massimo Buscema, Marco Intraligi**

* Dep. Architecture and Planning- Polytechnic of Milan-Milan
** Semeion Research Center- Rome

Cellular Automata (CA) are usually considered the most efficient technology to understand the spatial logic of urban dynamics: they are inherently spatial, they are simple and computationally efficient and are able to represent a wide range of pattern and situations.

Nevertheless the implementation of a CA requires the formulation of explicit spatial rules which represents the greatest limit of this approach. Whatever rich and complex the rules are, they aren't able to capture satisfactorily the variety of the real processes.

Recent developments in natural algorithms, and particularly in Artificial Neural Networks (ANN), allow to reverse the approach by learning the rules and the behaviours in urban land use dynamics directly from the Data Base, following a bottom-up process.

The basic problem is to discover how and to what extent the land use change of each cell *i* at time *t+1* is determined by the neighbouring conditions (CA assumptions) or by other social, environmental, territorial features (i.e. political maps, planning rules) which where holding at the previous time *t*. Once the NN has learned the rules, it is able to predict the changes at time t+2 and following.

In this paper we show and discuss the *prediction capability* of different architectures of supervised and ANN.

The Case study and Data Base concern the land use dynamics, between two temporal thresholds, in the South metropolitan area of Milan.

1. *Introduction*

Land use dynamics and fragmentation of settlements is a crucial question for planning. In the general framework of sustainability objectives, the policies to control a suitable process of urbanisation involve more and more deep knowledge on complex criteria of location chosen by the different agents. Planners realize that is crucial to understand and provide the best possible explanation for the observed spatial distribution of urban activities.

Principles and technologies of Artificial Intelligence (AI) in general, and of NN and CA in particular, offers the potentiality to increase the knowledge in urban dynamics by multiplying the information capacity of the GIS and by offering a new approach to territorial modelling. Most geocomputation currently deals with models on spatio-temporal dynamics in urban land-use and morphogenesis.

Among them some applications, mainly based on Cellular Automata, have opened more promising directions for the goal: Clarke, Hoppen and Gaydos (1997) modelled the historical development of San Francisco area; (Batty, Xie and Sun 1999; Wu 1998) built several urban models and in particular a model on the residential development in the fringe of Buffalo; Portugali, Benenson and Omer (1994; 1997) have focused their research on models of socio-spatial segregation; the many contributions of Engelen, Ulje and White (White and Engelen 2000) have produced several CA based models with integration of several economic theories.

Cellular Automata appear to be the most attractive and favoured technique for implementing high resolution models of spatial dynamics for a number of reasons:

- They are inherently spatial; their definition on a raster of cells, and on neighbouring relationships are crucial;
- They are simple and computationally efficient;
- They are dynamic and can then represent a wide range of situations and processes;

It is worthwhile to note that, in most of the models carried out until now, CA are based on explicit spatial rules which allow to simulate different dynamic behaviours on the base of a ”trial and error” procedure.

But this condition, the explicit and exogenous formulation of assumptions, represents the greatest limit of this approach, since it reduces the variability of the different territorial contexts on the base of few theoretical principia (spatial interaction, diffusion processes and so on), inhibiting the discovery and arise of new features in urban dynamics. Given the complexity and variability of the location behaviours it appears important to learn from the reality the true factors affecting the single location with respect to the surrounding conditions.

Recent developments in the natural algorithms, and particularly in Neural Networks, allow to reverse the approach by learning the rules and the behaviours directly from the Data Base, following an inductive bottom-up process.

The aim of this paper is therefore to present an integrated approach on land use dynamics where the transition rules of urban spatial evolution are learnt by Neural Network. The proposed innovation concerns the heart of the CA itself: the growth rules searching and identification.

In the paper the potentialities of NN are experimented with two different architectures: SOM (Self Organizing Maps), (Kohonen 1995) and a set of Supervised NN (Semeion 1998).

SOM allow to investigate the different dynamic behaviors by showing the strengths of the underpinning relationships with the environment. The classification produced by SOM identifies the most relevant clusters of cells for transition rules in quantitative and qualitative terms.

Then, for forecasting purposes, a set of Supervised NN is applied to learn the transition rules and to produce a possible future scenario of urbanization.

The case study is the south metropolitan area of Milan, whose extension is approximately 675 Km^2, which is a rich agricultural area with few historical small centers. The area is under pressure for the spillover, in fragmented residential and productive settlements, of Milan.

The paper is organized as follow:

the second section presents a short overview on NN and their potentialities in urban analysis and forecast; the third paragraph sketches a brief description of the study area and the GIS used. The methodology is explained in the following forth part which describes the research path.

Section 5 is devoted to show the NN SOM implementation results. The implementation of different architectures of Supervised NN is presented in the section 6-8:The input data and the methodology in section 6; the learning and validation phase in section 7 and the results obtained in prediction in section 8.

Some final comments and perspectives on the adopted approach conclude the paper in section 9.

2. *Neural Networks*

With the development of NN, which are Artificial Intelligence based technologies, in recent years news opportunities have emerged to enhance the tools we use to process spatial Data. Their specific advantage relies non only in the enhancement of speed and efficiency in handling urban Data, but specifically in providing a tool to develop new theories and techniques. While the traditional modelling approach is based on explicit "a priori" rules formulation, through an AI connessionistic approach rules are found "a posteriori" on the base of a learning process of a distributed "unit processing" architecture.

NN model is a parallel distributed Information system consisting of a set of adaptive processing elements (nodes) and a set of unidirectional data connections (weights).

The most successful applications in territorial Analysis and Planning rely on pattern classification, clustering or categorisation, optimisation (Openshaw and Abrahart 2000; Reggiani 2000; Leung and Fischer 2001), modelling scenic beauty from extracted landscape attributes (Bishop 1994), suitability analysis for development (Sui 1992; Deadman and Gimblett, 1995).

