

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

1 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 e Marinelli, 2009) regarding this concern highlight how the main evolutionary dynamics are oriented towards the reduction of the rural landscape in favour 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 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

54 employment, consumption, and conversion of non-urban land and the expansion of urban
55 land. The recent territorial environmental, energy, and landscape policies, which often are
56 bound by the Climate Change global commitments, appear to be closely related to the
57 knowledge of land use. In recent years, many GIS applications (Malczewski, 2004), have
58 specialized in this direction: among these applications are Artificial Intelligence models (AI)
59 used to describe complex forecast scenarios through simulation of human reasoning
60 reproduced by means of genetic algorithms, artificial neural networks, cellular automata and
61 fuzzy logic techniques. Used in various disciplines, ranging from economic to medical or
62 engineering (Pijanowski et al., 2002), the present work is based on the application of a model
63 of Artificial Intelligence to predict land use changes: the Artificial Neural Network
64 methodology (ANN). This model is used to forecast the "delicate" evolution of the urban
65 mosaic in particular contexts represented by multifunctional areas (MF), or important areas
66 from social-economic and environmental point of view. The area of Chianti in the province of
67 Florence, in Italy, is considered for this study; in this context, and within previous studies, the
68 author (Riccioli, 2007 and 2009) highlighted multifunctional zones. The variables involved in
69 the land use changes are first defined in order to subsequently build a model of artificial
70 neural network to predict the increase in urban areas and whether this increase may affect the
71 multifunctional areas.

72 The paper is organized as follows: in Section 2, model has been illustrated; in Section 3, case
73 study are introduced; in section 4 the models has been applied to multifunctional areas;
74 finally, Section 5 is dedicated to conclusions and future recommendations.

75

77 **2 The Artificial Neural Network model**

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

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

95 The analysis in this study is based on Artificial Neural Networks (ANN) for the model's
96 remarkable ability to adapt to the observed data, especially in the presence of database
97 characterized by incomplete information, with errors.

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

100 Lopez et al. (2001), Pijanowski et al. (2002), Engelen (2002) and Martinuzzi et al. (2007)
101 used ANN in predicting models for territorial planning: these models have in fact the ability
102 to estimate any type of function, without taking account of its degree of non-linearity and
103 without a priori knowledge of its functional form. On the other hand, ANNs have a high

104 degree of uncertainty in choosing the most favorable network structure. Furthermore, the
 105 major limitation in implementing ANN, as pointed out by Malczewski (2004), is their *black-*
 106 *box style* used to analyze spatial problems. The meaning of Black box style is related to the
 107 difficulty of explaining the internal elaborations (computations) of the AI models: "the 'black
 108 box' nature of the neural network methods is a limitation as far as real-world applications are
 109 concerned. "It is unlikely that a solution or a set of solutions obtained by AI-GIS techniques
 110 will be acceptable to those who make decisions regarding land use and the public, if it is
 111 difficult or even impossible to clearly present and explain to them the internal workings of the
 112 AI models. One needs a better answer then 'because my AI model says so' when faced with
 113 questions regarding a recommended land-use plan" (O'Sullivan and Unwin, 2003).
 114 The ANN model implemented in the study is based on the use of Multilayer Perceptron
 115 (MLP); it is based on the neuron through which the structure of the human mind tends to be
 116 simulated. Xia and Yeh (2002), propose a simple structure of neural network (figure 1)
 117 consisting of three layers: an input layer (which in our case is represented by the variables
 118 involved in the land use changes), a hidden layer and an output layer (represented by land use
 119 changes).

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122 **Figure 1** ANN diagram

123 The first layer (input) is represented by i th neurons, each of which is associated to a variable x
 124 involved in the land use changes. In turn, to each variable is assigned a weight w generating
 125 the signal that will be sent to the neuron of the next layer (equation 1).
 126

127
$$\text{net}_j = x_i \cdot w_{i,j}$$
 Equation 1

128 where,
 129 net_j = signal sent from the i th neuron of the input layer to the j th neuron of the hidden layer
 130 x_i = variable involved in the land use changes of the i th neuron of the input layer
 131 $w_{i,j}$ = relative weight of the input layer and hidden layer
 132

133 Subsequently, the signal (value) shown in equation 1 (net_j) is sent to the j th neuron belonging
 134 to the hidden layer. This layer is activated if and only if it reaches a certain predetermined
 135 threshold value (φ). Most common activation functions can be linear or sigmoidal (equation 2,
 136 relating to a sigmoidal activation function).
 137

138
$$\varphi_j =$$
 Equation 2

139 From the hidden layer, if activated, the signal is transferred to the next layer represented by
 140 the output: the output is format from the i th neuron, which values (p_i) represent the probability
 141 of conversion from a given land use to another (equation 3).
 142

143
$$p_i = w_{j,1} \varphi_j$$
 Equation 3

144 where,
 145 p_i = probability of conversion of the i th from the output layer
 146 $w_{j,1}$ = relative weight of the hidden layer and output layer
 147 φ_j = activation function of the j th neuron of the hidden layer

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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 , equation 3) is compared with a desired or known output called out_l : out_l represent 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 (equation 4). This training set is repeated until the error is less than a predetermined threshold.

