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Artificial neural network for multifunctional areas

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Abstract The issues related to the appropriate planning of the territory are particularly pronounced in highly inhabited areas (urban areas), where in addition to protecting the environment, it is important to consider an anthropogenic (urban) development placed in the context of sustainable growth. This work aims at mathematically simulating the changes in the land use, by implementing an artificial neural network (ANN) model. More specifically, it will analyze how the increase of urban areas will develop and whether this development would impact on areas with particular socioeconomic and environmental value, defined as multifunctional areas. The simulation is applied to the Chianti Area, located in the province of Florence, in Italy. Chianti is an area with a unique landscape, and its territorial planning requires a careful examination of the territory in which it is inserted.

Keywords Artificial neural network · GIS · Land use change · Territorial planning

Introduction

The change brought about by new spatial technologies is proposing the massive use of models able to modify the way to tackle today's complex dynamics of land use planning focused on the interaction between human activities and the environment. The last century was marked by intense anthropogenic (urban) development resulting in the loss of natural resources: The issue of making correct choices of spatial planning aimed at preserving the environment on the one hand and at the achievement of anthropogenic development on the other is inserted in this context. Different studies (i.e., Prieler 2005;European Environment Agency 2006; Bernetti and Marinelli 2009) regarding this concern highlight how the main evolutionary dynamics are oriented toward the reduction of the rural landscape in favor of two phenomena such as the abandonment and expansion (not always regulated) of urban areas (urban sprawl). The many complex variables involved in the land use changes require the development of decision support tools and forecasting models, which can simplify the planning choices and involve more disciplines. The geomatics engineering appears to be among the most

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appropriate, by focusing on the search for instruments that give the greatest possible knowledge about the changes of the territory, including the many aspects such as employment, consumption, and conversion of nonurban land and the expansion of urban land. The recent territorial environmental, energy, and landscape policies, which often are bound by the Climate Change global commitments, appear to be closely related to the knowledge of land use. In recent years, many GIS applications (Malczewski 2004) have specialized in this direction: Among these applications are artificial intelligence models (AI) used to describe complex forecast scenarios through simulation of human reasoning reproduced by means of genetic algorithms, artificial neural networks, cellular automata, and fuzzy logic techniques. Used in various disciplines, ranging from economic to medical or engineering (Pijanowski et al. 2002), the present work is based on the application of a model of artificial intelligence to predict land use changes: the artificial neural network methodology (ANN). This model is used to forecast the "delicate" evolution of the urban mosaic in particular contexts represented by multifunctional areas (MF) or important areas from social-economic and environmental point of view. The area of Chianti in the province of Florence, in Italy, is considered for this study; in this context, and within previous studies, the author (Riccioli 2007, 2009) highlighted multifunctional zones. The variables involved in the land use changes are first defined in order to subsequently build a model of artificial neural network to predict the increase in urban areas and whether this increase may affect the multifunctional areas.

The paper is organized as follows: In Sect. 2, model has been illustrated; in Sect. 3, case study is introduced; in Sect. 4, the models have been applied to multifunctional areas; and finally, Sect. 5 is dedicated to conclusions and future recommendations.

The artificial neural network model

Costanza and Ruth (1998) consider that in building mental models, humans typically simplify systems in particular ways. We base most of our mental modeling on qualitative rather than quantitative relationships, and we linearize the relationships among system components, disregard temporal and spatial lag treat systems as isolated from their surroundings, or limit our investigations to the system's equilibrium domain. When problems become more complex, and when quantitative relationships, nonlinearities, and time and space lags are important, we encounter limits to our ability to properly anticipate system change. In such cases, our mental models need to be supplemented. We must therefore resort to numerical methods, predictors that exploit the considerable potential of computers.

In literature, many works categorize and compare the models used to analyze land use changes. Some researchers gather the models according to their final purpose or to the scale of the work (Baker 1989). Lambin (1997) proposes a classification of monitoring methods of the Land Use Cover Change (LUCC) in tropical areas: He analyzes the usefulness of the descriptive, empirical, statistical, and dynamic models related to the study of the phenomena of deforestation and soil degradation. Agarwal et al. (2002) select 19 models of LUCC and analyze them according to their ability to represent the spatial and temporal complexity of a system.

