Bio-based and Applied Economics 2(2): 151-172, 2013

Post-2013 EU Common Agricultural Policy: predictive models of land use change

Severino Romano, Mario Cozzi[1], Paolo Giglio, Giovanna Catullo

Technical-Economic Department for the Management of Agricultural and Forest Land, Faculty of Agriculture, University of Basilicata, Italy

Abstract. This article presents a multi-temporal uncertainty-based method that incorporates a statistical regression model with a view to establishing the risk (probability) of land cover changes as a function of a set of environmental and socio-economic driving factors. The morphologic, climatic and socio-economic variables were examined using an Artificial Neural Network (ANN) model and the Multi-Layer Perceptron (MLP). Following the analysis, maps indicating the suitability to future changes were generated on the basis of observed transitions. From these maps two possible land use scenarios were built, applying the Markov chain principle. The region of Basilicata, in southern Italy, was selected for the analysis. The results highlight: *a*) a good inclination to change towards specialised crop systems, provided there is sufficient water supply; *b*) that some cropping patterns are not suitable for changes, partly because they are found in a context with severe limitations for alternative uses.

Keywords. Neural networks, multi-layer perceptron (MLP), Common Agricultural Policy, rural development.

JEL Codes. C45, Q58

1. Introduction

Agriculture and forestry play a crucial role in the production of environmental public goods, such as landscapes, agricultural lands, biodiversity, climate stability, and for their ability to prevent natural disasters, such as floods, drought and fires. On the other hand, many agricultural practices may have an environmental impact, thus causing soil degradation, water pollution as well as the destruction of natural habitats and biodiversity loss. This was reported in 2010 in the EC communication "CAP towards 2020", COM (2010) 672/5 (European Commission, 2010). The EC declaration emphasises that the role of agriculture and forestry is extremely important for the climate and the environment, both locally and globally.

Changes in land cover ensue from interacting processes which act at different scales in space and time and impact on human and physical environments (Munroe and Müller, 2007; Schneeberger *et al.*, 2007). At the same time, those processes are driven by biophysi-

[1] Corresponding author: mario.cozzi@unibas.it.

ISSN 2280-6180 (print)
ISSN 2280-6172 (online)

cal and socio-economic variables (driving forces), which shape landscape patterns and determine their spatial organisation (van Doorn and Bakker, 2007; Serra *et al.*, 2008).

This article aims seeks to analyse the spatial and temporal dynamics of land use, and the mechanisms leading to changes by using multi-temporal variables and socio-economic indicators. Understanding the above relationships is extremely important for enabling scientists, landscape managers and policy makers to design conservation/promotion strategies aimed at preserving the unique features of landscapes (Kates *et al.*, 2001).

Studies dealing with land use changes often make reference to research on global changes (Dai *et al.*, 2005; Turner, 1990; Turner *et al.*, 1994). Such models have been developed to assess the interactions between driving factors and land use changes, with a view to predicting variations in space and time (Pin Lin *et al.*, 2011). Over the last few years, several studies have highlighted different approaches, as classified by Agraval *et al.* (2002) and Verbug *et al.* (2004).

Such classifications include stochastic models of optimization, dynamic models of simulation and empirical models (Li and Yeh, 2002; Verburg *et al.,* 2002; Dai *et al.,* 2005; Castella *et al.,* 2007; Dendoncker *et al.,* 2007). In many cases, empirical models can correctly simulate the spatial processes of land use changes, although they are less reliable when they are confronted with human behaviour as the main factor affecting the changes in land use (Irwin and Geoghegan, 2001). This is not because empirical models do not take into account economic factors; on the contrary, they often include variables that catch economic effects (Irwin and Geoghegan, 2001). There are variables used in agriculture, such as the distance to roads, slope and agricultural GDP that help understand economic impacts. In addition to the empirical component, hybrid models also include simulation models that are designed to foresee all changes that are likely to occur in given scenarios. An example is provided by Markov chains, the aim of which is to simulate changes, as a function of explanatory variables.

The innovative aspect of this work consists in the real possibility to correlate spatial and temporal variations of land use to environmental and socio-economic variables and assess, at the same time, their possible effects on land use.

In fact, the primary sector has been largely influenced by the past CAP measures, notably those related to the direct payment system. A significant example is the *set-aside* measures: it has been proven that they have resulted in expanding uncultivated areas, with the subsequent increase in the risk of erosion and land abandonment (Boellstorff *et al.*, 2005). Moreover, the subsequent measures, such as the single farm payment and the mid-term review of the CAP, have produced direct impacts on the primary sector, causing, in particular, a decrease in the value of the agricultural landscapes (Riccioli *et al.*, 2007). In addition, it has been demonstrated recently that reducing direct payments would result in the reduction of arable lands in favour of areas intended for pastures and natural grasslands (Sieber *et al.*, 2013).

Changes in land use result from complex interactions between physical, but also social, economic and environmental, factors (Versterby and Heimlich, 1991; Dale *et al.*, 1993; Houghton, 1994; Pijanowski *et al.*, 2002; Erfu D., 2005). This means that the knowledge and understanding of territorial dynamics can help foresee the future trends of change. To do that, we need a modelling method that takes into consideration several variables and adjusts them over time to build reliable change scenarios (Chen *et al.*, 2010).

A typical approach to land use change modelling is based on the understanding of the cause-and-effect relationship between some variables and historic changes. Such relations will be the cognitive layer needed for the implementation of an analytical model to make future predictions of transition/change in land use.

To this purpose, it can be useful to use neural networks (*Artificial Neural Network*) and multivariate analyses for assessing the potential future transitions of land use. Through the simulation of a deductive logical path, neural networks constitute excellent models of space-time simulations. One of the most important classes of unidirectional feed-forward ANN with supervised training is the *Multi-Layer Perceptron* (Werbos, 1974; Rumelhart *et al.*, 1986). This procedure is able not only to assess the degree of relationship between the cause and effect variables of past phenomena, but can also simulate future scenarios of potential changes. Two possible scenarios are taken into account in our simulation: the *baseline scenario* describes a stationary trend of incentives projected into the future, while the *future CAP* scenario simulates the effects induced by the next agricultural incentive system provided for by the 2014-2020 CAP reform.

The ANN-MLP model has several advantages, including its non-linear modelling ability and the possibility to be spatialised. The results obtained represent a cognitive support and a valuable tool for decision-making intended to respond by way of targeted actions to the new economic and environmental challenges of the future.

2. Methodology

2.1 Artificial Neural Network Model

An ANN can be defined as an information/mathematical calculation model based on biological neural networks. The model includes several information interconnections, made up of artificial neurons, appropriately linked by connections[2]. Neurons receive and then elaborate some input stimuli, which are mathematically represented by weights. The result of such elaborations is called activation value and the neuron is activated when the result reaches a given threshold. Early stage neurons are connected to late stage neurons so as to form a neural network. A network is normally made up of three stages. In the first stage we have Inputs (I): this layer has the function to deal with inputs in order to adjust them to the requests of neurons; the second layer is the Hidden one (H) and deals with the real elaboration, and can also be made of several levels of neurons. The third layer is the Output (O) and deals with gathering the results together and adjusting them to the requests of the following block of the neural network. As compared to other predictive techniques, ANNs have the advantage of describing the existing relations between input and output variables, without previous knowledge of the links between the variables themselves. Moreover, they are able to identify the interactions and the nonlinear responses existing between the considered variables (Batchelor *et al.*, 1997). Application examples of ANNs have been carried out to quantify land use changes (Nemmour *et al.*, 2006) for risk analysis (Kanungo *et al.*, 2006) and for predicting environmental dynamics (Villa *et al.*, 2007; Follador, 2008).