159

$$e_l =$$


Equation 4

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161
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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

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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 (equation 5) to update the weights (equation 6).

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$$\delta_{lt} = \left\{ \begin{array}{l} e_l \varphi_l \\ \varphi_l \delta_{jt+1} w_{jlt+1} \end{array} \right.$$


Equation 5

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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} = 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 $t + 1$

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

Equation 6

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

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

188 η = learning speed of the neuron or rate of descent toward the minimum of the error² curve
189 δ = gradient of error
190 α = momentum factor, constant of proportionality which analyzes the probability of
191 oscillation of the weights³
192 $\Delta w_{ji(t)}$ = difference of weights between the hidden layer and the input layer after a number of
193 iterations t
194

195 The goal of the MLP is to minimize this gradient "adjusting" the random weights, and
196 bringing some gradual and progressive changes to them. In other words, the value of the
197 weights of the model varies through a number of iterations inducing thereby the value of the
198 output to vary *n times*. When the gradient is sufficiently reduced, the training phase would
199 have produced an *estimated output* very close to the *desired output*. At the end of the training
200 phase, the model will then be able to recognize the unknown relationship between the input
201 variables and the output variables. In addition, this enables to create predictions in time where
202 the output data are not known a priori. The final aim of the supervised learning is a prediction
203 of the value of output for each valid value of the input based only on a limited number of
204 examples of correspondence (input-output pairs of values). To achieve this, the system uses 2
205 principles: mathematical distribution (that links the delta of input values to the output values)
206 and likelihood function: once mathematical distribution has been identified the system
207 chooses the parameters that maximize the likelihood of the data and selects the correct
208 likelihood function.

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211 **3 Case Study: The multifunctional areas of Chianti**

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213 Chianti area includes 5 municipalities located in Tuscany (center of Italy) in the province of
214 Florence: Barberino val d'Elsa, Greve in Chianti, Impruneta, San Casciano in val di Pesa and
215 Tavarnelle val di Pesa.

216 The study area is located close to the south of the town of Florence (figure 2), and has a total
217 area of approximately 600 square kilometers and a total resident population of about 77000
218 inhabitants.

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

224 Using a spatial Multicriteria Analysis model (Riccioli, 2007 and 2009), the author analyze 5
225 functions, performed by agricultural activities in the area, which are: the socioeconomic, the
226 aesthetic, the hydrological, the territorial preservation, and the natural function. These
227 functions have been quantified through multidimensional indexes, and aggregated through
228 multicriteria operators.

229 Socioeconomic function has based on Rural Development Plan guidelines and ISTAT census
230 database (ISTAT, 2001); it has been analyzed by some specific indexes related to the farm
231 and farmer characteristics (compared to total farm surface) such as number of farmers with a
232 professional degree, number of farms with high quality wine production, number of farms
233 with farmer under 60 years old: these indexes have been aggregated using Ordered Weighted

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

234 Average (OWA) operator (Malczewski, 1999). Aesthetic function has been based on
235 landscape values of land use. An aesthetic value has been given to land use from panoramic
236 viewpoint such as wine road and farmhouses (Riccioli, 2004). Hydrological function has been
237 analyzed through Soil Conservation Service - Curve Number (SCS, 1969) method; it has used
238 to determine surface flows in specific soils. Territorial preservation has been analyzed by
239 density of forest and rural road and density of cultural human rural construction (for example
240 stone wall). Finally, natural function indexes have been based on Biopermeability Index
241 (hectares of continuous forest) and Shannon Index (degree of land use diversity): these
242 indexes have been aggregated using Weighted Linear Combination (WLC) operator
243 (Malczewski, 1999). The portions of territory showing the simultaneous presence of the 5
244 features were therefore considered multifunctional areas: in this phase an overlay (with AND
245 operator) of previous functions has been used (see Riccioli, 2007 and 2009 for more details).
246 The purpose of the next phases is to evaluate, which of these areas will be affected by the
247 processes of urbanization.