The novelty of our approach lies in the use of NN as a powerful tool for prediction and building virtual scenarios on urbanisation process. The results have been achieved through different categories of "training regimen" able to react to different information environment.

The training processes can be divided into three basic categories: monitored training, supervised training, and self-organisation. The monitored training is typical of associative networks, which are NN with essentially a single functional layer that associated one set of vector $\mathbf{x}_1$, $\mathbf{x}_2$, $\dots\mathbf{x}_n$ with another set of vector $\mathbf{y}_1$, $\mathbf{y}_2$, $\dots\mathbf{y}_n$. The primary classification of ANN are into feedforward and recurrent classes. Another categorisation of ANN is into autoassociative NN if $\mathbf{y}$ vectors are assumed to be equal to the corresponding $\mathbf{x}$ vectors. In a Heteroassociative network $\mathbf{y}_i \neq \mathbf{x}_i$.

There are many algorithms and procedures to optimize the weight matrix during the learning phase and many algorithms for dynamically query the ANN already trained.

In this research we used a Recirculation Neural Network (RCNN) (Hinton and McLelland, 1988). The ANN have shown to be highly efficient in determining the fuzzy similarities among different Records in any Data Base (DB) and the relationships of gradual solidarity and gradual incompatibility among the different Variables. The ability of ANN to produce *prototypical* generators, to discover *ethnotypologies* and to simulate possible scenarios was already experimented by the authors to investigate the complex structure of urban sustainability in the Italian cities (Diappi, Buscema, Ottanà, 1998).

Supervised training implies a regimen in which the NN is supplied with a sequence of examples ($\mathbf{X}_1$, $\mathbf{Y}_1$), ($\mathbf{X}_2$, $\mathbf{Y}_2$)… ($\mathbf{X}_k$, $\mathbf{Y}_k$).. of desirable or correct input/output pairs. As each input $\mathbf{X}_k$ is entered into the NN, the "correct output" $\mathbf{Y}_k$ also is supplied to the network. In our study the input is given by the territory information at time t and the "correct output" is the corresponding information at time t+1. Once the NN is trained and has learned the rules of transition, it will be able to produce the "desired" land use transformation of the present state of territorial system supplied as Input to the NN.

In self-organizing training, a network modifies itself in response to **X** Inputs. This category of training is able to obtain a surprisingly number of information processing capabilities: development of pattern categories based on clustering, estimation of probability density functions, development of continuous topological mapping from Euclidean space to curved manifolds (Hecht-Nielsen 1990). Self-organizing training includes the Self-Organizing Map (SOM), presented in section 5.

SOM is able to develop a continuous topological mapping $f : B \subset \mathbf{R}^n \rightarrow C \subset \mathbf{R}^m$ by means of self-organization driven by Y examples in C, where B is a rectangular subset of n-dimensional Euclidean space and C is a bounded sub set of m-dimensional Euclidean space, upon which a probability density function ρ ($\mathbf{Y}$) is defined. In the paper their ability to classify has been used to distinguish the prototypical land use dynamics in the case study area.

3. *The study case, the Data and the GIS*

The southern ring of metropolitan area of Milan presents large extensions of tilled land and natural parks with rare urban centres historically grown on agricultural activities. More recently, in the 70'ties the area has undergone a rapid urbanization process, principally produced by spill-over effects from the city of Milan.

The scattered and dispersed form of both residential and industrial new settlements is rapidly producing an high land consumption which is compromising the productivity of one of the richer agricultural areas in Europe. The forecast of urban sprawl is therefore a crucial issue which increases the scientific interest to test a new approach in urban modelling.

The available GIS on the area concern the land use coverage only at two temporal thresholds: 1980 and 1994. Even if this is an evident limit, it should be considered that urban sprawl in the area is a quite recent phenomenon whose interpretation and description would be biased if based on a longer temporal series of data.

The model uses a regular square grid of 500 m with 2703 cells in total. The land uses taken into consideration are: residential, commercial, industrial and "green" or unbuilt land wich denotes rural areas.

In this study the information given to the NN has the same structure of a CA. The following information for each cell are supplied to the Neural Network:

- Land use of the cell i at time t (1980)
- Land use of the neighbouring cells at time t (1980)
- Land use of the cell i at time t+1 (1994)

The state, of the cell or the neighbourhood, is described in term of *share* for each land use with respect to the total surface of the unit. We have processed only the three urbanized functions (residence, industry, commerce) because the unbuilt, green land use share is redundant, being a linear combination of the other three.

4. *The methodology*

The initial idea was to test the approach in a "toy" example, based on a small scale urbanisation process produced by a CA evolving for explicitly given rules. Implementing an Associative NN on the system at different time steps our aim was to test to what extent the NN are able to capture the imposed rules. The small toy was implemented using with different neighbourhood, size and time lags. At the end the experiment was successful: the NN was able to understand the CA rules, and relevant information on the sensitivity of the NN to the Data were also available (Bolchi, Diappi, Franzini, 2001).

But the same Associative NN, applied to the real Data Base of the south of Milan, produced very poor results.

The scenario reconstructed in the querying phase, depicted a static situation where even the estimated new residential cells were much lower than expected.

With an implementation of a different NN, the SOM (Self Organizing Map) we tried to investigate the fuzzy clusters of land use dynamics and to find out their prototypical profiles. These profiles, called *codebooks* show the different activation levels of the variables (nodes) allowing to investigate the underpinning relationships among variables.

Finally, for forecasting purposes a set of supervised NN had been implemented. The approach has been reversed: the state at *t* and *t+1* of cell becoming urbanized during the observed time lag represents a "model" which other cells will follow during the time lag *t+1*, *t+2*.