[2] Connections determine the information flow between the units. They can be unidirectional when information is transferred in one way, bidirectional when information is transferred in both ways.

There are many different types of ANN. Their main differences are represented by the applied function, the accepted values and the learning algorithm. For the present work, the selected ANN model is the one with a supervised learning algorithm based on back-propagation (Rumelhart et al., 1986).

This is an iterative gradient algorithm designed to minimize measurement errors between the real output of the neural network and the desired output.

In the case under study, we have used an ANN model based on the use of the *Multi-Layer Perceptron* (MLP). MLP is a recurring multilevel neural network with a feedback configuration. Such a neural structure is made up of three layers: an input layer (that in our case is represented by the variables involved in land use changes), one or more hidden layers and an output layer (represented by land use changes).

The first layer (input) is represented by i^{th} neurons; each of them is associated with a variable x involved in land use change. Each variable is in turn associated with a weight w, generating the signal, which will be sent to the neuron in the following layer:

$$net_j = \Sigma_i X_i \bullet W_{i,j} \quad (1)$$

Where net_j is the signal received by neuron j, X_i is the variable and $W_{i,j}$ is the weight related to the input layer i and the hidden layer j. Then, the signal net_j is submitted to j^{th} neurons of the hidden layer.

Such a layer is activated only if it reaches a given pre-established threshold. It may be calculated using a sigmoid function:

$$\varphi_j = \frac{1}{1+e^{-net_j}} \quad (2)$$

The sigmoidal-type activation function produces an output ranging from 0 to 1; hence the response of the network can be interpreted as a changing probability. This study predicts 5,000 interactions with an initial activation value of 0.1, as indicated by Eastman (2006).

From the Hidden layer, if activated, the signal will be transferred to the following layer (output), made up of l^{th} neurons, whose values represent the transition probabilities.

$$p_l = \Sigma_j w_{j,l} \varphi_j \quad (3)$$

Where p_l is the transition probability of l^{th} neuron of the output layer; $w_{j,l}$ is the weight related to the hidden layer and the output layer; j is the activation function of j^{th} neuron of the hidden layer.

The algorithm used for the generation of the output is a back-propagation algorithm. This type of algorithm was chosen since it can be applied to nonlinear functions, just like the cause-effect relationship considered in the analysis of land use changes.

It is a supervised learning algorithm by which the output estimated by the network is compared with a known or desired output (i.e. the actual changes in land use occurred in the period under examination). The purpose of this comparison is to obtain an estimated output, which is as close as possible to the desired output. The difference between the two outputs produces an error used to correct the weights.

In this study, the error is quantified using the standard deviation; the training set is repeated until the error function is reduced to an acceptable level

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

Where e_l is the error of lth neurons of the output layer; out_l is the output value of lth neuron of the output layer; p_l is the estimated output of lth neuron of the output layer.

The tested variables can be expressed in terms of presence/absence, or by a gradient, which measures the variation along well-defined sets of time, such as topographic data, i.e. slopes and exposures, and climate data, i.e. rainfall and temperature.

Sometimes there is no linear relationship between the two types of variables, whereas non-linear mathematical relations may occur, so it is necessary to carry out statistical regression assessments.

The output layer has 2 neurons that correspond to 2 possible states: 1 = transition, 2 = permanence.

The result of the transition is a raster (risk) map containing values ranging from zero (no likelihood of change) to 1.0 (maximum likelihood of change).

2.2 Scenario analysis

Upon obtaining the risk maps, we built some possible future land use change scenarios by means of the Markov chain methodology. A Markov chain is a dynamic process made up of a finite number of states and some known probabilities in discrete sets of time (Logofet and Lesnaya, 2000; Yemshanov and Perera, 2002).

An existing discrete state u_t can be used to predict an existing discrete state u_{t+1} multiplied by a transition probability matrix P_t, corresponding to the current set of time t:

$$u_{t+1} = u_t \bullet P_t \tag{5}$$

Thus, the transition probability $P_{i,j}$ (that is from state i to state j) generally derives from a transition sample, which occurs in a set of time. The assessment of maximum likelihood of transition probability (Anderson and Goodman, 1957) is given by:

$$P_{i,j,t} = n_{ij} / \sum_{j=1}^{n} n_{ij} \tag{6}$$

Where n_{ij} is the number of transitions from state i to state j.

Once the potential transitions at a given time have been obtained, it is necessary to localize them in space. One of the most widely used and tested methods is the multi-objective analysis, the main function of which is to determine the set of all efficient solutions, which allows for the allocation of land across multiple use classes.

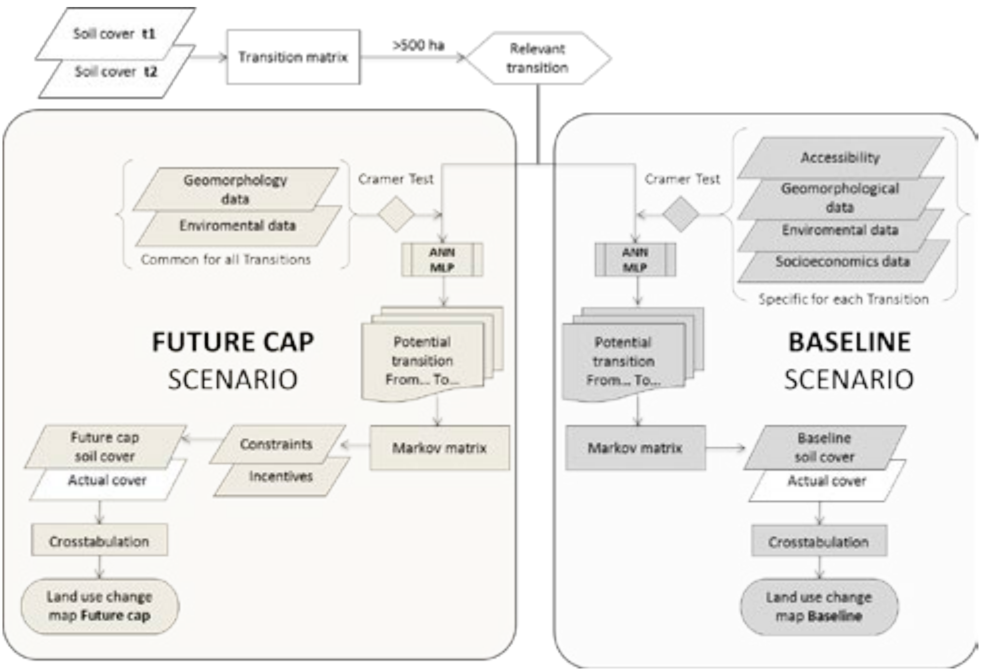
If we observe the ith pixel which passes from the land use u' to u ($xiu \rightarrow u$'), and the transition potential of the ith pixel pi $u \rightarrow u$', and considering the surface demand for the land use u (*Su*), the allocation of changes is calculated in compliance with the principle of the function maximization, by using whole numbers according to the following equation:

$$MAX \sum_{K,U} x^{U' \to U} \bullet P_l^{U' \to U} \tag{7}$$

We use the principle of function maximization since in the final phase of the analysis it is necessary to place the ith pixel, which passes from the use *u'* to *u*, where it is most likely to occur. If we do not apply this principle, the potential transitions calculated up to this point would not have the right space location but would be randomly distributed in the territory under examination.

In the case study carried out, we used a simulator, the land change modeller, which was positively tested in a survey on the most important land change prediction models (Bibby and Sheperd, 2000). This simulator, operating in a GIS environment, enables taking into account any constraints (presence of protected areas, ope-legis constraints, etc.) and present and future incentives/disincentives (environmental and socio-economic parameters, etc.), through the creation of suitable maps that have a considerable impact on potential transition and change in land use (Figure 1).