The analysis in this study is based on artificial neural networks (ANN) for the model's remarkable ability to adapt to the observed data, especially in the presence of database characterized by incomplete information, with errors.

ANN can be defined as nonlinear statistical data modeling tools having a main purpose to reproduce typical activities of the human brain.

Lopez et al. (2001), Pijanowski et al. (2002), Engelen (2002), and Martinuzzi et al. (2007) used ANN in predicting models for territorial planning: These models have in fact the ability to estimate any type of function, without taking account of its degree of nonlinearity and without a priori knowledge of its functional form. On the other hand, ANNs have a high degree of uncertainty in choosing the most favorable network structure. Furthermore, the major limitation in implementing ANN, as pointed out by Malczewski (2004), is their *black-box style* used to analyze spatial problems. The meaning of Black box style is related to the difficulty of explaining the internal elaborations (computations) of the AI models: "The 'black box' nature of the neural network methods is a limitation as far as real-world applications are concerned." It is unlikely that a solution or a set of solutions obtained by AI-GIS techniques will be acceptable to those who make decisions regarding land use and the public, if it is difficult or even impossible to clearly present and explain to them the internal workings of the AI models. "One needs a better answer then 'because my AI model says so' when faced with questions regarding a recommended land-use plan" (O'Sullivan and Unwin 2003).

The ANN model implemented in the study is based on the use of Multilayer Perceptron (MLP); it is based on the neuron through which the structure of the human mind tends to be simulated. Xia and Gar-On Yeh (2002) propose a simple structure of neural network (Fig. 1) consisting of three layers: an input layer (which in our case is represented by the variables involved in the land use changes), a hidden layer, and an output layer (represented by land use changes).

The first layer (input) is represented by *i*th neurons, each of which is associated to a variable *x* involved in the land use changes. In turn, to each variable is assigned a weight *w* generating the signal that will be sent to the neuron of the next layer (Eq. 1).

$$\mathrm{net}_j = \sum_j x_i \cdot w_{i,j} \tag{1}$$

where

net_j signal sent from the *i*th neuron of the input layer to the *j*th neuron of the hidden layer
x_i variable involved in the land use changes of the *i*th neuron of the input layer
$w_{i,j}$ relative weight of the input layer and hidden layer

Subsequently, the signal (value) shown in Eq. 1 (net_j) is sent to the *j*th neuron belonging to the hidden layer. This layer is activated if and only if it reaches a certain predetermined threshold value (φ). Most common activation functions can be linear or sigmoidal (Eq. 2, relating to a sigmoidal activation function).

$$\varphi_j = \frac{1}{1+e^{-\mathrm{net}_j}} \tag{2}$$

From the hidden layer, if activated, the signal is transferred to the next layer represented by the output: The output is format from the *i*th neuron, which values (p_l) represent the probability of conversion from a given land use to another (Eq. 3).

$$p_l = \sum_j w_{j,l} \cdot \varphi_j \tag{3}$$

where

p_l probability of conversion of the *l*th from the output layer
$w_{j,l}$ relative weight of the hidden layer and output layer
φ_j activation function of the *j*th neuron of the hidden layer

The algorithm used for the generation of the output is the "back-propagation" which is a supervised learning, through which the output estimated by the network (p_l, Eq. 3) is compared with a desired or known output called out: Out represents the actual land use changes that have occurred in the period examined.

The purpose of this comparison is to obtain an output estimated as similar as possible to the desired output. The difference between the two outputs produces an error (*e*) used to correct the weights (weights were initialized with random values at the beginning of the training). In our case, the error is quantified by the standard deviation (Eq. 4). This training set is repeated until the error is less than a predetermined threshold.

$$\mathrm{e_l} = \sqrt{\sum_l (out_l - p_l)^2} \tag{4}$$

where

e_l relative error at the *l*th neuron of the output layer
out_l known output of the *l*th neuron of the output layer
p_l estimated output of *l*th neuron of the output layer

In the "back-propagation" mechanism, the error is propagated "backwards" in the previous layers of the model associating it with the weights. This mechanism follows the *Delta rule*[1] that is a learning rule based on the decrease in the gradient δ (Eq. 5) to update the weights (Eq. 6).