5. *The classification of the land use dynamics with SOM*

The NN SOM, a powerful tool of classification, have been developed mainly by Kohonen (1995) between 1979 and 1982. As said before SOM are AutoPoietic NN, where the target is not predefined, but dynamically built up during the learning phase. Their architecture comprises two layers: an input one, acting simply as a buffer, that doesn't modify the data, and an output one, known as Kohonen layer (or matrix), which is formed by units regularly organized in the space and which evolves during the training following a spatial organization process of the data characteristics, named Feature Mapping (Fig. 1*a*). The construction of these maps allow a close examination of the relationships between the items in the training set.

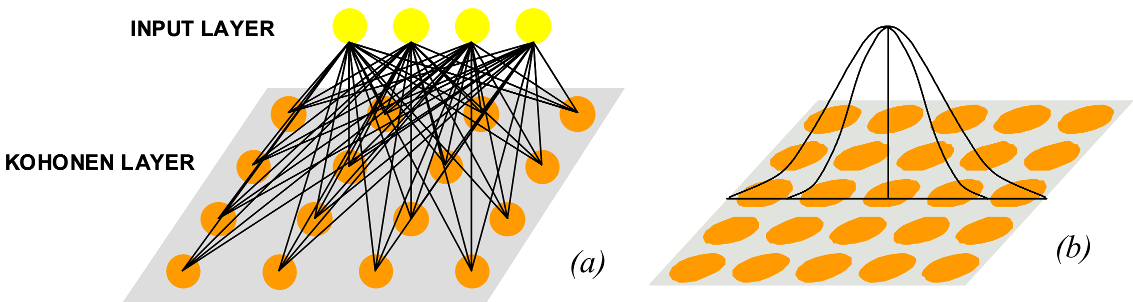
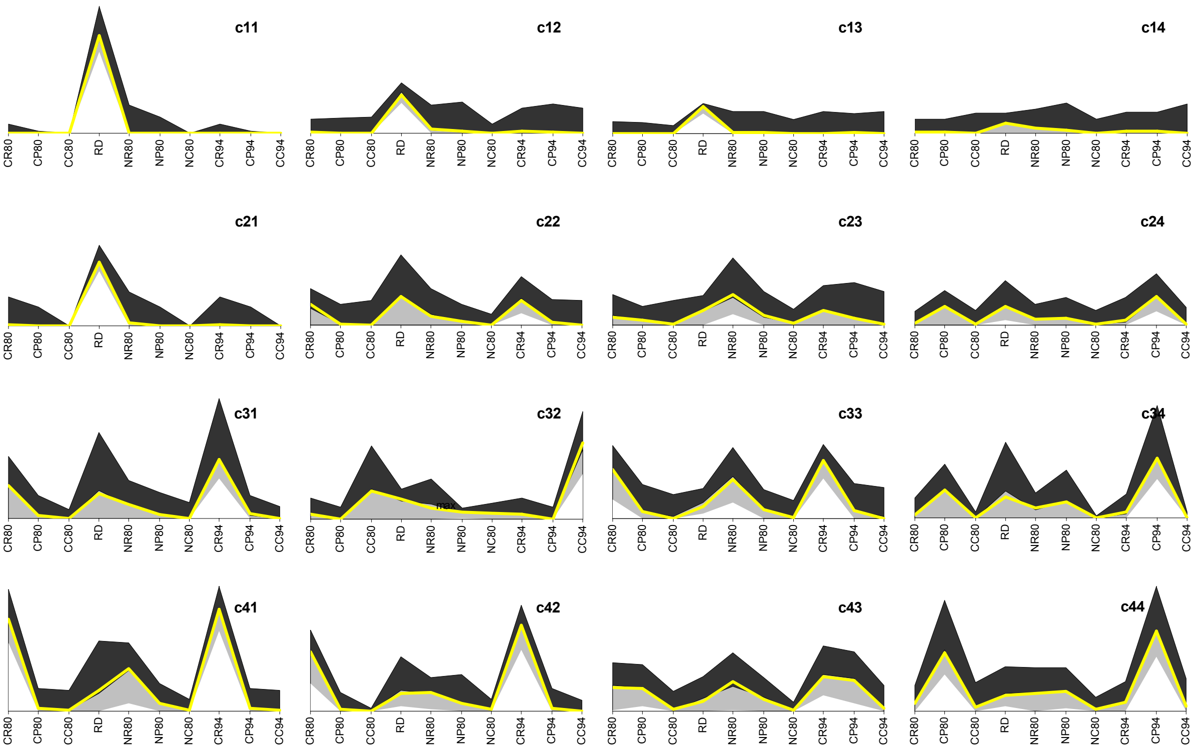


Figure 1 - the SOM topology *(a)* and the weight update function *(b)*

When the training phase has calculated the weight matrix, the *classification* maps each input vector to the output unit with the minimum Euclidean distance from the *codebook*. The SOM attitude to "classify" makes possible to perform a *mapping* with two main peculiarities:

- Clustering: the net performs a logical division of the input space into regions (cluster), associating a point in the N-dimensional input space to the two-dimensional output matrix. In the dimension reduction process the principal components discriminating data are dominant.
- Self-organisation: before the training the weights vectors topology depends only on the initialising criterion: if it is random weights will be casually organised into their hyper-cube. The learning criterion tends to move the weights vectors toward the input vectors seen during the training. The vector moving affects not only the winner

unit vector, but also its neighbourhood according to a decreasing function (fig 1*b*). SOM NN on square grids of 9,16, 25 nodes have been trained to group the data. The more explaining output was obtained with a 4x4 nodes grid; this resulted the best in order to show each group sufficiently different from each other.