Figure 1. Applied simulation model.



2.3 Study area and characterization of land use

Basilicata is a southern Italian region the geographical position of which is marginal compared to the main driving centres of Italian economic life. The region covers a territory of 9,992 square kilometres. Despite its high diversity, it has a Mediterranean climate, characterised by hot and dry summers, cold rainy winters, with continental characteristics in the hinterland. The clear orographic diversification between the western and eastern parts of the region corresponds to a clear differentiation in climate between the territories of the two provinces. Rainfall is lower in the east, whereas the eastern-most part of the region usually records values ranging from 500 to 600 mm/year, which is typical of semi-arid or arid climates.

According to the specific morphologic and climate conditions, land use distribution is quite heterogeneous, ranging from extensive agricultural systems and natural areas, mostly in the western area of the region, to more specialised agricultural systems in the hilly and flat lands of the eastern part of the region.

Such a distribution has been accepted in the national planning instruments (National Strategic Plan for Rural Development, 2009) that classify the region as a totally rural territory (less than 150 inhab./km^2), in which the following areas may be distinguished:

B: flat area deemed to be a "rural area with specialised intensive agriculture"

This area is located on the Ionian side of Basilicata region; it accounts for 8% of the regional surface area and includes six municipalities. It is characterised by flat land and access to water resources. Its agriculture is specialised, intensive and profitable. In fact, on an agricultural area accounting for 9.4% of the regional Utilised Agricultural Land, the value added of the primary sector in this area is 25% of the value added of the regional primary sector (Basilicata Rural Development Plan 2007-2013).

D: hilly and mountainous "rural areas with severe limitations for development" (92% regional surface; 125 municipalities). Within the macro-area D the following districts may be distinguished:

- D1: areas with more advanced farming models. This district covers 39% of the regional surface area and includes 60 municipalities. Its land area is mostly hilly with alternating plains. The agricultural activities in this district basically include arable crops and pastures, with specialised crop production in flat areas, specialised tree crops that account for 12% of the district Utilised Agricultural Area (Basilicata Rural Development Plan 2007-2013).
- D2: the hinterland of hilly and mountainous areas. This district is located in the central area of Basilicata region; it accounts for 53% of the regional surface area and includes 65 municipalities. It encompasses mostly mountainous lands with large woodland and pasture areas. Specialised crop systems are practiced only on 5% of the district Utilised Agricultural Area (Basilicata Rural Development Plan 2007-2013), due largely to the elevation and slope of the area that is unfavourable to those crops.

2.4 Multivariate analysis of potential future transitions

Once the most significant changes were identified, the multivariate analysis of potential future transitions was applied by examining a set of possible causes for changes.

The variables taken into account in land use changes can have a different level of correlation depending on the changes that have already occurred. Moreover, as reported by Irwin and Geoghegan (2001), the empirical models of land use change include the explanatory variables acquired from different sources and calculated in a GIS. In accordance with the literature (Bernetti *et al.*, 2010; Lombardo *et al.*, 2005; Pijanowski *et al.*, 2002), physical (distances, land type, slopes, altitude) and socio-economic variables (population, Gross Domestic Product) are taken into account.

In order to highlight a statistical correlation between the cause (accessibility, climate, geomorphologic, and socio-economic data) and the subsequent change, we used Cramer's test V[3] (Cramer, 1999). This test was useful for the selection of the most significant variables to be taken into account for change. The choice of test V as a correlation measurement is due to the data structure in the raster matrix, which does not show the same number of lines and columns.

This method represents a symmetric index of association that takes values ranging from 0 to 1, extremes included. Its value is 0 only if there is independence between the characters, while it is 1 if there is a perfect connection, namely at least one of the two characters perfectly depends on the other. Cramer's V gives non-significant information if it is referred to continuous characters; its objective is to supply indications on the level of non-structured association between characters, especially qualitative and/or nominal ones.

In the present study the applied V coefficient is >0.15, since beyond such a value there is good intensity of dependence between the variable and the considered change (Eastman 2006). The choice of the variables, reported in Table 1, is based on the literature (Bernetti *et al.*, 2010; Lombardo *et al.*, 2005; Pijanowski *et al.*, 2002) and is statistically confirmed by Cramer's test V.

Each variable was included in the model as a raster datum; in particular the first group of variables includes information concerning the accessibility, defined as the easiness of reaching a specified point within the area under analysis. Moreover, among the three accessibility variables we have considered the distance from current soil cover, assuming that bordering areas between two different covers may have a higher transition probability.

The second group of variables refers to morphology, where the associated information layers express a different level of influence on land use. They were included as variables in the model since they help calculate several operational limitations, by restricting land uses and the level of mechanization.

The third group reports climate data. The environmental variables have been considered as being important in the analysis, as their values affect the crop choices for different areas.

Lastly, the fourth group includes different socio-economic variables concerning the primary sector. The value reported in the information layers is obtained from the following equation:

---

[3] The test is used to assess the correlation level between the variables considered. V is calculated from the standard deviation, according to the following function:

$V = SQRT(\chi 2 / (n (k - 1)))$

Where $\chi 2$ is the standard deviation, and K is the lowest number of rows and columns in the matrices of the raster map.

Table 1. Tested Variables.

Factor	Variable	Description
Accessibility	Road distance (m) Urban land cover distance (m) Distance from current soil cover (m)	Binary maps (presence/absence) on which the distance was calculated.
Geomorphologic data	Digital Elevation Model* (mamsl) Slope* (%)	Layers reporting the altitude and grade of slope of the area (100mx100m resolution).
Climate data	Total precipitation* (mm) Mean temperature* (°C)	Layers reporting total yearly rainfall, and average annual temperatures of the area; both calculated as average values.
Socio-economic data	GDP in agriculture (€) Agricultural employment (%) Change of bred cattle (%) Change of sheep cattle (%)	All variables refer to the municipality unit and are calculated as the percent variation recorded in the reference period.

* Variable used in the creation of change suitability maps for the "Future CAP" scenario".

$$\frac{\text{Final value - Initial value}}{\text{Initial value}} \times 100 \tag{8}$$

where the final and the initial values represent, respectively, the variables' values at the end and at the beginning of the reference period of the analysis.

The land use maps, considered in different time frames, refer to CORINE (CO-ordination of INformation on the Environment, Heymann, 1994) Land Cover (CLC) database. The complete nomenclature includes 44 classes organised in 3 levels; in the specific case it has been reclassified into 14 land use classes (Table 2) indicating also the extent and percentage of regional surface in each class.

As for the agricultural sector, cereals are mainly cultivated in hilly regions, while fruit and vegetables are almost exclusively concentrated in the flat and irrigated area. Pastures are instead spaced out by cereals in hilly areas and are associated with husbandry.

The analysis of the agricultural and rural context highlighted the widespread presence of agricultural and forestry activities, which may have beneficial effects on land management, protecting the environment, and enable processes of enhancement of endogenous resources (De Vivo and D'Oronzio, 2007).

In analysing the land cover corresponding to the two time frames, according to the scheme reported in Table 2, there are 196 combinations (14 classes t x 14 classes t+1). Among these combinations we highlighted the ones that have a surface larger than 500 ha (0.5% regional surface). Table 3 shows the transitions drawn from the comparison between CLC1990 and CLC2000. The testing and training set represent, respectively, the number of pixels on which the network performances are verified and the number of pixels on which the network is "trained".

The accuracy indicates the level of precision recorded at the end of the iterations. Its value is not constant across land uses , as it depends on the dimension of the testing set and on the number of variables involved in the change process.