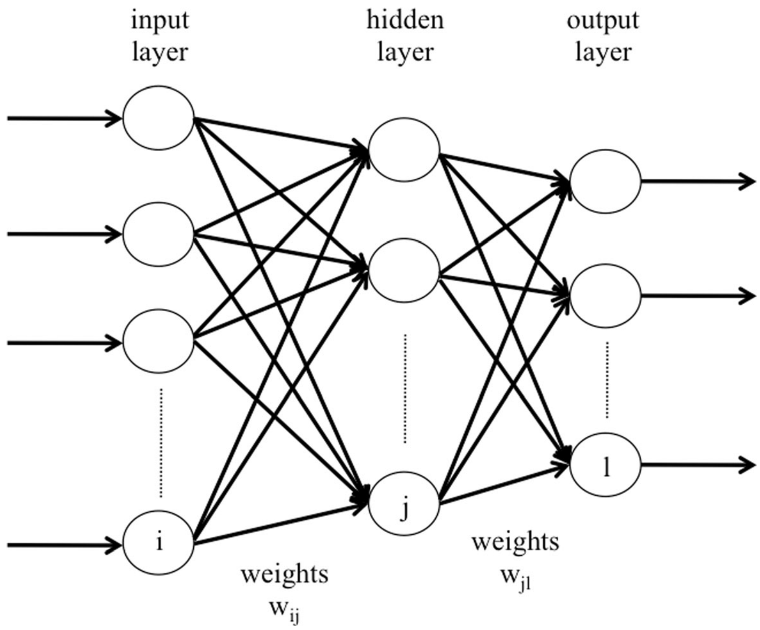
$$\delta_{\mathrm{lt}} = \begin{cases} \mathrm{e_l}\,\varphi_\mathrm{l} \\ \varphi_\mathrm{l} \sum_j \delta_{\mathrm{jt+1}}\ \ \mathrm{w_{jlt+1}} \end{cases} \tag{5}$$

where

δ_{lt} gradient error of the *l*th neuron of the output layer at time t
e_l relative error at the *l*th neuron of the output layer
φ_l activation function of the *l*th neuron of the output layer
δ_{jt+1}

[1] The delta rule is based on the "gradient descent," a non-linear optimization algorithm, used to identify the local minimum of a function.

Fig. 1 ANN diagram



gradient error of the *j*th neuron of the hidden layer at time t +1

w_{jlt+1} relative weight to the hidden layer and to the output layer at time t +1

$$\Delta w_{ji(t+1)} = \eta\, \delta_{ji}\, x_i + \alpha\, \Delta w_{ji(t)} \tag{6}$$

where

$\Delta w_{ji(t+1)}$ difference of weights between the hidden layer and the input layer after a number of iterations $t+1$

η learning speed of the neuron or rate of descent toward the minimum of the error[2] curve

δ gradient of error

α momentum factor, constant of proportionality which analyzes the probability of oscillation of the weights[3]

$\Delta w_{ji(t)}$ difference of weights between the hidden layer and the input layer after a number of iterations t

The goal of the MLP is to minimize this gradient "adjusting" the random weights, and bringing some gradual and progressive changes to them. In other words, the value of the weights of the model varies through a number of iterations inducing thereby the value of the output to vary *n* times. When the gradient is sufficiently reduced, the training phase would have produced an *estimated output* very close to the *desired output*. At the end of the training phase, the model will then be able to recognize the unknown relationship between the input variables and the output variables. In addition, this enables to create predictions in time where the output data are not known a priori. The final aim of the supervised learning is a prediction of the value of output for each valid value of the input based only on a limited number of examples of correspondence (input-output pairs of values). To achieve this, the system uses two principles: mathematical distribution (that links the delta of input values to the output values) and likelihood function—once mathematical distribution has been identified, the system chooses the parameters that maximize the likelihood of the data and selects the correct likelihood function.

Case study: the multifunctional areas of Chianti

Chianti area includes five municipalities located in Tuscany (center of Italy) in the province of Florence: Barberino val d'Elsa, Greve in Chianti, Impruneta, San Casciano in val di Pesa, and Tavarnelle val di Pesa.

[2] If the speed is too low, the training phase may be too expensive in terms of time and resources, if too high could lead to inaccurate results.