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250 **Figure 2 Case Study map**

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252 **4 The ANN model applied to multifunctional areas potentially involved in the process of** 253 **urbanization**

254

255 *4.1 Creation of transition of land use rules*

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257 The preliminary phase of the investigation focused on the analysis of land use changes that
258 have emerged in the decade between 1990 and 2000. This was undertaken by using vector
259 thematic maps of the case study land use. This analysis was influenced, as noted by Matheron
260 (1978 and 1989) by the set objectives, as well as by the available data. Accordingly, the used
261 source was based on the Corine Land Cover (CLC) - European Regulation on Information
262 Region (ENV 12657). The CLC being the only source available allowing analyzing the area
263 through a multi-temporal reading.

264 It is possible to observe how during the above mentioned period, 7 typologies of land use
265 were changes: more particularly the increase in wooded areas, in woody and agricultural
266 crops, and urban areas are registered on the one hand, and a decrease of heterogeneous
267 agricultural areas⁴ and arable land on the other.

268 The next phase is oriented towards the definition of the variable involved in the land use
269 changes. The literature review (Pijanowski et al., 2002, Lombardo et al., 2005) shows that
270 these variables are essentially related to the morphology of the territory and the anthropogenic
271 activity. Based on the data available, *environmental variables* such as slope and topography
272 and *anthropogenic variables* such as human settlements (cities, towns, and small villages) and
273 roads were selected. So 4 layers were implemented through a Geographic Information System
274 (GIS) that diversify the land use changes according to:

- 275 1. distance from roads;
- 276 2. distance from inhabited centers;
- 277 3. slope and
- 278 4. altitude.

279

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

280 A statistical analysis of spatial independence of the above 4 layers was carried out. This was
281 done through the application of tests based on the comparison of pairs of layers (maps) in
282 order to verify the reliability of the selected variables. As suggested by Bonham-Carter
283 (1994), the Cramer's V index was used for the analysis.

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

291 The four variables involved in the land use changes were then entered as input data in the
292 model of Artificial Neural Network. This was done in order to "train" the MLP by combining
293 them with random weights. In the training phase two constraints related to the maximum
294 tolerable error between the estimated output and the desired output (less than or equal to
295 0.0001) and the number of iterations (set at 5000) were fixed. The following are the technical
296 parameters used in the model.

- 297 • Speed of training (η) = 0.005
- 298 • Momentum factor (α) = 0.5
- 299 • Tolerance error value (ϵ) = 0.0001
- 300 • Number of iterations (t) = 5000

301

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

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

- 311 1. the areas next to the roads;
- 312 2. the areas next to inhabited centers;
- 313 3. the areas with minor slopes and
- 314 4. the areas located at minor altitude.

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316

317 **Figure 3** Potential areas of Urbanization

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319 4.2 Validation of the transition probability of land use

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

329 By using the map of the potential transitions (figure 3) a land use map of year 2006 was
330 therefore created. This was done by applying Markov chain (Eastman and Toledano, 2000)
331 which is a stochastic process where the transition probabilities (equation 3) have been used in
332 a matrix (P_t) to obtain a projection to 2006 (W_{t+1}) of the changes occurring in the time interval
333 from 1990 to 2000 (W_t) as shown in equation 7.

$$334 \quad W_{t+1} = W_t \cdot P_t \quad \text{Equation 7}$$

336 where,

337 W_{t+1} = land use at t+1

338 W_t = land use at t

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

340

341 *table no caption*

342

343 where n is the number of discrete states in the Markov chain and p_{ij} are the transition
344 probabilities (between 0 and 1) from the state j to the state i in the time interval between t and
345 $t + 1$. As described by Coquillard and Hill (1997), the matrix obtained describes a system that
346 changes through discrete increments of time, in which the value of each variable, at a given
347 time, is the sum of percentages of the values of the variables in the previous instant. The sum
348 of the fractions along a row of the matrix is equal to one, the diagonal contains the
349 percentages instead of pixels that do not change between the start and end date.

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

352

353 **Table 1** Transition matrix at year 2006

354 The prediction map at 2006 was compared with the reference map (CLC 2006) by the Cohen
355 coefficient of correlation (Cohen's Kappa). Due to the use of raster maps, the index has been
356 calculated by comparing the spatial distribution and quantity of pixels for each category of
357 land use. The statistical analysis has shown a good degree of agreement with a value of
358 0.7893 (as suggested by Landis and Koch, 1977), statistically validating the transition
359 probability of land use obtained.

360

361 *4.3 Multifunctional areas potentially involved in the process of urbanization*

362

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

369

370 **Figure 4** MF areas potentially involved in an urbanization process

371

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

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

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

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382
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5 Conclusions and Future Recommendations

384 This paper is based on the study of the territory of a sensitive area from the urban point of
385 view in which the territorial aspect must be preserved (the Chianti, despite being a rich areas
386 with high environmental value, it is very close to major industrial urban agglomerations).
387 Based on a previous work, the case study has been analyzed looking at what the rural
388 activities of man can offer from the economic, social and environmental point of view, and
389 highlighting multifunctional areas. By applying a model of spatial multicriteria analysis, each
390 of the three aspects (economic, social and environmental) has been evaluated through
391 multidimensional indexes. The indexes were appropriately aggregated with multicriteria
392 rules, and have allowed us to highlight the multifunctionality of the territory. The decision to
393 focus on multifunctional areas was dictated by the increasing importance that these areas play
394 in the recent Common Agricultural Policy (especially within the Rural Development pillar).