Table 2. Land use classes considered in the analysis.

Land use classes	3rd level CLC	Extension (ha)	Regional surface %
Urban areas	111-142	14314	1.43%
Arable land	211-213	369882	37.05%
Permanent crops	221-223	39002	3.91%
Pastures	231	12626	1.26%
Complex cultivation patterns	241-242	92546	9.27%
Land principally occupied by agriculture, with significant areas of natural vegetation	243-244	56317	5.64%
Broad-leaved forest	311	264556	26.50%
Coniferous forest	312	9634	0.96%
Mixed forest	313	13718	1.37%
Natural grasslands	321	40555	4.06%
Moors and heathland	322	17739	1.78%
Transitional woodland-shrub	324	42628	4.27%
Open spaces with little or no vegetation	331-334	20044	2.01%
Wetlands	411-523	4826	0.48%

Source: Corine data elaboration, 2006.

The variables reported in Table 1 have been used for building transition potential maps, or suitability maps for the "baseline" scenario. As in the case of suitability maps for the "future CAP scenario" (see Figure 1), they were designed by considering the same geomorphologic and climate variables in all of the transitions considered (Table 3), with an average level of accuracy of 75%.

We have generated a suitability map of each considered transition, reporting the most significant ones in Figure 2. The maps indicate the suitability of a given land area or territory to undergo a transition, and provide an indication of locations susceptible to change in the future. We have reported the two most significant maps, in terms of potential land use changes: the former shows the potential abandonment of scarcely productive arable areas, while the latter indicates the potential degradation of forests, above all in hard-to-reach areas.

2.5 Scenario building and simulation

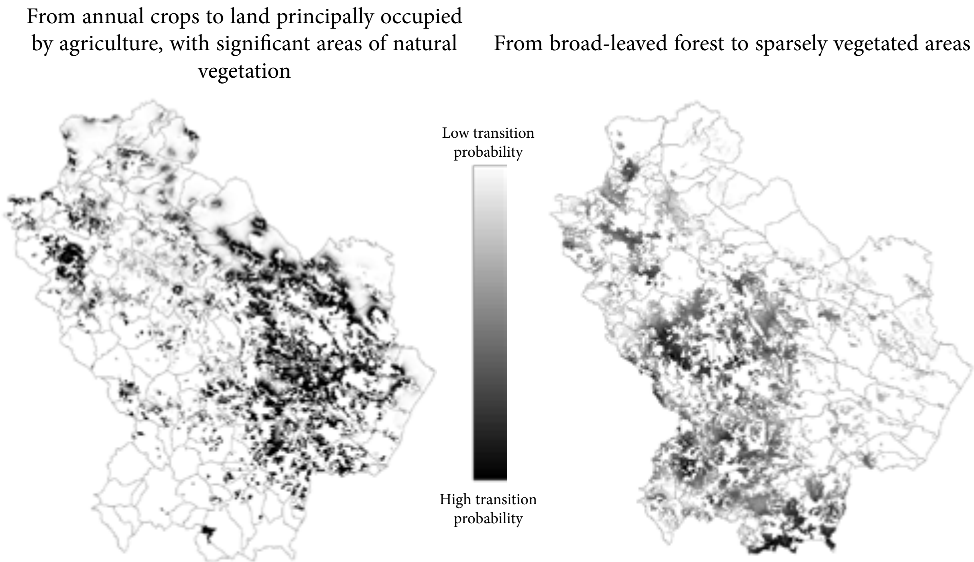
The scenario analysis supplies a strategic planning method aimed at supporting decision-makers in making flexible long-term plans. It is based on the development and assessment of a future series of structurally different but plausible scenarios, which include the main uncertainties of the given context (Wack, 1985).

Based on transition potential maps, or suitability maps (Figure 2), we designed land use maps for 2050, by applying the Markov chain (Eastman and Toledano, 2000). To this end, we opted to perform the analysis on a broad time horizon, because rural development measures do not produce "immediate" effects.

Table 3. Matrix of potential future transitions (baseline scenario).

Transition: From	Transition: To	Description	Variables	Testing and training set (number of pixels)	Accuracy
Annual crops associated with permanent crops	Arable land	Poorly productive associated crops converted in arable land	Digital Elevation Model (DEM, mamsl) Slope (%) Mean temperature (°C) Total annual precipitation (mm/y) Distance from arable land (m) GDP from agriculture (€/y) Agricultural employment (%)	169	79.84%
Land principally occupied by agriculture, with significant areas of natural vegetation	Arable land	Local increase in arable land, with cultivation in shrub lands	Dem (mamsl) Slope (%) Mean temperature (°C) Total annual precipitation (mm/y) Distance from arable land (m) GDP from agriculture (€/y) Change of cattle farms (%) Change of sheep and goat farms (%)	354	79.55%
Annual crops associated with permanent crops	Fruit trees and berry plantations	Areas which have specialised in fruit plantations	Dem (mamsl) Slope % Mean temperature (°C) Total annual precipitation (mm/y) Distance from orchards (m) GDP from agriculture (€/y) Agricultural employment (%)	287	95.47%
Land principally occupied by agriculture, with significant areas of natural vegetation	Annual crops associated with permanent crops	Increase of arable lands and permanent crops, with the transformation of shrub lands	Dem (mamsl) Slope (%) Mean temperature (°C) Total annual precipitation (mm/y) GDP from agriculture (€/y) Agricultural employment (%) Change of sheep and goat farms(%)	307	89.77%
Arable land	Land principally occupied by agriculture, with significant areas of natural vegetation	Scarcely productive arable lands, left to natural spontaneous vegetation	Dem (mamsl) Slope (%) Mean temperature (°C) Total annual precipitation (mm/y) GDP from agriculture (€/y) Agricultural employment (%)	327	87.18%
Land principally occupied by agriculture, with significant areas of natural vegetation	Broad-leaved forest	Scarcely productive arable lands, partially covered with shrubs, left to natural woodland	Dem (mamsl) Slope (%) Mean temperature (°C) Total annual precipitation (mm/y) Distance from Broad-leaved forest (m) Change of cattle farmers (%) Change of sheep and goat farmers (%)	154	79.74

Figure 2. Examples of suitability maps.



This was a stochastic process where the transition probabilities (Table 4) were used in a matrix (P_t). Starting from the analysis of the changes that occurred in the time interval 1990-2000 and using the probability matrix P_t, it is possible to implement a forecast for 2050 (u_{t+1}).

Table 4. Stochastic matrix.

	Status i (t+1)				
Status j (t)	p11	p12	…	…	p1n
	p21	p22	…	…	p2n
	…	…			…
	…	…			…
	pn1	pn2	…	…	pnn

Where n is the number of discrete statuses of Markov chain, and p_{ij} the transition probabilities (included between 0 and 1) from status j to status i in the time interval between t and t+1 (Coquillard and Hill, 1997). The matrix obtained describes a system that changes by time-discrete increases, where the sum of the fractions along a line of the matrix is equal to one; the diagonal, instead, gathers the number of pixels which do not undergo a transition between the initial (t) and the final (t+1) date.

Some authors (Schwartz 1991, Roxburgh 2009) suggest the creation of just a small number of sufficiently distinct scenarios - usually two to four -, to demonstrate more clearly the existing differences. In the present study two scenario analyses were proposed. Scenarios were constructed by long-term simulations (2050) :

- "Baseline" scenario, based on current socio-economic trends;
- "Future Cap" scenario to highlight the effects of the next CAP Reform 2014-2020.