[3] The momentum in practice analyzes the weights to determine direction in which to search for the minimum error.

The study area is located close to the south of the town of Florence (Fig. 2) and has a total area of approximately 600 km^2 and a total resident population of about 77,000 inhabitants.

Chianti Area is characterized by a predominantly hilly topography; the average annual temperature varies between 11.6 and 15 °C, while the rainfall conditions are estimated around 800 mm per year. The major land uses of the Chianti region are the forest and the vineyards from which is produced the famous Chianti wine DOC (controlled origin) and DOCG (controlled and guaranteed origin).

Using a spatial multicriteria analysis model (Riccioli 2007, 2009), the author analyzes five functions, performed by agricultural activities in the area, which are the socioeconomic, the aesthetic, the hydrological, the territorial preservation, and the natural function. These functions have been quantified through multidimensional indexes and aggregated through multicriteria operators.

Socioeconomic function has based on Rural Development Plan guidelines and ISTAT census database (ISTAT 2001); it has been analyzed by some specific indexes related to the farm and farmer characteristics (compared to total farm surface) such as number of farmers with a professional degree, number of farms with high-quality wine production, and number of farms with farmer under 60 years old: These indexes have been aggregated using ordered weighted average (OWA) operator (Malczewski 1999). Aesthetic function has been based on landscape values of land use. An aesthetic value has been given to land use from panoramic viewpoint such as wine road and farmhouses (Riccioli 2004). Hydrological function has been analyzed through Soil Conservation Service - Curve Number (SCS, 1969) method; it has used to determine surface flows in specific soils. Territorial preservation has been analyzed by density of forest and rural road and density of cultural human rural construction (for example stone wall). Finally, natural function indexes have been based on Biopermeability Index (hectares of continuous forest) and Shannon Index (degree of land use diversity): These indexes have been aggregated using Weighted Linear Combination (WLC) operator (Malczewski 1999). The portions of territory showing the simultaneous presence of the five features were therefore considered multifunctional areas: In this phase, an overlay (with AND operator) of previous functions has been used (see Riccioli 2007, 2009 for more details). The purpose of the next phases is to evaluate, which of these areas will be affected by the processes of urbanization.

The ANN model applied to multifunctional areas potentially involved in the process of urbanization

Creation of transition of land use rules

The preliminary phase of the investigation focused on the analysis of land use changes that have emerged in the decade between 1990 and 2000. This was undertaken by using vector thematic maps of the case study land use. This analysis was influenced, as noted by Matheron (1978, 1989) by the set objectives, as well as by the available data. Accordingly, the used source was based on the Corine Land Cover (CLC) - European Regulation on Information Region (ENV 12657). The CLC being the only source available allowing analyzing the area through a multi-temporal reading.

It is possible to observe how during the abovementioned period, seven typologies of land use were changed: More particularly, the increase in wooded areas, in woody and agricultural crops, and urban areas is registered on the one hand, and a decrease of heterogeneous agricultural areas[4] and arable land on the other.

The next phase is oriented toward the definition of the variable involved in the land use changes. The literature review (Pijanowski et al. 2002; Lombardo et al. 2005) shows that these variables are essentially related to the morphology of the territory and the anthropogenic activity. Based on the data available, *environmental variables* such as slope and topography and *anthropogenic variables* such as human settlements (cities, towns, and small villages) and roads were selected. So, four layers were implemented through a Geographic Information System (GIS) that diversify the land use changes according to:

1. Distance from roads
2. Distance from inhabited centers
3. Slope
4. Altitude

[4] Heterogeneous agricultural areas are considered temporary crops associated with permanent crops, cropping systems, and particle complex. Areas are predominantly occupied by agricultural fields with significant natural areas and areas of agricultural woods.

Fig. 2 Case study map

A statistical analysis of spatial independence of the above four layers was carried out. This was done through the application of tests based on the comparison of pairs of layers (maps) in order to verify the reliability of the selected variables. As suggested by Bonham-Carter (1994), the Cramer's V index was used for the analysis.

A high Cramer's V indicates that the potential explanatory value of the variable is good but does not guarantee a strong performance since it cannot account for the mathematical requirements of the modeling approach used and the complexity of the relationship. His value varies between 0 (max independence) and 1 (max dependence). The correlation of each variable with land use changes was accordingly analyzed. The analysis revealed a good relationship of dependency between the data analyzed with values greater than 0.15, as suggested by Eastman (2006).