CR80 Cell, residential, 1980
CP80 Cell, productive, 1980
CC80 Cell, commercial, 1980
RD Road distance
NR80 Neighbourhood, residential, 1980
NP80 Neighbourhood, productive, 1980
NC80 Neighbourhood, commercial, 1980

CR94 Cell, residential, 1994
CP94 Cell, productive, 1994
CC94 Cell, commercial, 1994

Codebooks range, values over the mean
Codebooks range, values under the mean
Codebook

Figure 2 - The codebooks

The spatial analysis carried out by SOM has been displayed by:

- cluster profiles and their codebook;
- charts with colour hatched plot of the zones, based on output units assignment.

In figure 2 all the *codebooks*, as prototypical profiles of each cluster, shows the most relevant features in land use dynamics. On the x-axis are the variables, on the y-axis their activation level. On the figure is charted the envelope of the records assigned to each single cluster and, in yellow line, the *codebook*.

The colour map (Fig.3) shows the spatial organisation of the classes; it is crucial to know if cells belonging to the same class are also spatially clustered, or if similar dynamic behaviour affects cells scattered in the territory.

In Fig.2, the first row (CL 1-1 ÷ CL 1-4) shows groups of stable (in the period) agricultural areas; but moving right along the first row the level of naturality is decreasing; no significant different land uses are taking place but the mean distance to the roads drops showing potential “risk” of urbanisation. In Fig. 3 and CL 1-3 and 1-4 free cells are close to urbanised areas.

Shifting from CL 1-1 along the column an increasing road equipment copes with new residential settlements, which, in CL 4-1 infill the consolidated urban centres.

In the fourth column the industrial land use dynamics emerges both in less infrastructured and isolated areas (CL 3-4) and near the exiting ones. Looking in the map (fig. 3) it is worthwhile to note that industrial settlements tend to aggregate spatially, near or far from the urban centres, and road accessibility is not an essential prerequisite for them.

In the fourth row the infilling processes in existing urban areas are represented: from the residential growth in CL 4-1 and to the expansion near the existing industrial areas (CL 4-4); between the two groups CL 4-2 shows peripheral residential growth near industrial areas and CL 4-3 classifies the emergence of new linear forms of urbanisation with land use mix along the main roads. The spatial logic of commercial activities is shown in CL

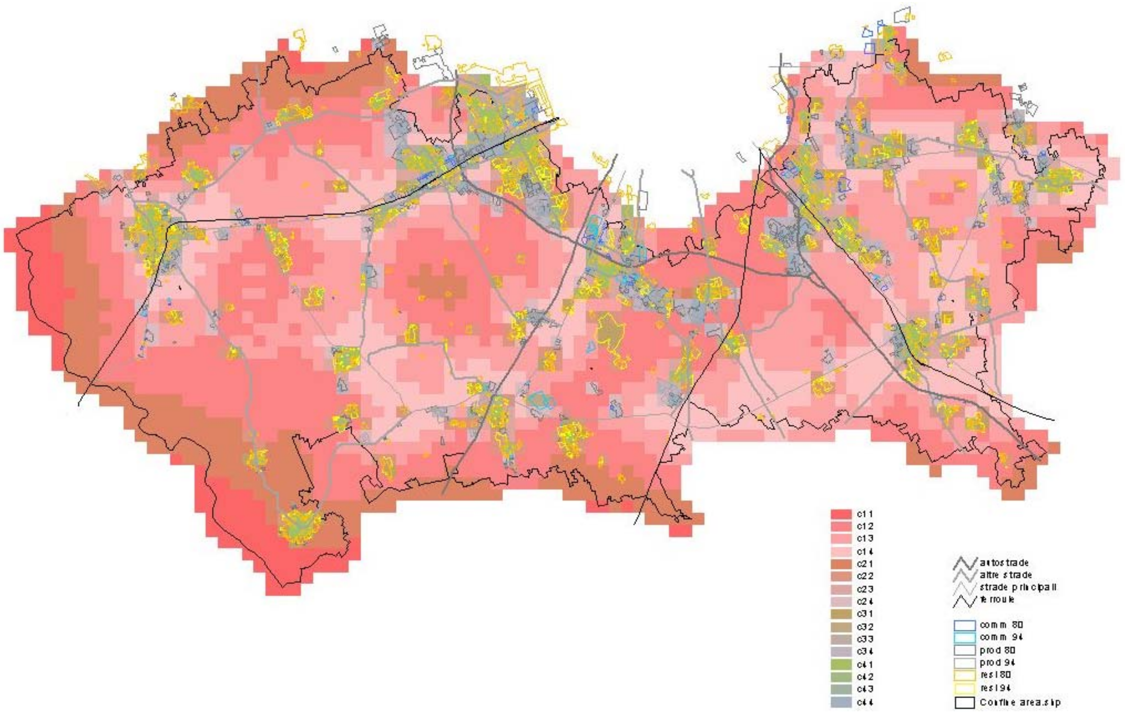


Figure 3 – The spatial distribution of the SOM clusters

3-2 where, as expected, a concentration process near the most important urban centres is taking place.

In conclusion, the adoption of the SOM as a tool to investigate the different dynamics seems fruitful and opens new research directions. In fact the different Codebooks may be interpreted in a "if then else " approach: given these surrounding conditions at time *t* at time *t+1* the dynamics will change in this way.

6. *The prediction through Supervised ANN*

The NN which generates prediction on land use dynamics is Supervised (SANN). Trained on the base of Input/Output examples the NN is able to reproduce the expected Output starting from the same Input. This means that the NN should learn, from the set of cells which change their land use in the time lag considered, the connections between the final state at time *t+1* (the target) and the local and neighbouring conditions at time *t*.

The record supplied to the SANN contains 6 input variables and 3 output ones. The input describe the state of the cell and of its neighbourhood at the time *t*, the output variables represent only the cell state at the time *t+1*.