The two scenarios have been distinguished on the basis of the possible application of post-2013 measures. Thus the "baseline" scenario that simulates the persistence of current EU policy, with no hypotheses of future interventions, was solely created on the basis of the current socio-economic trends, determined by the CAP rules in force. Therefore, it is a strongly "deterministic" scenario because it forecasts that such trends will continue in the future.

On the contrary, the "future CAP" scenario that simulates the implementation of new post-2013 measures may not be affected by the current socio-economic trends. Thus the transition probabilities included in the Markov matrix are only determined by geomorphologic and climate variables; this allows the identification of the effects of the post-2013 measures, simulated by incentive/disincentive maps, that modify the transition probabilities of the matrix. The scenarios obtained do not predict the future situation per se, but are rather a tool to improve the understanding of the possible long-term consequences of present and future trends of incentives/disincentives in the agricultural and agro-environmental sector. Accordingly, we chose a long-term projection, without allowing for intermediate stages which could divert attention from the focus of the analysis and which would provide partial results or a poor differentiation between the scenarios.

Within the agricultural policies we find plenty of driving forces which can result in meaningful future projections; however, building scenarios that include all of the components would ultimately make the analysis and assessment phase too confusing. Therefore, we opted to choose some specific measures relative to both the new direct payment system and the new priorities of rural development.

The scenario was built by adopting raster maps of constraints/incentives. Constraints values equal to 0 indicate an absolute constraints, and values equal to 1 indicate areas free to evolve . For incentives, values lower than 1 act as disincentives, whereas values above 1 act as incentives.

Following this approach, three 'new' CAP measures have been "translated" into three raster maps, two being connected with the new direct payment system and the other concerning the new rural development plan, differentiated on the basis of different effects that measures would have on the area, according to the land use.

The aim of these information layers is to modify the transition probabilities reported in the Markov matrix, in order to orient the change processes. In other words, a layer of incentives corresponds to an increase in the transition probability in the direction it translates, while a layer of constraints corresponds to a decrease in the transition probability in the direction indicated by the layer itself.

The first raster map of CAP measures (2014-2020) was built by considering a significant innovation in the *direct payment system*, as money allocation to fruit and vegetable crops and vineyards was not previously allowed, except for tomatoes, citrus orchards and processed fruit. Based on these remarks we have created an information layer of incentives for the irrigated areas, which could potentially host fruit and vegetable crops but which are now widely used for extensive cereal cultivation, since there is no incentive to transform them into more complex cropping patterns.

The second information layer was created by modifying the new direct payment system and simulating the compliance with *greening measures*. This results in a constraint map that does not actually allow for the transformation of the meadow and permanent pasture areas into arable lands.

Finally, the third variable we introduced is once again an incentive, spatially differentiated on the basis of land use. Such an information layer was built on the new priorities of the rural development policy, putting emphasis on the contents of priorities 4 and 5 of the new rural development policy, namely "Protecting and improving ecosystems depending on agriculture" and "Transition towards a low carbon economy", respectively. Such priorities include a large number of measures ranging from environmental sustainability to forestation. These measures have been thus translated into an information layer with different incentive levels. More specifically, this layer provides incentives to permanent wooded areas, mixed and broad-leaved woods, areas presently occupied by shrubs and evolving woods, to turn them into permanent woods. Incentives are also foreseen, to a lesser extent, to meadow and permanent pasture areas, which were already stimulated in the previous information layer, while the other land uses are left free to evolve, with no particular constraints, or incentives. This information layer is extremely important for the reference land, characterised by large areas directly concerned by the measures simulated by the layer.

As previously indicated, the measures associated with rural development may produce results only in the medium-long term, therefore the effects of raster maps were simulated until 2050 so as to be able to assess their impact, notably on forestry.

3. Results

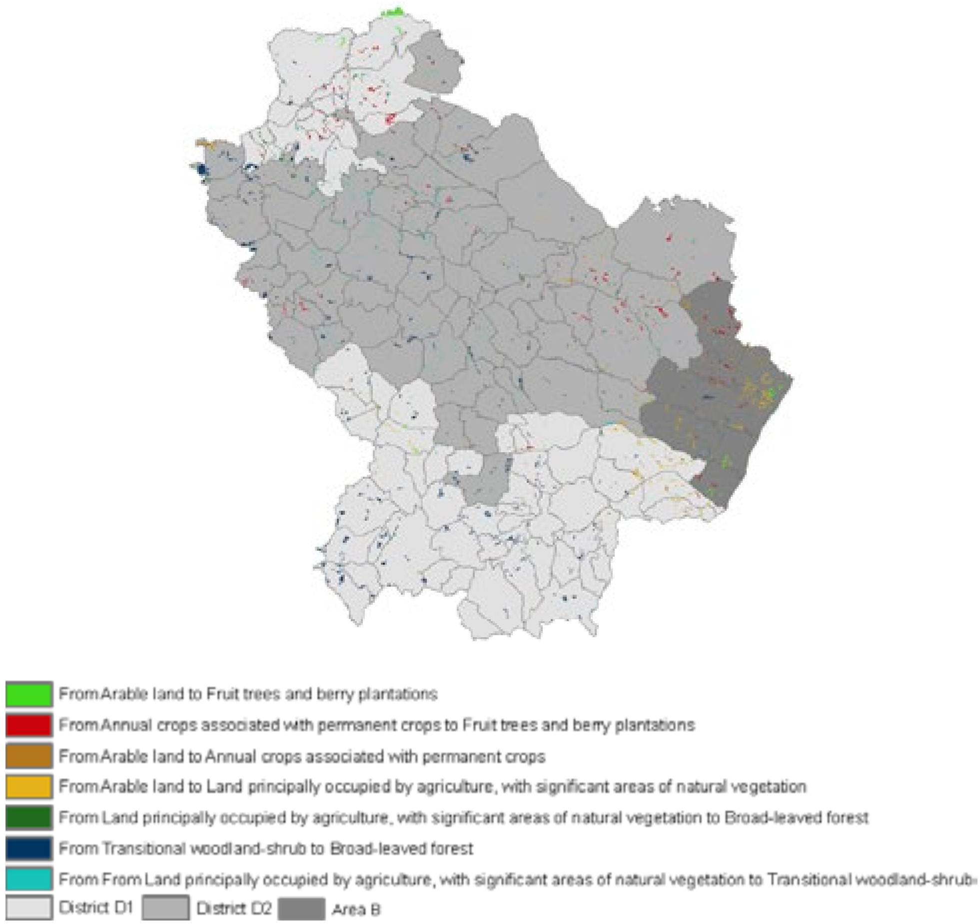
Figures 3 and 5 show the localization of the changes recorded in the individual areas highlighted in the comparison (cross-tabulation) between the present land cover and the cover foreseen for 2050, respectively for the baseline and the future CAP scenarios. Figures 4 and 6 show the land use changes as percent distribution of the area type to which they were recorded in 2010.

In line with what has already been emphasised in the previous paragraph, the areas intended for pasture are expected to further decline (-16.50%) in the future, as a possible consequence of a progressive decrease in the number of raised heads. In the remaining areas we do not notice any particular change compared to the current state, except for a slight increase in wooded areas.

The decline in pasture areas can be explained by the lack of a policy specially targeted to protect those lands. The moderate increase in woodland areas may, instead, be linked to the abandonment of marginal areas and the subsequent transformation of the same areas that, if left uncultivated, would evolve towards natural environments.

The observation in Figure 3 highlights how almost all transitions concerning arable land are localized in the area characterised by a hilly topography, with difficult access to water resources. On the contrary, the transitions concerning the forestry sector are mostly recorded in area D2, where most of the regional woodlands are located.

Figure 3. Land use change map: "Baseline" scenario.



