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Improved Understanding of Urban Sprawl Using Neural Networks

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Abstract: It is widely accepted that the spatial pattern of settlements is a crucial factor affecting quality of life and environmental sustainability, but few recent studies have attempted to examine the phenomenon of sprawl by modelling the process rather than adopting a descriptive approach. The issue was partly addressed by models of land use and transportation which were mainly developed in the UK and US in the 1970s and 1980s, but the major advances were made in the area of modelling transportation, while very little was achieved in the area of spatial and temporal land use. Models of land use and transportation are well-established tools, based on explicit, exogenously-formulated rules within a theoretical framework. The new approaches of artificial intelligence, and in particular, systems involving parallel processing, (Neural Networks, Cellular Automata and Multi-Agent Systems) defined by the expression "Neurocomputing", allow problems to be approached in the reverse, bottom-up, direction by discovering rules, relationships and scenarios from a database. In this article we examine the hypothesis that territorial micro-transformations occur according to a local logic, i.e. according to use, accessibility, the presence of services and conditions of centrality, periphericity or isolation of each territorial "cell" relative to its surroundings. The prediction capabilities of different architectures of supervised Neural networks are implemented to the south Metropolitan area of Milan at two different temporal thresholds and discussed. Starting from data on land use in 1980 and 1994 and by subdividing the area into square cells on an orthogonal grid, the model produces a spatial and functional map of urbanisation in 2008. An implementation of the SOM (Self Organizing Map) processing to the Data Base allows the typologies of transformation to be identified, i.e. the classes of area which are transformed in the same way and which give rise to territorial morphologies; this is an interesting by-product of the approach.

1. INTRODUCTION

Land use dynamics and fragmentation of settlements is a crucial question for planning. In the general framework of sustainability objectives, the policies that control a suitable process of urbanisation increasingly involve a deep knowledge of complex criteria of location chosen by the different agents. Planners realize that it 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 Neural Networks (NN) and Cellular Automata (CA) in particular, offer the potential 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 CA, 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.

CA 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 process models that deal with state changes;
- 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 the simulation of different dynamic behaviours on the basis of a “trial and error” procedure.

However 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 basis of few theoretical principia (spatial interaction, diffusion processes and so on), inhibiting the discovery and appearance of new features in urban dynamics. Given the complexity and variability of the location behaviours it appears important to learn from reality the most relevant factors affecting the single location with respect to the surrounding conditions.

Recent developments in the natural algorithms, and particularly in Neural Networks, allow the reversal of the approach by learning the rules and 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 NN. 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 permit the investigation of 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.

Secondly, 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, and which is a rich agricultural area with few historical small centers. The area is under pressure from the spillover, in fragmented residential and manufacturing 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 section sketches a brief description of the study area and the GIS used. The methodology is explained in the following fourth part which describes the research path.

Section 5 shows the NN SOM implementation results. The implementation of different architectures of Supervised NN is presented in sections 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 ANN (Artificial NN), which are AI based information processing systems, in recent years new opportunities have emerged to enhance the tools we use to process spatial Data. Their specific advantage lies not 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 the Neural Networks processing approach, rules are found a posteriori on the base of a learning process of a distributed "unit processing" architecture.

NN structure consists in 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; Fischer and Leung 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 for building virtual scenarios on urbanisation processes. 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 associates one set of vectors x_1, x_2, $\ldots x_n$ with another set of vectors y_1, y_2, $\ldots y_n$. The primary classification of ANN are into feedforward and recurrent classes.

In a feedforward associative network the x-vector input to the single functional layer of the processing elements leads to the y'-vector output in a single feedforward pass. In a recurrent associative network the output signals of the processing elements of the layer are connected to those same processing elements as input signals. The output vector y' is ignored until the system converges (that is stabilizes and ceases to change significantly).

Another categorisation of ANN is into autoassociative NN, if y vectors are assumed to be equal to the corresponding x vectors. In a Heteroassociative network $y_i \neq x_i$.

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

In this research we used a Recirculation Neural Network (RCNN) (Hinton and McLelland, 1988). The ANN have been 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 Italian cities (Diappi, Buscema, Ottanà, 1998).

Supervised training implies a regimen in which the NN is supplied with a sequence of examples (X_1, Y_1), (X_2, Y_2)… (X_k, Y_k).. of desirable or correct input/output pairs. As each input X_k is entered into the NN, the "correct output" Y_k is also 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 high 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 $f: B \subset R^n \rightarrow C \subset R^m$ 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 (Y) is defined. In the paper their ability to classify has been used to define the prototypical land use change rules in the case study.