The four variables involved in the land use changes were then entered as input data in the model of artificial neural network. This was done in order to "train" the MLP by combining them with random weights. In the training phase, two constraints related to the maximum tolerable error between the estimated output and the desired output (less than or equal to 0.0001) and the number of iterations (set at 5000) were fixed. The following are the technical parameters used in the model.

- Speed of training (η) = 0.005
- Momentum factor (α) = 0.5

- Tolerance error value (e) = 0.0001
- Number of iterations (t) = 5000

Observing these constraints, the MLP has produced *estimated output* evaluated from known relationships between the input variables and the output (the desired output), and generating "rules (probability) of transition." These probabilities were used successively to predict future scenarios of the land use changes.

Figure 3 shows the results of the application of these rules. It highlights which areas of arable land, and heterogeneous agricultural areas, will have in the future high probability of being incorporated into the urban areas. The highest values (the areas with the most intense chromatic scale) belong to the areas having the highest probability of becoming urban. In other words, the four variables involved in land use changes are

1. The areas next to the roads
2. The areas next to inhabited centers
3. The areas with minor slopes
4. The areas located at minor altitude

Validation of the transition probability of land use

In the next phase, the accuracy of the data was verified through validation. The validation process involves the comparison of a land use map of a specific year developed by using the general transition rules of MLP (*forecasting map*) and a land use map used as reference (*reference map*). Based on the available cartography, year 2006 map was established as a reference (2006 is the most recent year for which the Corine Land Cover is available): This was considered the reference map. The forecasting map at 2006 was successively created. The literature highlights the *Markovian approaches* among the successful methods used to develop hypothetic scenarios of land use changes (Aaviksoo 1995; Logofet and Lesnaya 2000).

By using the map of the potential transitions (Fig. 3), a land use map of year 2006 was therefore created. This was done by applying Markov chain (Eastman and