In this area we record a 10.5% increase of woodland.

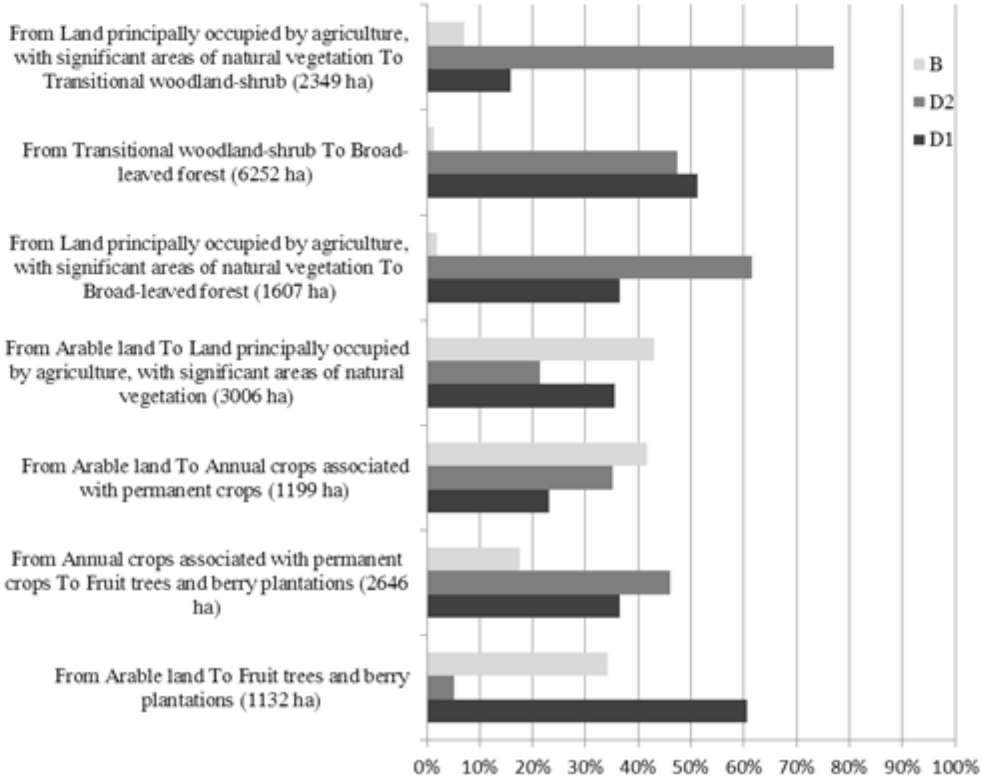
The limited transitions involving the fruit and vegetable sector are localized in the area b that is characterised by a flat trend and the possibility to irrigate. In this area the fruit and vegetable area increases by 10.15% (Figure 4).

Observing the map of "Future CAP" scenario shown in Figure 5, there are no new land conversions into arable crops, and the loss of wooded areas is prevented. This is the result of the pasture protection policy, simulated through the interaction of direct payments and rural development measures (first and third information layers). The analysis points out that natural grasslands and pasture areas declined compared to the baseline scenario, evolving towards wild woodlands.

At the same time, there are more specialised crops as well as better infrastructures in the areas featured by favourable geomorphologic and climate conditions.

The increase in crop specialisation is related to the second information layer applied,

Figure 4. Distribution of "Baseline" scenario transitions (in brackets the areas that shifted from use u to u').



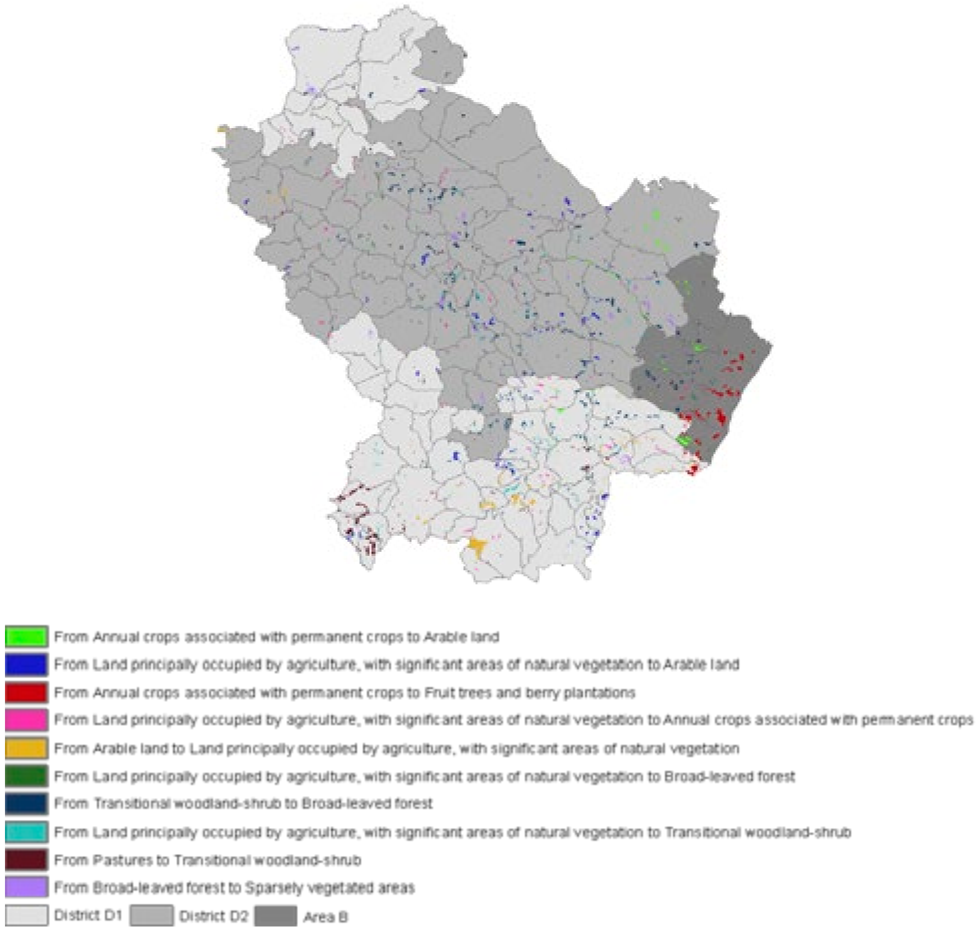
that simulates an incentive for the irrigated areas that could be intensively farmed. The incentive system applied led to an increase in crop specialisation mostly reserved to area B. This is an area characterised by better access to water resources and more efficient and modern infrastructures.

Figure 6 shows that the transitions concerning the fruit and vegetable sector are mostly concentrated in area b, where specialised agriculture is practised. Within this scenario the fruit and vegetable land is shown to increase by 25.7% that is significantly higher than 10.15% observed in the baseline scenario.

The other transitions concerning wood and pasture covers are distributed rather unevenly between the areas D1 and D2.

The comparison of the two change maps shows how the adoption of targeted CAP measures may play a role in the evolution of land use, in particular for the preservation of some natural environments that would be exposed to the risk of degradation and abandonment in the absence of appropriate measures aimed at recovering their protective function. The simulation of EU measures through the incentive/disincentive layers leads to the permanence of agricultural activities in areas D1 and D2 and the reduction of agricultural land abandonment, compared to an evolution that would not be guided by targeted measures.

Figure 5. Land use change map: "Future CAP" scenario.