3. THE CASE STUDY, THE DATA AND THE GIS

The southern ring of the 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's 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 a 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 includes 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 handling a longer sequence of temporal data.

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

The construction of the GIS has been based, for each period, on the superposition of two maps: the Lombardy Regional Technical raster Map and the Master Plan Mosaic of the Municipalities of the Province of Milan ("Mosaico Informatizzato degli Strumenti URbanistici Comunali", Provincia di Milano – Settore Pianificazione Territoriale - SIT) showing the different land uses.

The partition of each land use has been executed by ArchView. Then the superposition of the grid has allowed to measure the quantity of land use for each cell.

In this study the information given to the NN has the same structure as 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 neighbourhood size is based on the 8 contiguous cells.

The cell and the neighbourhood state are described in terms of *share* for each land use with respect to the total surface of the unit or of the whole neighbourhood. Only the three urbanized functions (residence, industry, commerce) have been processed since the unbuilt cell or neighbouring share is 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 urbanisation process produced by a CA evolving with explicitly given rules. The small toy was implemented with different neighbourhood sizes. On the resulting pattern at different time steps an Associative NN has been implemented, with the aim to test to what extent the NN should be able to understand the imposed rules. The results of the experiment were successful: the NN was able to understand the CA rules, and, moreover, the test has produced relevant information on the sensitivity of the NN to the Data (Bolchi, Diappi, Franzini, 2001).

However the same Associative NN, applied to the real Data Base of the south of Milan, produced very poor results. The NN didn't understood many rules of change and the scenario, generated in the querying phase, depicted a quite static situation where even the residential growth, quite numerous and relevant in the period, were much lower than expected.

Then, with an implementation of the SOM (Self Organizing Map), a NN able to classify the pattern in fuzzy clusters of land use dynamics and to produce their prototypical profiles, we tried to find out the rules of change. These profiles, called *codebooks* show the different "average" activation levels of the variables (nodes) of the records in the class, allowing to discover the underpinning relationships among the "average" initial and final state of the group of cells.

Finally, a set of supervised NN had been implemented for forecasting purposes. The approach was 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 Self Organised 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: the Feature Mapping (Fig. 1*a*). The construction of these maps allows a close examination of the relationships between the items in the training set.

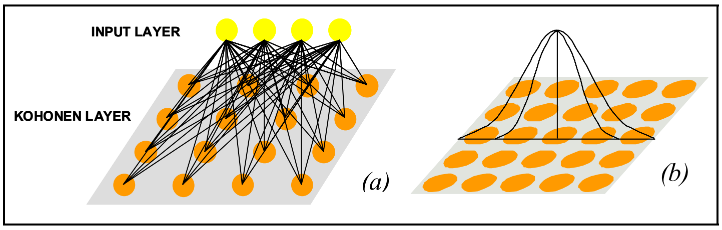

Figure 1. The SOM topology *(a)* and the weight update function *(b)*

When the training phase has calculated the weight matrix, the map shows clusters where each input vector is assigned to the closest codebook in terms of minimum Euclidean distance.

The SOM attitude to "classify" makes it 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 towards 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. 1b).

