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Fuzzy definition of Rural Urban Interface: An application based on land use change scenarios in Portugal

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A B S T R A C T

Land cover dynamics influence the spatio-temporal evolution of the Rural-Urban Interface (RUI). This represents the most prone area for human-caused forest fires ignitions in Mediterranean countries. Traditionally, RUI mapping is based on the measurement of the distances among specific land covers. This methodology suffers from the definition of pre-established fixed parameters. To avoid this arbitrariness, a new procedure based on Multilayer Perceptron and Fuzzy Set Theory is introduced in this paper. This allows to develop continuous non-categorical maps expressing the possibility of being part of this interface. Thus, an innovative way for assessing the uncertainty in identifying RUI is presented. The proposed methodology has been applied to the case study of Portugal, elaborating a future scenario for the RUI. The results show how the framework proposed in this paper is able to correctly identify the areas belonging to this interface, providing useful information for forest fires -prevention policies.

1. Introduction

Wildland-Urban Interface (WUI) was first defined as the area “where humans and their development meet or intermix with wildland fuels” (USDI - US Department Of The Interior and USDA - US Department Of Agriculture, 2001). Lately, compounded by climate changes, urban growth and the fragmentation of rural areas, WUI became the central focus of wildland fire policy (Stewart et al., 2007).

Several approaches have been proposed by the scientific community to map the WUI (Bar-Massada et al., 2013; Conedera et al., 2015; Herrero-Corral et al., 2012; Lampin-Maillet et al., 2010; Radeloff et al., 2005). These are prevalently GIS based, where the boundaries of the WUI area are defined through a fixed-distance buffer around buildings and overlapping the wild vegetation/forest. This assumption relies on the observation that human presence, associated to factors such as the population and buildings density or the proximity to roads or single houses, positively affects the probability of forest fires occurrences. Therefore, the spatial extent of WUI is determined by anthropogenic variables, wild vegetation and the buffer value.

Such WUI maps are useful support tools for fire managers, but suffer the definition of fixed parameters and a pre-established buffer's width. It was pointed out that maps relying on the same broad definitions and input data can result in hugely different WUI classifications due to differences in the analytical methods used to produce them (Stewart et al., 2009). Moreover, even when similar conceptual models, data sources, parameters and metrics are applied, details of the implementation can lead to different estimates of the WUI's extent (Platt, 2010). Nevertheless, all these methods are appropriate and necessary to give precise indication for fire protection and prevention, provided that their limitations are made explicit, as well as the purpose for which such maps were developed, the quality of the data and the method of analysis.

WUI is not a static concept; to the contrary, it dynamically changes in space and in time, driven by different anthropogenic and environmental factors. For instance, the abandonment of remote rural areas and the consequent urbanization processes favours the expansion of the WUI and enhances the probability that forest fires reach houses and infrastructures (Theobald and Romme, 2007; Viedma et al., 2015; Zhang et al., 2008). Deforestation and afforestation are other factors affecting the WUI dynamics.

Land use and land cover changes (LULCC) are closely related to

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the delimitation of an interface area between urban and rural/wildland surfaces, where human-caused forest fires are more likely to occur, and represent a main hazard for people, houses and infrastructures. In the last few decades LULCC in European Mediterranean countries have been marked by the progressive abandonment of rural areas under the pressure of urbanization and the expansion of costal tourist centers (Alados et al., 2004). As a consequence, rural activities, such as low-intensity agriculture and grazing practices, were progressively discarded leading to the intensification of forest covers and scrubland vegetation, especially in remote and poor accessible areas (Antrop, 2004; Millington et al., 2007; Poyatos et al., 2003). Urbanization is a very complex and dynamic process that involves natural and the rural lands: these are progressively converted into urban and industrial areas, driven by physical conditions (e.g. topography) and the accessibility to the area (e.g. road network) (Antrop, 2000; Kim et al., 2017). Specifically in Portugal, that in terms of burned area and number of forest fires is among the first three countries in Europe (Moreira et al., 2001; Nunes et al., 2005; Oliveira et al., 2017), the abandonment of rural lands in marginal areas and the coastal urbanization characterized the landscapes changes since 1980 (Diogo and Koomen, 2012; Nunes et al., 2016; Van Doorn and Bakker, 2007).