395 The focus has therefore shifted on the analysis of land use changes in order to highlight what
396 has altered over time, how anthropogenic (urban) development may evolve, and how it may
397 affect the multifunctional areas. The main purpose is to pursue a balanced socio-economic
398 and environmental urban development without arresting the latter but by regulating its
399 growth. Multitemporal analysis of land uses was then carried out by implementing an ANN
400 model using the Multilayer Perceptron (a model of non-linear analysis); in order to create a
401 map of areas potentially affected by urbanization. The data were validated through a
402 procedure that took advantage of Markov chains to create a map of land use forecasts to 2006
403 appropriately compared with a reference map (Corine Land Cover 2006) by the statistical
404 index of Cohen. Subsequently, the map of areas potentially affected by urbanization has been
405 used to identify which of the multifunctional areas would be involved in this process.

406 In order to use and read the results of the proposed model it is important to start from the
407 assumption that the size of the multifunctional areas and the urban development are constant
408 over time. This persistence of the conditions is a limitation of the model as stresses Tang et al.
409 (2005) which can be overcome through the use of new data such as the evolution of the road
410 network, or a more detailed land use changes especially from the temporal point of view
411 (Verburg et al., 2002).

412 This work can be classified then as an application of an effective method of Artificial
413 Intelligence based on artificial neural networks, applied in the environmental field to create
414 predictive models of land use changes. Some current researches have been conducted using
415 this methodology. Alsharif and Pradhan (2014), Mahbood et al. (2015) analyze respectively
416 development of urban areas in Tripoli and Pakistan using remote sensing and landsat
417 imageries, Mazzocchi et al. (2014) explore (through ANN) the evolution of agricultural and
418 natural areas near Milano from environmental, cultural and recreational point of view,
419 Grekousis et al. (2013) and Triantakonstantis and Stathakis (2015) use ANN methodology for
420 the analysis of urban sprawl in Athens concluding that urban development depends on the
421 available funds, accessibility improvement (railway and metro networks), land speculation
422 and lack of land use control. Basse et al. (2014) combine ANN and cellular automata with the
423 aim of identification of driving forces that are behind land use and land cover changes. Park et
424 al. (2011) analyze various methods (also ANN method has been examined) to determine
425 which best explained urban growth until the present for modeling future urban growth in
426 Korea. All of these works aim to more accurate forecast of development of urban areas but

427 they do not analyze their relationship with the characteristics of surrounding territory that may
428 be a crucial issue in territorial planning processes.

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

434 The proposed methodology is a good compromise between adaptability of the model to input
435 variables selected or able to be selected, and the ability to understand the results. The results
436 being able to be integrated and modified to further refine the research. For example, in order
437 to expand the temporal range and the degree of detail of analysis, it may be useful to derive
438 land uses from satellite photos. The extraction of rules for decision making may include a
439 greater number of variables involved in the land use changes, through perhaps, the use of
440 discrete models (Choice Experiment) able to describe human behaviors useful in
441 understanding the evolutionary dynamics. Furthermore, to forecast and develop future
442 scenarios, the analyzed data could be used to implement a Cellular Automata (Basse et al.,
443 2014) able to consider the evolutionary dynamics by considering the so-called neighborhoods,
444 or areas adjacent to the area being analyzed.

445 In conclusion, authors emphasize how the spatial - temporal simulation, integrated with socio-
446 economic information, is the new frontier of territorial analysis. As emphasized by Steyaert
447 (1993), the evolutionary dynamics in the real world typically take place in three dimensions,
448 time-dependent, and are extremely complex. This complexity often includes nonlinear
449 behavior and stochastic components. The study of such behavior goes through the formulation
450 of hypotheses and rules to explain its functioning. The rules can, in turn be expressed by
451 mathematical formulas or logical relationships, which often lead to a series of theoretical
452 simplifications to reduce the number of equations used. The mathematical models are based
453 on programming languages that realistically simulate the evolution of spatial patterns over
454 time, that are increasingly used for quantitative analysis, and no more only for qualitative
455 analysis, of the complex issues at the local, regional, or global level. The goal is, ultimately,
456 the realization of decision support tools that are characterized by promptness, cost-efficiency,
457 ease of use, aiming at achieving a better understanding and management of the territory.

459

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