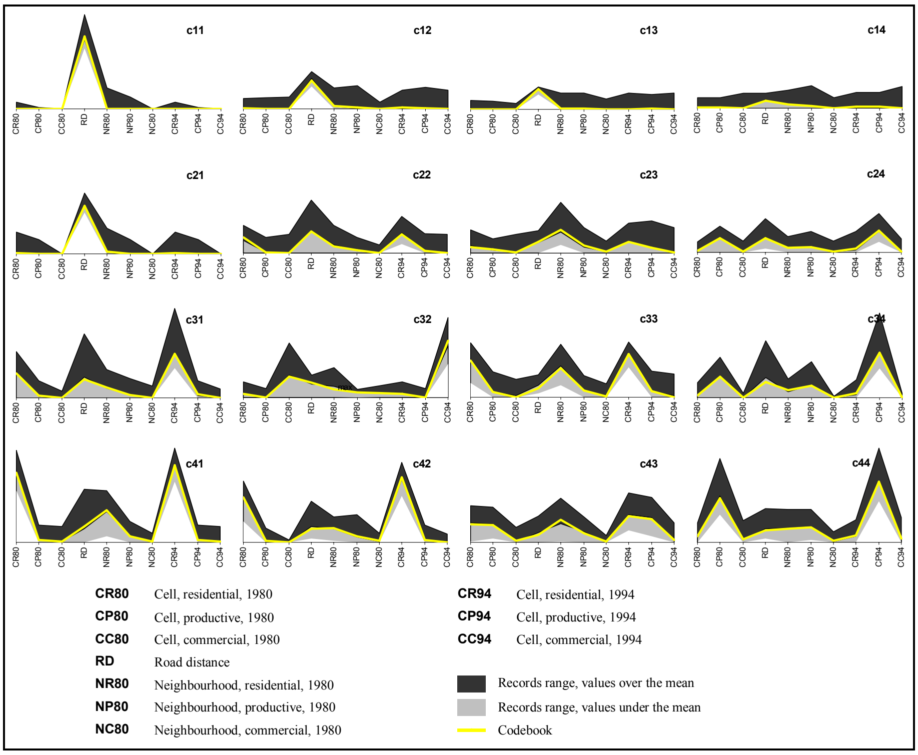

Figure 2. The cluster profiles and the codebooks

SOM NN on square grids of 9,16, 25 nodes have been trained to group the data. The best explaining output was obtained with a 4x4 nodes grid; this result was the best in sufficiently differentiating each group from the other group.

The spatio-temporal classification carried out by SOM has been displayed by:

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

Figure 2 shows the clusters and the codebooks; the variables are on the x-axis, and their activation level is on the y-axis. The envelope of the records assigned to each single cluster is charted in grey and black and the codebook is the yellow line.

Figure 3 shows the spatial allocation of the clustered cells; it is crucial to know if cells with similar dynamic behaviour are also spatially contiguous, or are scattered in the territory.

In Fig.2, the first row (C 1-1 ÷ C 1-4) shows groups of stable (in the period) agricultural areas; however moving right along the first row, if no significant different land uses are taking place, the mean distance to the roads drops showing potential "risk" of urbanisation. In Fig. 3, cells of the group C 1-3 and C1-4 are close to urbanised areas.

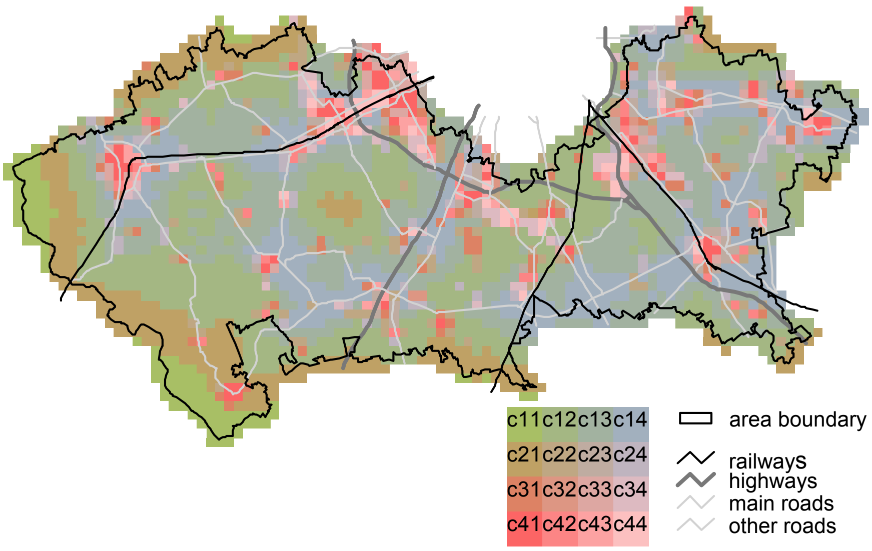

Figure 3. The spatial allocation of the SOM clusters

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

In the fourth column the industrial land use dynamics emerges both in less infrastructured and isolated areas (C 3-4) and near the exiting ones (C 4-4). 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, while 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 C 4-1 and to the expansion near the existing industrial areas (C 4-4); between the two groups C 4-2 shows peripheral residential growth near industrial areas and C 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 C 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. Indeed, 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.