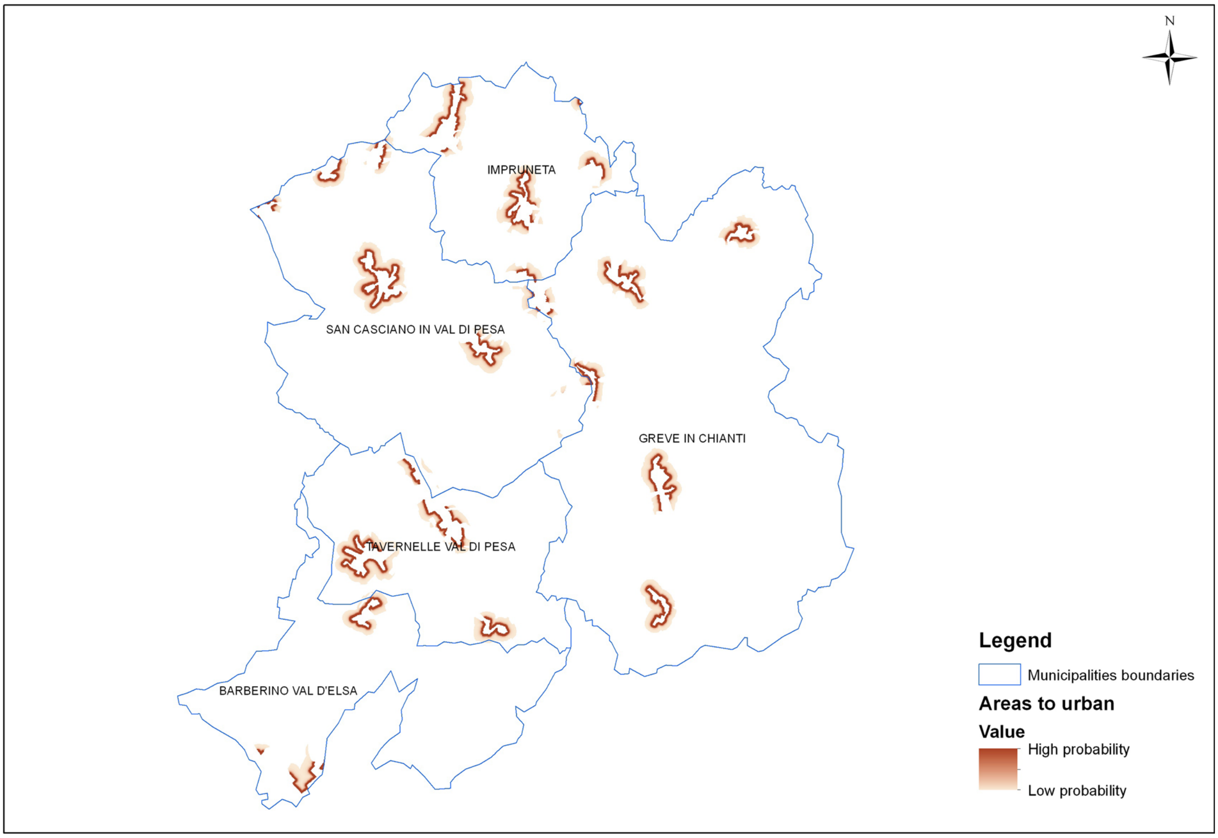


Fig. 3 Potential areas of urbanization

Toledano 2000) which is a stochastic process where the transition probabilities (Eq. 3) have been used in a matrix (P_t) to obtain a projection to 2006 (W_{t+1}) of the changes occurring in the time interval from 1990 to 2000 (W_t) as shown in Eq. 7.

$$W_{t+1} = W_t \cdot P_t \tag{7}$$

where

W_{t+1} land use at $t+1$

W_t land use at t

P_t transition probability matrix or stochastic matrix $n \times n$ of values p_{ij}

	state i ($t+1$)		
state j (t)	p_{11}	p_{12}	p_{1n}
p_{21}	p_{22}	p_{2n}	
p_{n1}	p_{n2}	p_{nn}	

where n is the number of discrete states in the Markov chain and p_{ij} are the transition probabilities (between 0 and 1) from the state j to the state i in the time interval between t and $t+1$. As described by Coquillard and Hill (1997), the matrix obtained describes a system that changes through discrete increments of time, in which the value of each variable, at a given time, is the sum of percentages of the values of the variables in the previous instant. The sum of the fractions along a row of the matrix is equal to one, and the diagonal contains the percentages instead of pixels that do not change between the start and end date.

Table 1 shows the transition matrix relative only to the considered land use changes (arable land and heterogeneous agricultural areas involved in urbanization processes).

The prediction map at 2006 was compared with the reference map (CLC 2006) by the Cohen coefficient of correlation (Cohen's Kappa). Due to the use of raster maps, the index has been calculated by comparing the spatial distribution and quantity of pixels for each category of land use. The statistical analysis has shown a good degree of agreement with a value of 0.7893 (as suggested by Landis and Koch 1977), statistically validating the transition probability of land use obtained.

Table 1 Transition matrix at year 2006

		Land use at $t+1$ (2006)		
		Urban	Arable land	Hetero. Agr. Area
Landuse at t (2000)	Urban	1.0000	0.0000	0.0000
	Arable land	0.0853	0.9147	0.0000
	Hetero. Agr. Area	0.1352	0.0027	0.8621

Multifunctional areas potentially involved in the process of urbanization

In order to highlight the probability that the multifunctional areas have to be involved in a process of urbanization, an overlay of maps using the logical operator of intersection AND was used. This was done by overlapping areas with probability of conversion to urban (Fig. 3), with the MF areas (shown in different shades of orange in Fig. 4). The result is shown in Fig. 4 in which multifunctional areas potentially interested in urbanization (MFu) are highlighted in black.

Table 2 shows the hectares of areas, subdivided by municipalities, potentially interested by the urbanization.

The MFu areas stretch along approximately 110 ha equivalent to 7.1 % of the total MF areas within the study area (1550 ha). The threatened areas are located exclusively in the municipalities of Greve in Chianti and San Casciano representing respectively 7.4 and 8.5 % of the total MF areas of the municipality.