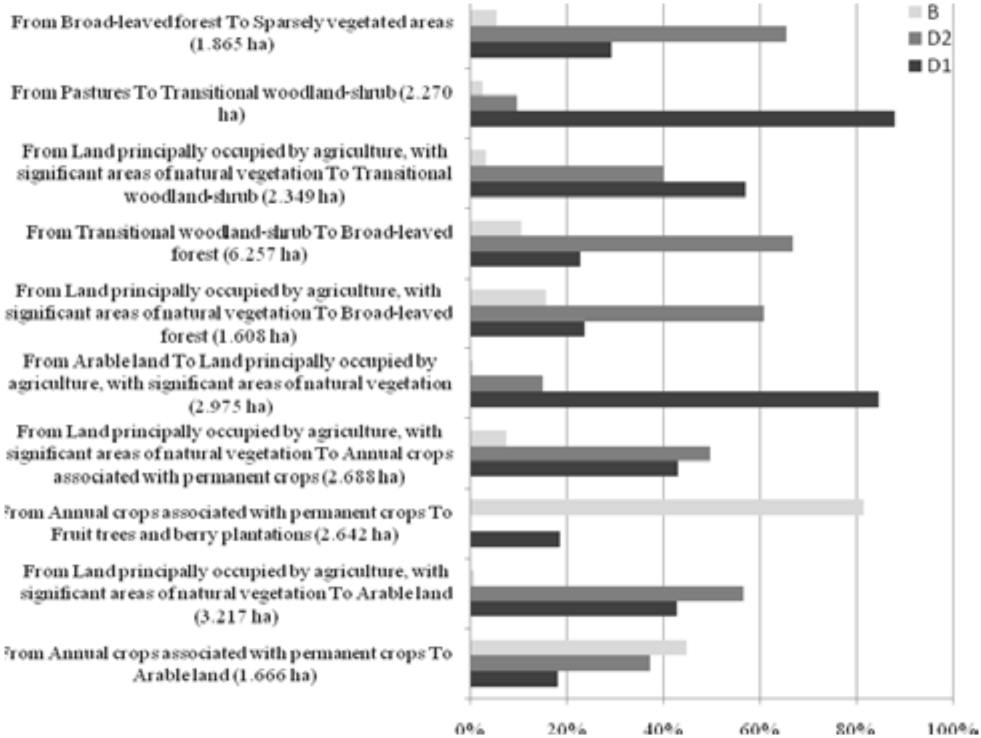


Therefore, it is worth highlighting how the area covered by sparse vegetation, which is increasing in the baseline scenario, would decrease as a result of the adoption of the measures predicted in the "Future CAP scenario", particularly following the application of priorities 4 and 5 of the rural development policy.

In particular, we can observe that when shifting from the "Baseline" scenario to the "Future CAP" scenario, arable land decreases while wooded areas, as well as pastures and grasslands, increase.

These two different evolutions are associated with the interaction between the first and third information layers applied in the "Future CAP" scenario. The concurrent use of these two layers has, on one hand, hampered the conversion of pastures into arable lands (that occurred in the baseline scenario) and, on the other, by encouraging wooded areas, it resulted in the increase of natural areas and the decline of marginal land abandonment observed in the baseline scenario.

Figure 6. Distribution of "Future CAP" scenario transitions.



4. Conclusions

In the model applied we have planned three post-2013 macro-interventions related to both the new system of direct payments and the new rural development priorities. In particular, we have envisaged incentive measures for the fruit and vegetable sector, programs targeted to limit the increase in annual (arable) crops, instruments aimed at improving the maintenance of wooded areas, and forestation actions.

Using these models in the regional context has revealed the different levels of reactiveness of the Basilicata territory to the driving forces leading to change.

In particular, the model underscored the low transition potential of areas D1 and D2, characterised by a geomorphologic system that has severe limitations and difficult access to water resources. In fact, such areas are characterised by vast rain-fed arable lands. Moreover, due to incentives to more specialised crops, they are poorly susceptible to change.

On the other hand, we have observed a high transition potential in specialised fruit and vegetable cropped areas where geomorphologic and climate conditions are susceptible to change, notably where water resources are easily accessible. In these areas we have observed that the implementation of specific measures could actually lead to turn extensive crops into specialised fruit and vegetable production resulting in higher income per surface unit.

Moreover, the "Future CAP" scenario showed the positive influence of the incentive layer for shrubs and woodlands, mainly found in areas D1 and D2 as well as in the regions characterised by hillsides at risk of erosion. Thus, the safeguard of forest cover reduces the risk of hydrogeological instability.

The analysis of results confirms that the applied approach can be a valuable tool for studying the prediction of future land change scenarios and understanding the impacts of current policy strategies, which include actions involving land use in general and agronomic practices in particular. Its main advantage lies in the possibility to gather a large number of variables in the model that affect, to a varying extent, the evolution of land use change.

The strength of such an approach lies in the possibility of formulating *ex-ante* assessment models of local development policies, on the basis of the results obtained. The reliability of the model is closely connected to the availability of the spatial data involved in the change processes; hence, it is better to have a wide basis of geo-referenced variables to emphasise the positive effects of some policies and mitigate the possible undesired consequences.

The limitations of the applied model are above all the quality and the level of spatial detail of input variables. For improving the accuracy of the analysis it would be useful to consider a higher number of variables involved in land use changes, maybe by means of discrete choice models (Choice Experiment) that can effectively describe behaviours, thus getting closer to understanding the actual evolutionary dynamics.

Future developments of the model would require the use of dynamic climate variables in order to assess the effects of changes more accurately and identify the strengths and weaknesses of agriculture and forestry, which are playing an increasingly important role in the dynamics of climatic and environmental changes.

Acknowledgements

We are grateful to the referee for useful suggestions. We would furthermore like to thank Prof. Davide Viaggi for valuable comments on the manuscript.

References

Agarwal, C., Green, G. L., Grove, M., Evans, T., and Schweik C. (2002). A Review and Assessment of Land-Use Change Models: Dynamics of Space, Time, and Human Choice. Center for the Study of Institutions Population, and Environmental Change. Indiana University.

Anderson, T. W. and Goodman, L. A. (1957).Statistical inference about Markov chains. *Annals of Mathematical Statistics* 28: 89-110.

Batchelor, W. D., Yang, X. B. and Tschanz, A. T. (1997). Development of a neural network for soybean rust epidemics. *Transaction of ASAE* 40: 247–252.

Bernetti, I. and Marinelli, N. (2010). Evaluation of Landscape Impacts and Land Use Change: a Tuscan Case Study for CAP Reform Scenarios. *Aestimum* 56: 1-29.

Bibby, P. and Sheperd, J. (2000). GIS, land use, and representation. *Environment and Planning B: Planning and Design* 27: 583-598.

Boellstorff, D., Benito, G. (2005). Impacts of set-aside policy on the risk of soil erosion in central Spain. *Agriculture, Ecosystems and Environment*. 107: 231-243.

Castella, J.C., Kam, S.P., Quang, D.D., Verbug, P.H., Hoanh, C.H. (2007). Combining topdown and bottom-up modelling approaches of land-use/ cover change to support public policies: application to sustainable management of natural resources in northern Vietnam. *Land-use Policy* 24(3), 531-545.

Chen, H. and Pontius, R. G. Jr (2010). Diagnostic tools to evaluate a spatial land change projection along a gradient of an explanatory variable. *Landscape Ecology* 25: 1319-1331, doi: 10.1007/s10980-010-9519-5.

Coquillard, P., Hill, D.R.C. (1997). Modélisation et simulation d'écosystèmes des modèles déterministes aux simulations à événements discrets, Collection "Recherche en écologie", Paris, Masson éd.

Cramér, H. (1999). Mathematical Methods of Statistics, Princeton University Press.