For the implementation of supervised NN, it is crucial to select "good examples "to feed the network. Therefore the records have been split into two different sets (Fig. 4).

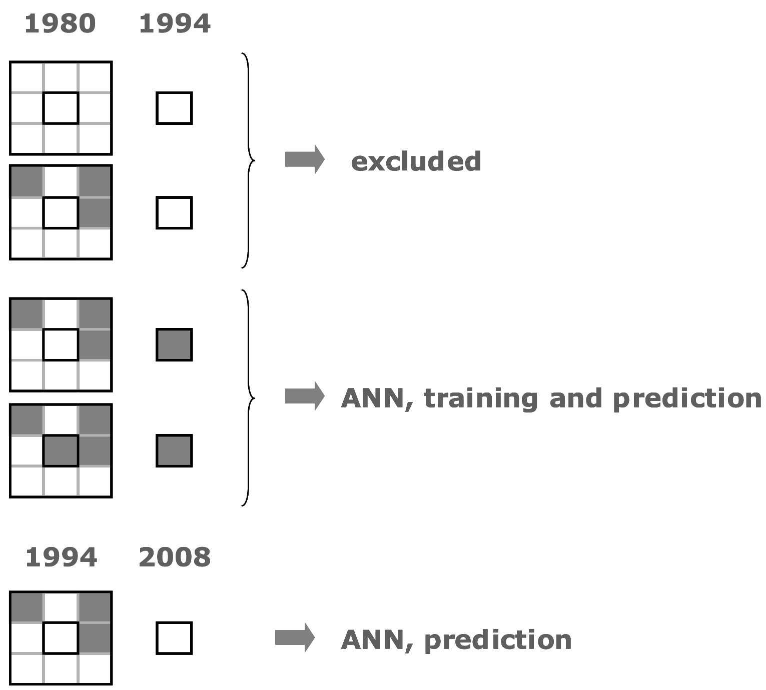


Figure 4 – The record sets used for the different processing phases

- The first one, composed by 1662 records of "stable green" cells at both the times, has been excluded from NN processing.
- The second one, containing 1041 records for the cells urbanised at one of at both times, has been used for training and prediction.
- The third one, concerning green cells with urbanised neighbourhood at 1994, has been used only for prediction;

The split into three sets tries to improve the learning capability of the SANN avoiding the simultaneous presence of records in which the same Input generates different Outputs. In fact although one of the peculiarity of the SANNs is their ability to deal with fuzzy behaviours, the process of inconsistent patterns should lead to misinterpretations and errors.

The 1041 pattern selected for the experimentation have been randomly divided into two sets (Set 1 and Set 2). Ten different architectures of SANNs have been trained with Set 1 and validated with Set 2. The same SANNs have been also trained with Set 2 and validated with Set 1. In both cases the SANNs performances have been evaluated through statistical functions.

In this way it was possible to evaluate the SANNs prediction capability on the whole 1041 records set.

At the end, the average of the 1041 prediction values of the 10 SANNs have been calculated, and again the prediction capability have been evaluated through statistical functions. In Fig. 5 is shown a flow diagram of the procedure.

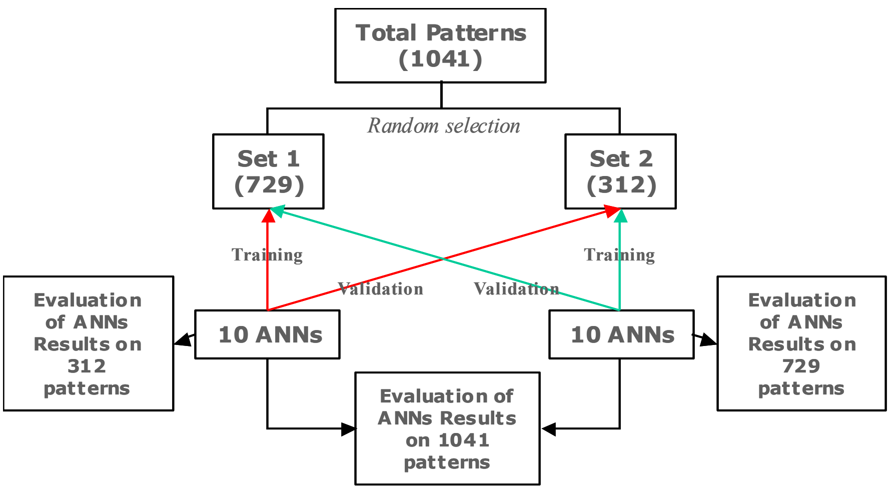


Figure 5 - the training and validation procedure for the SANNs

The used NN are listed in table 1.

Set 1			Set 2		
Topology	**Order**	**Learning Law**	**Topology**	**Order**	**Learning Law**
FF		Bm	FF		Bm
FF		Bp	FF		Bp
FF		Sn			
Self	DA	Bp	Self	DA	Bp
			Self	DA	Bm
			Self	SA	Bm
			Self	SA	Bp
Tasm	DA	Bm	Tasm	DA	Bm
Tasm	DA	Bp	Tasm	DA	Bp
Tasm	SA	Bm	Tasm	SA	Bm
Tasm	SA	Bp	Tasm	SA	Bp
Tasm	SA	Cm			
Tasm	SA	Sn			

Learning Law: Bp = Back Propagation (standard)
Sn = Sine Net (Semeion)
Bm = Bi-Modal Network (Semeion)
Cm = Contractive Map (Semeion)

Topology: FF = Feed Forward (standard)
Self = Self Recurrent Network (Semeion)
Tasm = Temporal Associative Subjective Memory (Semeion)

Order: DA = Dynamic and Adaptive Recurrency (Semeion)
SA = Static and Adaptive Recurrency (Semeion

Table 1 – The different architectures of SANN

7. *Learning and validation of the SANNs*

The Statistical functions used to evaluate the results are presented in Annexe 2. Each function measures, separately, the error of each output vector component of SANNs related to the correspondent Target value given in Input.