Conclusions and future recommendations

This paper is based on the study of the territory of a sensitive area from the urban point of view in which the territorial aspect must be preserved (the Chianti, despite being a rich areas with high environmental value, is very close to major industrial urban agglomerations). Based on a previous work, the case study has been analyzed looking at what the rural activities of man can offer from the economic, social, and environmental point of view, and highlighting multifunctional areas. By applying a model of spatial multicriteria analysis, each of the three aspects (economic, social, and environmental) has been evaluated through multidimensional indexes. The indexes were appropriately aggregated with multicriteria rules and have allowed us to highlight the

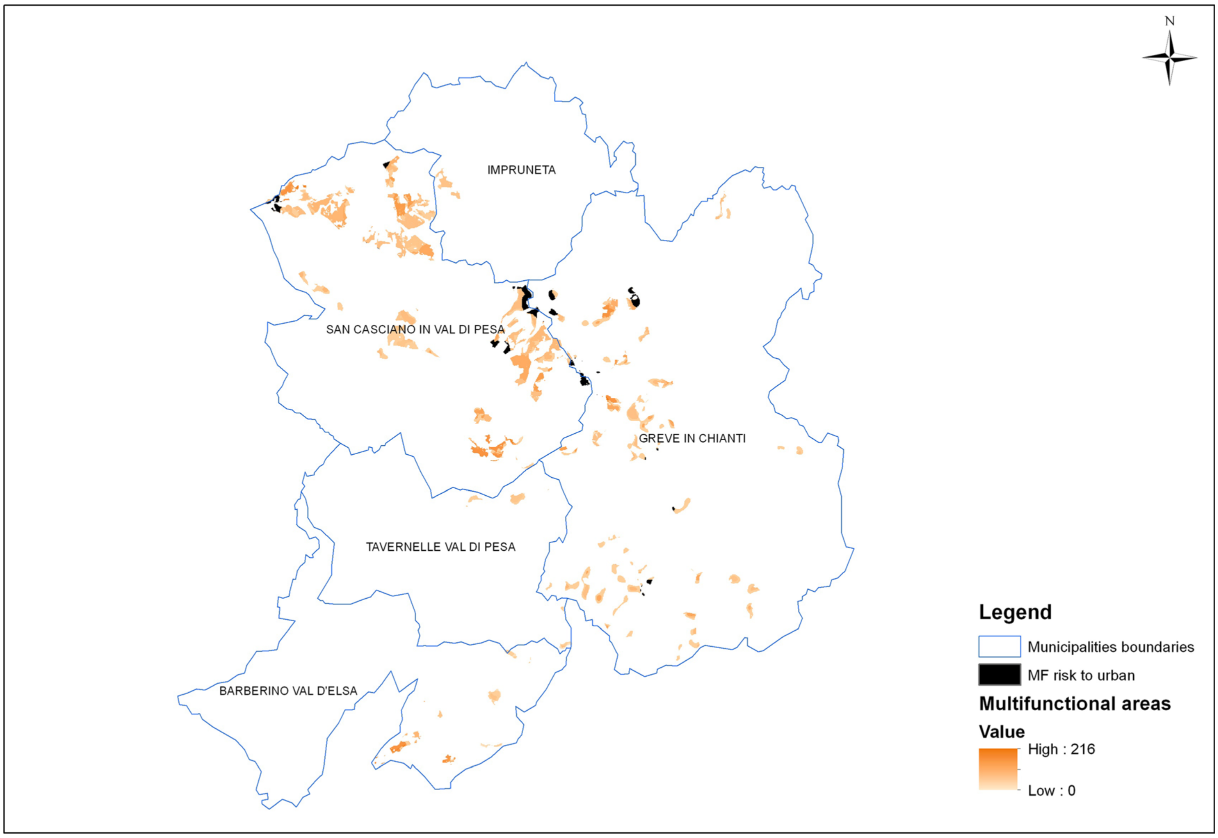


Fig. 4 MF areas potentially involved in an urbanization process

multifunctionality of the territory. The decision to focus on multifunctional areas was dictated by the increasing importance that these areas play in the recent Common Agricultural Policy (especially within the Rural Development pillar).

The focus has therefore shifted on the analysis of land use changes in order to highlight what has altered over time, how anthropogenic (urban) development may evolve, and how it may affect the multifunctional areas.