Dai, E., Wu, S.H., and Shi, W.Z., (2005). Modeling change-pattern-value dynamics on land-use: an integrated GIS and artificial neural networks approach. *Environmental Assessment* 36(4), 576-591.

Dale, V., ONell, R., Pedlowski, M., Southworth, F. (1993). Causes and effects of land use change in Central Rondonia, Brazil. *Photogrammetric Engineering & Remote Sensing* 59: 997-1005.

De Vivo, C., D'Oronzio, A. (2007). Il PSR Basilicata 2007-2013: Partenariati forti e strategie di sviluppo di qualità. *Rivista dello Sviluppo Rurale* 9: 21-25.

Dendoncker, N., Rounsevell, M., and Bogaert, P. (2007).Spatial analysis and modeling of land-use distributions in Belgium.*Computers, Environment and Urban Systems*, 31(2): 188-205.

Eastman, J.R. (2006). IDRISI Andes, Tutorial, MA, USA, Clark Labs, Clark University.

Eastman, J.R., Toledano, J. (2000). Markov Chain and Cellular Automata Approaches to Land Cover Change Modeling, Workshop presentation (invited), 4th International Conference on Integrating GIS and Environmental Modeling, Banff, Alberta, Sept. 2-8, 2000.

Erfu, D., Shaohong, W., Wenzhong, S., Chui-kwan, C., Ahmed, S. (2005).Modeling Change-Pattern-Value Dynamics on Land Use: An Integrated GIS and Artificial Neural Networks Approach. *Environmental Management* 36(4): 576-591, DOI: 10.1007/s00267-004-0165-z

European Commission (2010). The CAP towards 2020: Meeting the food, natural resources and territorial challenges of the future. Communication from the commission to the european parliament, the council, the european economic and social committee and the committee of the regions.

Follador, M. (2008). Modellizzazione spazio-temporale delle dinamiche di uso del suolo ed analisi comparata di differenti approcci predittivi. PhDdissertation, Università degli Studi di Bologna.

Irwin, E. G. and Geoghegan, J. (2001). Theory, data, methods: developing spatially explicit economic models of land use change. *Agriculture, Ecosystems and Environment* 85: 7-23.

Heymann, Y. (1994). CORINE land cover: Technical guide. European Commission, Directorate-General, Environment, Nuclear Safety and Civil Protection.

Houghton, R. A. (1994). The world-wide extent of land-use change. *Bioscience* 44: 305-313.

Kanungo, D.P., Arora, M. K., Sarkar, S. and Gupta, R. P. (2006). A comparative study of conventional, ANN black box, fuzzy and combined neural and fuzzy weighting procedures for landslide susceptibility zonation in Darjeeling Himalayas. *Engineering Geology* 85: 347-366.

Kates, R.W., Clark, W.C., Corell, R., Hall J.M., Jaeger, C.C., Lowe, I. (2001).Environmental and development – sustainability science. *Science* 292: 641-642.

Li, X., and Yeh, A. G. O.(2002). Neural-network-based cellular automata for simulating multiple land use changes using GIS. International *Journal of Geographical Information Science* 4: 323-343.

Lombardo, S., Pecori, S., Petri, M. (2005), Investigating territorial dynamic using decision tree. Conference proceedings.Cupum 2005.

Logofet, D. O. and Lesnaya, E. V. (2000). The mathematics of Markov models: what Markov chains can really predict in forest successions. *Ecological Modelling* 126: 285-298.

Ministero delle Politiche Agricole Alimentari e Forestali (2009). Piano Strategico Nazionale per lo Sviluppo Rurale. 8 april 2009.

Munroe, D. K., Muller, D., (2007). Issues in spatially explicit statistical land-use/cover change (LUCC) models: Examples from western Honduras and the Central Highlands of Vietnam. *Land Use Policy* 24(3): 521-530.

Nemmour, H. and Chibani, Y. (2006). Multiple support vector machines for land cover change detection: an application for mapping urban extension. *ISPRS Journal of Photogrammetry & Remote Sensing* 61: 125-133.

Pijanowski, B.C., Brown, D.G., Shellito, B.A., and Manik, G.A. (2002). Using neural networks and GIS to forecast land use changes: A Land Transformation Model. *Computers, Environment and Urban Systems* 26: 553-575.

Pin Lin, Y., Jay Chu, H., Chen, F., Verburg, H. (2011). Predictive ability of logistic regression, auto-logistic regression and neural network models in empirical land-use change modeling – a case study. *International Journal of Geographical Information Science* 25(1): 65-87.

PSR 2007-2013 Regione Basilicata.Delibera n. 410 del 5 marzo 2010.

Riccioli, F., Scozzafava, G. (2007). Il pagamento unico e la condizionalità nella modifica del paesaggio rurale: un caso di studio. Firenze University Press. XXXVI Incontro di Studio Ce.S.E.T., pp. 233-248.

Roxburgh, C. (2009). The use and abuse of scenarios. McKinsey Quarterly November: 1-10.

Rumelhart, D. and McClelland, J. (1986).*Parallel Distributed Processing*. MIT Press, Cambridge, Mass.

Sieber, S., Amjath-Babu, T.S., Jansson, T., Müller, K., Tscherning, K., Graef, F., Pohle, D., Helming, K., Rudloff, B., Saravia-Matus, B.S., Gomez y Paloma, S. (2013). Sustainability impact assessment using integrated meta-modelling: Simulating the reduction of direct support under the EU common agricultural policy (CAP). *Land Use Policy* 33: 235-245.

Schneeberger, N., Bürgi, M., and Kienast, P. D. (2007). Rates of landscape change at the northern fringe of the Swiss Alps: historical and recent tendencies. *Landscape and Urban Planning* 80(1): 127-136.

Schwartz, P. (1991). The art of the long view: planning for the future in an uncertain world. 1st ed. Doubleday, New York.

Serra, P., Pons, X., and Sauri, D. (2008).Land-cover and land-use change in a Mediterranean landscape: a spatial analysis of driving forces integrating biophysical and human factors. *Applied Geography* 28(3): 189-209.

Turner, B. L. II. (1990). Two types of global environmental changes: Definitional and spatial scale issues in their human dimensions. *Global Environmental Change* 1: 14-22.

Turner, B. L. II, Meyer W. B., and Skole D. (1994). Global landuse land-cover change: towards an integrated study. *Ambio* 23: 91-95.

Van Doorn, A. M., and Bakker, M. M. (2007). The destination of arable land in a marginal agricultural landscape in South Portugal: an exploration of land use change determinants. *Landscape Ecology* 22(7): 1073-1087.

Verburg, P.H., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V., Mastura, S.A. (2002). Modelling the spatial dynamics of regional land use: the CLUE-S model. *Environmental Management* 30(3): 391-405.

Verburg, P.H., Schot, P., Dijst, M. J., Veldkamp, P. (2004). Land use change modelling: current practice and research priorities. *GeoJournal* 61: 309–324.

Versterby, M., and Heimlich, R.. (1991). Land use and demographic change: results from fast-growing countries. *Land Economics* 67: 279-291.

Villa, N., Paegelow, M., Camacho, O. M. T., Cornez, L., Ferraty, F., Ferré, L. and Sarda, P. (2007). Various approaches for predicting land cover in mountain areas. *Communication in Statistics-Simulation and Computation* 36: 73-86.

Werbos, P. J. (1974). Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences. PhD dissertation, Harvard University, Cambridge, Mass.

Wack, P. (1985). Scenarios: shooting the rapids. *Harvard Business Review* 63: 139–150.

Yemshanov, D. and Perera, A. H. (2002). A spatially explicit stochastic model to simulate boreal forest cover transitions: general structure and properties. *Ecological Modelling* 150: 189-209.