The first evaluation of the results is given by the statistical functions in table 2.

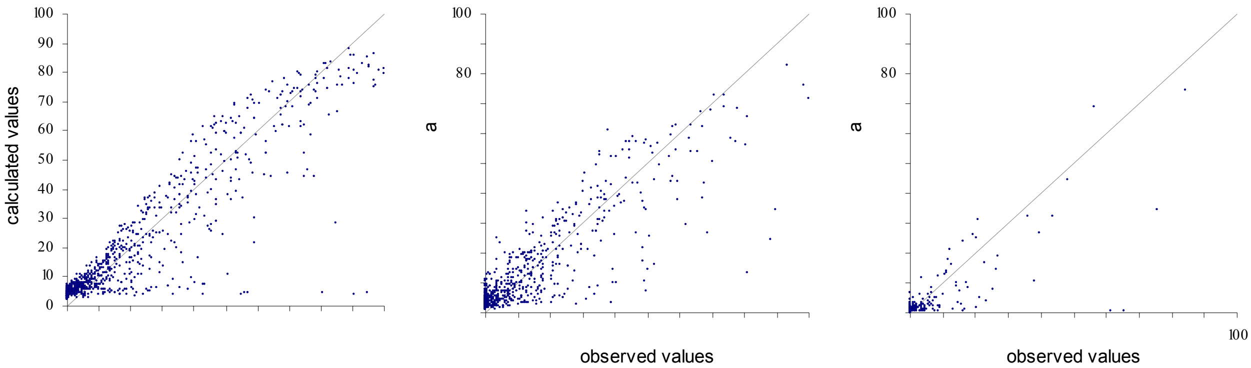
	Residential	Industrial	Commercial	Average
RMSE	0.06756	0.05543	0.03290	0.09338
Real Error	-0.00262	-0.00938	-0.00550	-0.00583
Relative Error	0.05983	0.04911	0.01867	0.04254
Error Variance	0.11412	0.09735	0.05214	0.08787
NMSE	0.15737	0.22162	0.38873	0.25591
Squared R	0.84310	0.78374	0.62216	0.74967
Linear Corr.	0.91820	0.88529	0.78877	0.86409

Table 2 – Statistical measures of validation

It should be observed that, from a statistical point of view, the results are quite good for the residential use, a little less for the industry and not so good for the commerce. The difference is probably due to the different sample size for the three land uses. Since the recent urbanisation process in the south of Milan concerns mainly residential sprawl, many records are "good examples" for this land use. On the contrary the commercial use, which is the less frequent, gives the worst results. This is shown on the scatter diagram of observed (on the *x* axis) and calculated values (on the *y* axis) for each land use (figures 6 a, b and c).

The spatial representation of "errors" allows to evaluate the spatial logic of the SANNs output.

Figure 7 shows the errors concerning the residential land use. Errors are measured in ratio over the whole cell surface. One large underestimation is evident, just in the centre



(*a*) (*b*) (*c*)

Figure 6 - The scatter diagrams of observed and calculated values of land use in each cell

of an agricultural area totally not urbanised and not infrastructured. This is due to an entirely new settlement for affluent people, "Milano 3", which is the result of a negotiation between big investors and the local municipality. Evidently it was impossible for the SANN to predict an event which is totally extraneous to his logic.

Other errors are mainly due to planning constraints, often forbidding a "natural" growth and forcing the development elsewhere. As mentioned earlier in this experiment road infrastructures have been ignored, whereas their topical role emerges in the already mentioned SOM classification.