Table 2 Statistics related to the MFu areas (data expressed in hectares and percentage over the total municipal MF areas)

Municipality	MF Ha	MFu Ha	MFu on MF %
Barberino	65.03	0	–
Greve	488.07	41.47	8.5
Impruneta	25.63	0	–
San Casciano	939.30	69.31	7.4
Tavarnelle	33.31	0	–
Totale	1551.34	110.78	7.1

The main purpose is to pursue a balanced socioeconomic and environmental urban development without arresting the latter but by regulating its growth. Multitemporal analysis of land uses was then carried out by implementing an ANN model using the Multilayer Perceptron (a model of nonlinear analysis), in order to create a map of areas potentially affected by urbanization. The data were validated through a procedure that took advantage of Markov chains to create a map of land use forecasts to 2006 appropriately compared with a reference map (Corine Land Cover 2006) by the statistical index of Cohen. Subsequently, the map of areas potentially affected by urbanization has been used to identify which of the multifunctional areas would be involved in this process.

In order to use and read the results of the proposed model, it is important to start from the assumption that the size of the multifunctional areas and the urban development are constant over time. This persistence of the conditions is a limitation of the model as stresses Tang et al. (2005) which can be overcome through the use of new data such as the evolution of the road network, or a more detailed land use changes especially from the temporal point of view (Verburg et al. 2002).

This work can be classified then as an application of an effective method of artificial intelligence based on artificial neural networks, applied in the environmental field to create predictive models of land use changes. Some current research studies have been conducted using this methodology. Alsharif and Pradhan (2014) and Mahbood et al. (2015) analyze respectively development of urban areas in Tripoli and Pakistan using remote sensing and landsat imageries, Mazzocchi et al. (2014) explore (through ANN) the evolution of agricultural and natural areas near Milano from environmental, cultural, and recreational point of view, and Grekousis et al. (2013) and Triantakonstantis and Stathakis (2015) use ANN methodology for the analysis of urban sprawl in Athens concluding that urban development depends on the available funds, accessibility improvement (railway and metro networks), land speculation, and lack of land use control. Basse et al. (2014) combine ANN and cellular automata with the aim of identification of driving forces that are behind land use and land cover changes. Park et al. (2011) analyze various methods (also ANN method has been examined) to determine which best explained urban growth until the present for modeling future urban growth in Korea. All of these works aim to more accurate forecast of development of urban areas, but they do not analyze their relationship with the characteristics of surrounding territory that may be a crucial issue in territorial planning processes.

Starting with this consideration, by relating this application to the definition of multifunctional areas, we intend to provide the decision-maker with a powerful planning tool that can "guide" the urban development by controlling anthropogenic development, and the other parts of the country deemed interesting from the economic, social, and environmental point of view.

The proposed methodology is a good compromise between adaptability of the model to input variables selected or able to be selected, and the ability to understand the results. The results are able to be integrated and modified to further refine the research. For example, in order to expand the temporal range and the degree of detail of analysis, it may be useful to derive land uses from satellite photos. The extraction of rules for decision making may include a greater number of variables involved in the land use changes, through perhaps, the use of discrete models (Choice Experiment) able to describe human behaviors useful in understanding the evolutionary dynamics. Furthermore, to forecast and develop future scenarios, the analyzed data could be used to implement a Cellular Automata (Basse et al. 2014) able to consider the evolutionary dynamics by considering the so-called neighborhoods or areas adjacent to the area being analyzed.

In conclusion, authors emphasize how the spatial-temporal simulation, integrated with socioeconomic information, is the new frontier of territorial analysis. As emphasized by Steyaert (1993), the evolutionary dynamics in the real world typically take place in three dimensions, time-dependent, and are extremely complex. This complexity often includes nonlinear behavior and stochastic components. The study of such behavior goes through the formulation of hypotheses and rules to explain its functioning. The rules can, in turn, be expressed by mathematical formulas or logical relationships, which often lead to a series of theoretical simplifications to reduce the number of equations used. The mathematical models are based on programming languages that realistically simulate the evolution of spatial patterns over time that are increasingly used for quantitative analysis, and no more only for qualitative analysis, of the complex issues at the local, regional, or global level. The goal is, ultimately, the realization of decision support tools that are characterized by promptness, cost-efficiency, and ease of use, aiming at achieving a better understanding and management of the territory.

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