In this context, the notion of WUI has to be redefined, taking into account the related rural-urban process and the changes of the landscape. Therefore, the broader concept of Rural–Urban Interface (RUI) is more appropriate. RUI has been identified by recent studies as the most fire prone area in Mediterranean countries (Badia-Perpinyá and Pallares-Barbera, 2006; Catry et al., 2009; Moreira et al., 2009). LULCC and RUI have a strong mutual influence: on the one hand, each vegetated land cover type has a specific fire proneness (Pereira et al., 2014; Oliveira et al., 2014); on the other hand, fire affects the landscape pattern and dynamics by changing the vegetation structure and soil processes (Pausas et al., 2008; Viedma, 2008). This suggests the opportunity of investigating the spatio-temporal changes of the RUI and make prevision about its future evolution by analysing and modelling LULCC.

Land use science is an extremely investigated field (Foley et al., 2005; Kalnay and Cai, 2003; Ramankutty and Coomes, 2016). In the last decades, particular attention was paid to LULCC and broad ranges of models have been developed for research and management purposes. These include tools to analyse and quantify changes incurred between two or more periods and can incorporate sophisticated models to predict land use/land cover future scenarios (Martellozzo et al., 2018). Several of these last LULCC models have been designed to facilitate decision-making processes in the field of landscape protection, natural hazards and disaster risk management, urban growth regulation (Foley et al., 2011; Amato et al., 2015, 2016; Muñoz-Rojas et al., 2015; Di Palma et al., 2016; Nunes de Oliveira et al., 2017; Young, 2017). Routines and software developed to predict LULCC and future scenario implement models that can broadly be classified as based on deductive or inductive approaches (Overmars et al., 2007a, 2007b). The latter are based on past land use/land cover (LULC) in a raster format (i.e. pixel units) to estimate the change transition potential, and apply mathematical/statistical functions including explanatory spatial variables to predict future scenarios. Inductive models are commonly used in land change science, in which emphasis is placed on fitting parameters to observations. In contrast, deductive approaches (including agent-based models) simulate the interactions among a set of so-called agents (e.g. land use, householders, farmers, etc.) to analyse their effects on the system as a whole, attaining deeper knowledge of the process. These models, focusing on actors' behaviours, are more popular among economists and decision makers (d'Aquino et al., 2002; Parker et al., 2003; Robinson et al., 2007).

This paper proposes an innovative approach to define the RUI avoiding the definition of rigid boundaries and eliminating their dependence on predefined parameters, such as the buffer width around the concerned land cover classes. A spatio-temporal analysis of RUI has been performed here, based on LULCC model, which allowed to define future scenario maps. These represent a useful support tool for the development of effective fire prevention policies. The methodology has been applied to the case study of Portugal (Western Europe), an area particularly affected by fires.

2. Materials and methods

In this study we introduce a spatially explicit inductive approach to analyse spatio-temporal changes of the RUI and to simulate future scenarios based on the evolution and prediction of the RUI in Portugal from 1990 up to 2030. Among the existing implemented approaches, we selected the Land Change Modeler (LCM™, also available as an ArcGIS® extension); it includes a supervised neural network model, namely Multilayer Perceptron (MLP) trained by backpropagation, to produce probability maps allowing to elaborate future scenarios. This approach fits well when the process under study is non-linear, as it is the case for simulating urban growth and rural development. Moreover, compared with other models/software, LCM provides an higher accuracy of simulations when using MLP (Eastman et al., 2005).