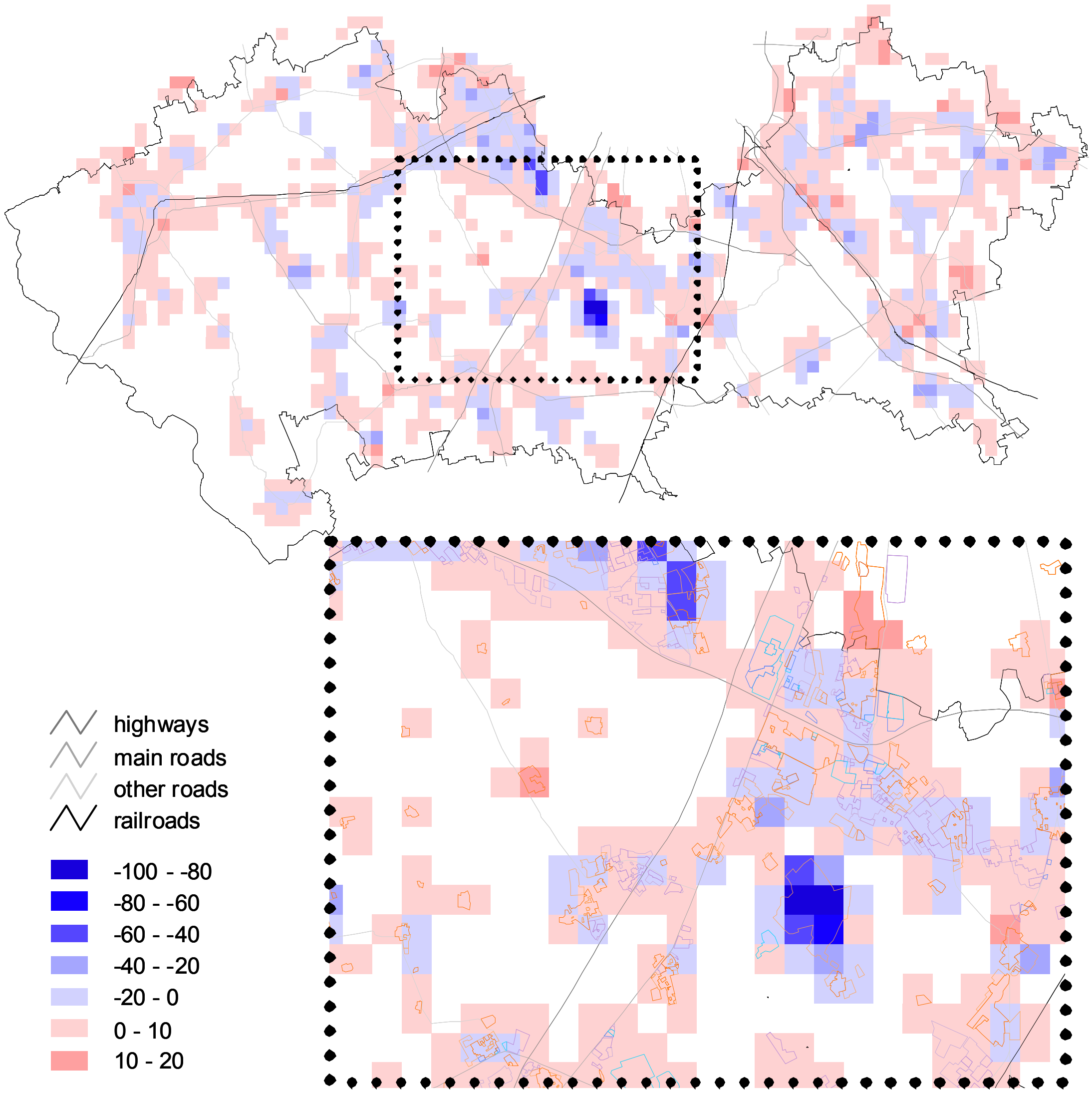


Figure 7 – the differences between observed and calculated values, in blue the underestimations, in red the overestimations

8. *The prediction capabilities of the SANN*

Once the learning and testing phase has been concluded, the averaged weight matrix of the SANNs is processed with the Data set of cells "potentially" in urbanisation in the next time lag (1994-2008). The prediction concerns "green" cells with urbanized neighbourhood at 1994.

Figure 8 shows the estimated surfaces for each land use. As expected the trend is linear, given the availability of only two temporal thresholds.

The resulted pattern shows a probable scenario (fig. 9 - Residence prediction) where prevailing urbanisation process takes place at the boundaries of the cities and villages

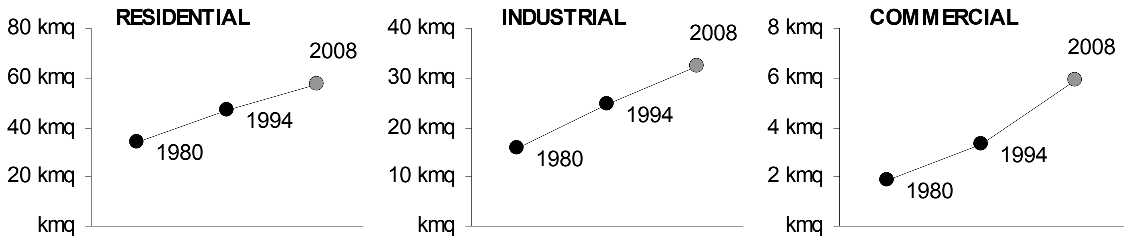


Figure 8 – The surface growth for each land use

and, surprisingly, along the roads; this result is unexpected because, as said earlier, the record does not include information about road accessibility.

Moreover, the new residence seems to be attracted by the proximity to other activities (industry and commerce). Indeed, this spatial feature characterizes the urban quality of the Italian historical cities and villages and holds particularly in this territory.

New productive settlements will be based mainly around the existing large industrial areas, showing a location criterion mainly driven by agglomeration economies. Such behaviour characterizes also the larger new settlements predicted from the NN for commerce, which, in the considered area, are clustering around new development poles near the highway and far from the urbanised areas.

On the contrary, small and diffused expansions in industry and commerce will take place in and around the existing urban areas, improving the urban mix and urban agglomeration economies.

What is worthwhile to note is that the SANN findings, in terms of spatial patterns, are

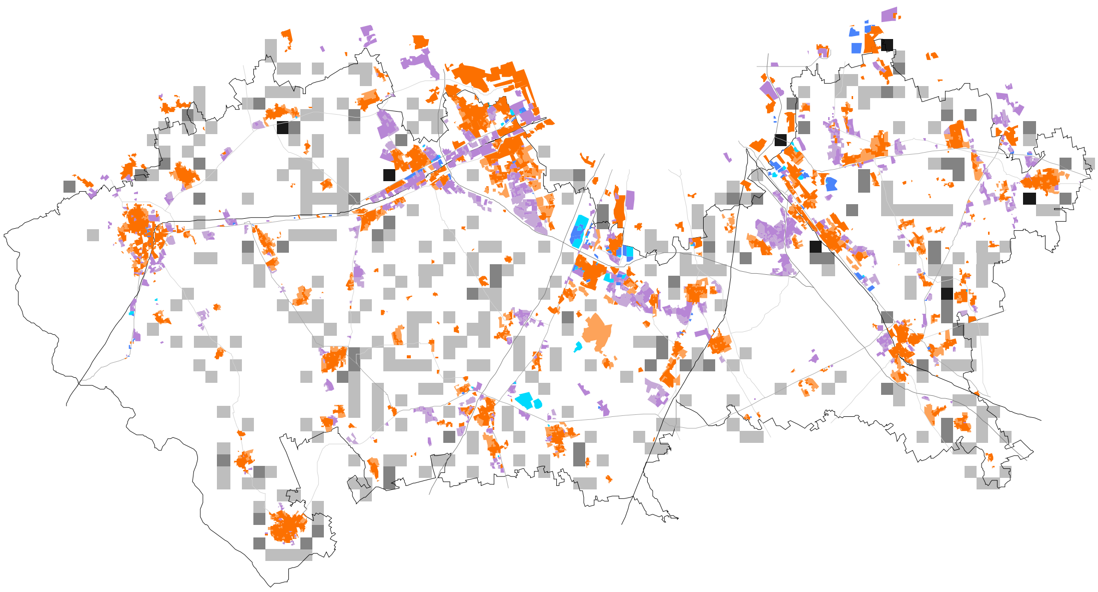


Figure 9 – the predicted residential growth at 2008 (grey tones)

consistent with the SOM behavioural rules, shown in the codebooks.