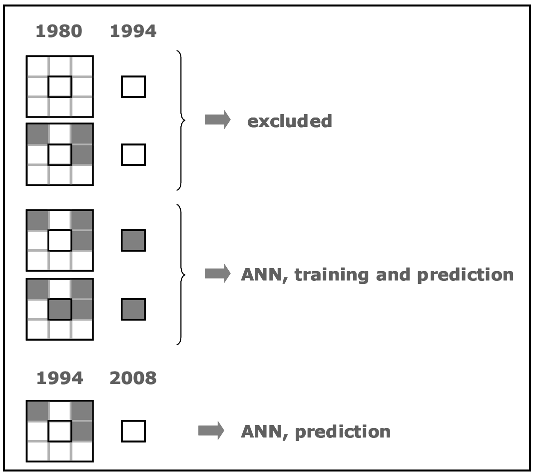

Figure 4. The record set used for the different processing phases

6. THE PREDICTION THROUGH SUPERVISED ANN

The NN which generate prediction on land use dynamics are Supervised (SANN). Trained on the basis of Input/Output examples the SANN is able to reproduce the expected Output starting from the same Input. This means that the network 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 ones 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 SANN, it is crucial to select "good examples" to feed the network. Therefore the records have been split into three different sets (Fig. 4):

- 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 or 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.

Table 1. The different architectures of SANN

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)

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. Indeed, although one 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 (Table 1) 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.

Finally the average of the 1041 prediction values of the 10 SANNs has been calculated, and again the prediction capability has been tested through statistical functions. Fig. 5 shows a flow diagram of the procedure.

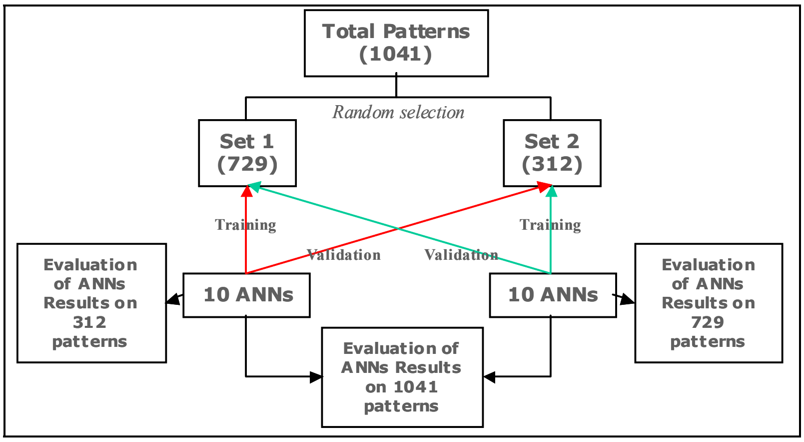

Figure 5. The training and validation procedure for the SANNs

7. LEARNING AND VALIDATION OF THE SANNS

A first evaluation of the results is given by usual statistical functions shown in Table 2.

It should be observed that, from a statistical point of view, the results are quite good for the residential use, a little less so for the industry and not so good for commerce. The difference is probably due to the different sample sizes 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 the evaluation of the spatial logic of SANNs output.

Figure 7 shows the errors concerning the residential land use. Errors are measured in ratio over the whole cell surface.

Table 2. Statistical measures of validation

	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

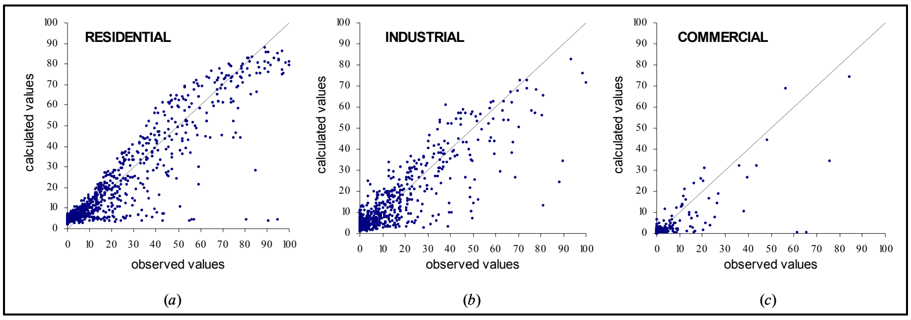

Figure 6. The scatter diagrams of observed and calculated values of land use in each cell

One large underestimation is evident, just in the centre 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 the rules of change discovered by the NN.

Other errors are mainly due to planning constraints, often inhibiting a "natural" growth and forcing the development elsewhere. In fact a limit of the present work is the absence of the information on planning rules, which should allow to capture how planning constraints should play in generating spatial pattern of urbanisation. This is crucial information, which necessarily will be introduced in the future developments of the approach.