2.1. Study area

Portugal is located in the south-western Europe. It covers the western coast of the Iberian Peninsula for about 200 km (Fig. 1). Mainland has surface of 89,000 km^2 with an altitude range from sea level to about 2000 m in the north central region. Continental Portugal has a temperate climate characterized by wet and mild winters and dry summers, warm in the northern area and hot in the southern. This typical Mediterranean type of climate suffers from the influence of the Atlantic Ocean that bathes its western and southern coasts (Instituto Português do Mar e da Atmosfera, 2018). The country is split by the Tagus River in two parts of approximately the same size, but characterized by a different topography and subclimatic conditions. In the northern area prevails a mountainous landscape interspaced with river valleys, with an annual average temperature ranging from 8 °C to 12 °C. The southern part is characterized by rolling plains with an average annual temperature of about 17 °C. Vegetation grows in the spring season, while it experiences hydric and thermical stress during the summer months, when most fire occurrences are reported. In agreement with the climate and the local topography, forests are predominant in the northern half of the country, while in the southern area prevail agricultural lands and scrub types of vegetation in the south coast(EEA, 1994) Urban areas are mostly located in the northwestern part of the country; here there are the two metropolitan areas of Porto and Lisbon. In the southern part only the Algarve coastal region, which has its administrative centre in the city of Faro, is densely populated.

Fire events in Portugal display a regime strongly related to climate and weather conditions, resulting in about 90% of burned areas concentrated in the summer season (June to September). Many studies report that in the Iberian Peninsula, weather and climate are responsible for about two-thirds of variability of the total annual burned area (Pereira et al., 2013, 2005; Trigo et al., 2016). As regards to the distribution in space and in time of forest fires and burned area in the last decades, the northern Portuguese area is much more affected than the southern: namely, in the period 1990–2013, 25,322 fires were registered in the first, compared with 1951 in the second (considering only burned areas > 5 ha) (Tonini et al., 2017b). Density maps derived from this