To conclude the SANNs process seems able to capture and predict a sound spatial logic for future trends in urbanisation and to drive suitable territorial policies towards the facilitation or the inhibition of the “organic” processes of the considered urban system.

9. Concluding remarks

The experiments presented allow to accept NN as powerful tool for investigation in urban dynamics. The original aim of the paper was to compare NN performances with the well known CA forecasting capabilities; therefore information provided is that of a prototypical CA, which is limited to the local and neighbouring land use conditions.

But the big advantage offered by NN consists in investigating the connections in whatever other data: density, urban morphology, spatial relationships with central functions, planning constraints, political view of the local authority and so on. Further research with enlarged Data Base would produce an important improvement on location theory and on territorial morphology dynamics studies.

The SOM run was able to show significantly different dynamic behaviours and to clearly distinguish the spatial location pattern of the urban functions considered: compact and urban the commercial activities, compact and peripheral the industry, more scattered and invasive of natural resources the residence, particularly in the last few years.

In each of the models produced, the codebook points out the degree of relevance of each variable in explaining the considered behaviour.

The SANN has produced a suitable scenario of the future urbanisation, even if with the assumption of stability of the transition rules and with only two temporal thresholds supplied for training. Again, NN should be able to learn more complex dynamics if provided with larger temporal series of data, unavailable at the moment.

The overview depicted gives an idea of the level of “urbanisation risk” for each agricultural cell and the level of infilling in urbanised areas, in centres and along the roads. It seems quite a probable scenario which could steer the territorial policies towards a sustainable development approach.

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Annexe 1 -Parameters in the SOM processing

1. net architecture

Input Unit	Number of units in the input vector (12)
K Units	Number of units in the output matrix (from 9 to 49, depending on the simulation)
K Rows	Number of rows in the output matrix (from 3 to 7, depending on the simulation)
K Cols	Number of columns in the output matrix (from 3 to 7, depending on the simulation)
K Dimension	Output matrix dimensions (2)
K Topology	Output matrix space topology (Euclidean)
N Topology	Winner unit neighbourhood space topology (square)

2. parameters

N function	Parameter defining the function to update the units connections in the WU neighbourhood (Gaussian)
Alpha Max	Maximum width for the *N function* (1)
Alpha Min	Minimum width for the *N function* (0)
Alpha Inc	Factor reducing *Alpha Max* in each epoch (0.01)
Set Weight	Maximum weight value during the initialisation
Alpha W Func	Input/output weights correction function (constant)
Alpha W Max	Initial value of weight correction factor (0.1)
Alpha W Min	Minimum value of weight correction factor (0)
Alpha W Inc	Decreasing amount of the weight correction factor (0.001)
Epochs	The epochs number for an experiment is automatically calculated by this formula: $$Epochs = \frac{AlphaMax - AlphaMin}{AlphaInc}$$

3. Input record

Patterns	Number of records in the input sample (2703)

Annexe 2 – Statistical functions for validation of the SANNs

x(p) is the generic output component for the *p*-th input pattern, and the correspondent target is *t(p)*. *M* is the number of patterns considered for the statistical measure.

Root Mean Squared Error (RMSE), evaluating the squared root of the semi-mean of the squared prediction errors: $$RMSE = \sqrt{\frac{1}{2M}\sum_{p=1}^{M}(x(p)-t(p))^2}\ .$$
Normalized Root Mean Squared Error (NMSE), evaluating the squared root of the mean of the squared prediction errors, where target and output values was before normalized between 0 and 1: $$NMSE = \sqrt{\frac{1}{M}\sum_{p=1}^{M}\left(\left(\frac{x(p)-\min_k\{x(k)\}}{\min_k\{x(k)\}-\max_k\{x(k)\}}\right)-\left(\frac{t(p)-\min_k\{t(k)\}}{\min_k\{t(k)\}-\max_k\{t(k)\}}\right)\right)^2}\ .$$
Real Error (ERR) evaluating the mean of the prediction error: $$ERR = \frac{1}{M}\sum_{p=1}^{M}(x(p)-t(p))\ .$$
Relative Error (ABSERR) evaluating the mean of the absolute prediction errors: $$ABSERR = \frac{1}{M}\sum_{p=1}^{M}\left\lvert x(p)-t(p)\right\rvert\ .$$
Squared R (R2), evaluating the squared of the linear correlation coefficient between target and prediction values: $$R^2 = \left(\frac{\sum_{p=1}^{M}\left(\left(x(p)-\left(\frac{1}{M}\sum_{k=1}^{M}x(k)\right)\right)\cdot\left(t(p)-\left(\frac{1}{M}\sum_{k=1}^{M}t(k)\right)\right)\right)}{\sqrt{\sum_{p=1}^{M}\left(x(p)-\left(\frac{1}{M}\sum_{k=1}^{M}x(k)\right)\right)^2}\cdot\sqrt{\sum_{p=1}^{M}\left(t(p)-\left(\frac{1}{M}\sum_{k=1}^{M}t(k)\right)\right)^2}}\right)^2\ .$$