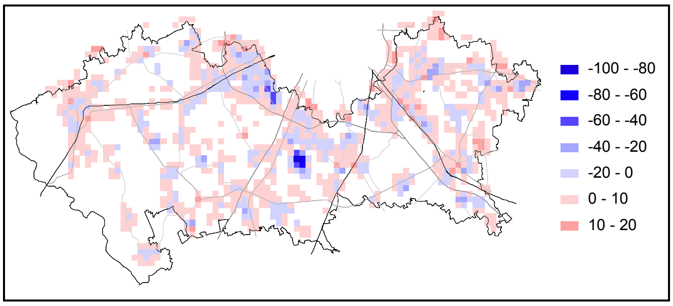

*Figure 7.*The differences between observed and calculated values *(in blue the underestimations, in red the overestimations)*

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 in1994.

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

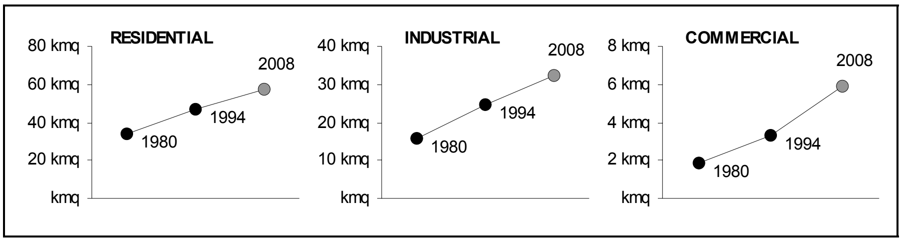

*Figure 8.*The predicted land use growth

The resulted pattern shows a probable scenario (Fig. 9 - Residence prediction) where the prevailing urbanisation process takes place at the boundaries of the urban centres, and, out of the urbanized areas, along the roads. 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.

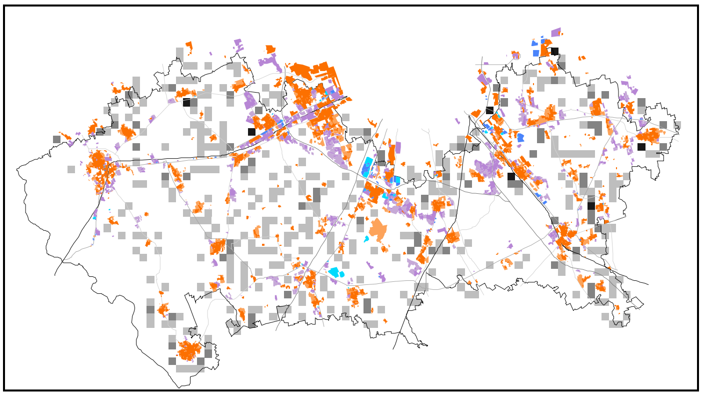

*Figure 9.*The predicted residential growth at 2008 (grey tones)

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 showing the existence of urban agglomeration economies.

What is worthwhile noting is that the SANN findings, in terms of spatial patterns, are consistent with the SOM behavioural rules, shown by 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 demonstrate that NN is powerful tool for investigation of urban dynamics. The original aim of the paper was to integrate the spatial local logic of CA with the bottom- up knowledge construction of NN in pointing out the rules of change; therefore the information provided is that of a prototypical CA, which is limited to the local and neighbouring land use conditions.

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 for commercial activities, compact and peripheral for industry, more scattered and invasive of natural resources for residence, particularly in the last few years.

In each of the produced models, 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 limit of the stability of transition rules, which have been extracted by training in period 1980-1994 and applied in period 1994-2008 for forecasting purposes. But this is a limit due to the availability of Data, not to the method used. NN should be able to learn more complex dynamics if provided with larger temporal data set, unavailable at the moment.

As said before, these quite satisfactory results should be further improved by feeding the networks with other essential information concerning planning constraints, density, morphology, spatial relationships with central functions, political trend of local authorities and so on. Further research with an enlarged Data Base would enrich the knowledge on location dynamics with empirical findings and allow an updating of the concepts and assumptions of urban sprawl phenomenon.

Moreover, the scenario depicted gives an idea of the level of "urbanisation risk" for unbuilt cells, important information for territorial policies in order to drive future settlements towards less spread out spatial pattern.

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