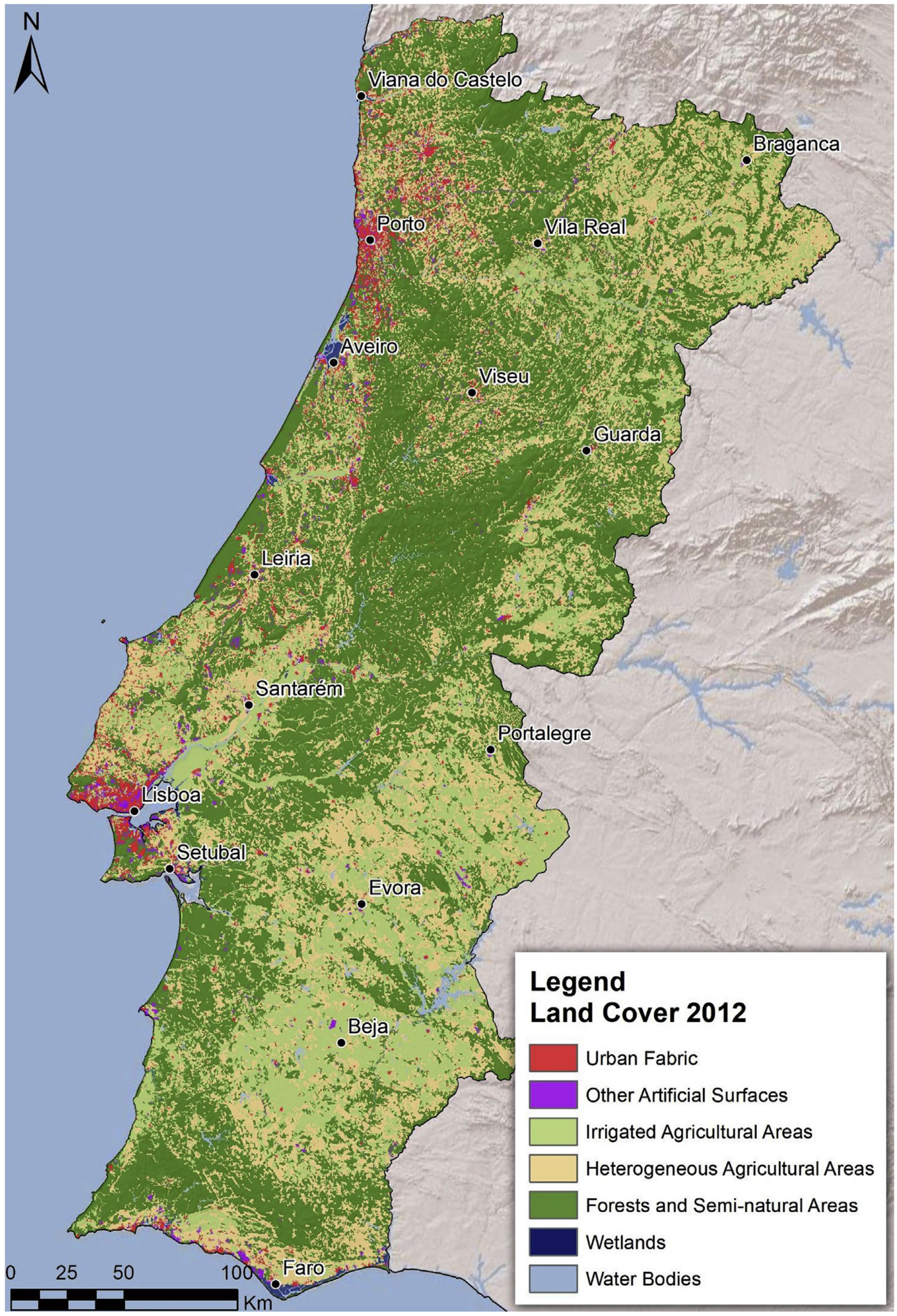

Fig. 1. Land cover classsification based on the second level of the CORINE Land Cover (CLC) 2012 inventory.

same dataset revealed the presence of hot spots almost each year in the northern region, with a higher concentration in the north-eastern more populated areas.

2.2. Data acquisition and pre-processing

To perform the simulation, three land cover maps were used as inputs. These were collected from the CORINE Land Cover (CLC) inventory (Copernicus Programme, http://land.copernicus.eu). CLC maps have been produced for the years 1990, 2000, 2006, 2012. However, the 2006 map has not been considered in this work, in order to have more homogeneous time-step between the time-periods. CLC has a minimum mapping unit (MMU) of 25 ha for areal phenomena, and a minimum width of 100 m for the linear ones. Land covers are classified into 44 classes articulated over three levels. For the present purpose, CLC maps have been reclassified with reference to the second level as reported in Table 1.

From a parallel research study focused on the assessment of RUI and related land covers in Portugal (Tonini et al., 2017a), it resulted that forest and semi-natural areas, jointly with heterogeneous agricultural areas, constitute in this country the vegetated burnable area. Therefore, the RUI's boundaries, needed to validate the model, were defined by spatially intersecting these classes with areas surrounding artificial surfaces. The buffer's width was fixed at 1 km,

Table 1
Land cover classsification based on the second level of the CORINE Land Cover (CLC) nomenclature.

Proposed Classification	CLC Nomenclature (Level 2)
Urban fabric	Urban fabric
Other artificial surfaces	Industrial, commercial and transport units
	Mine, dump and construction sites
	Artificial, non-agricultural vegetated areas
Irrigated agricultural areas	Arable land
	Permanent crops
	Pastures
Heterogeneous agricultural areas	Heterogeneous agricultural areas
Forest and semi-natural areas	Forest
	Shrub and/or herbaceous vegetation associations
	Open spaces with little or no vegetation
Wetlands	Inland wetlands
	Coastal wetlands
Water bodies	Inland waters
	Marine waters

which is consistent with worldwide-applied values (i.e. 1.5mi (~2.4 km) in USA (Radeloff et al., 2005) and from 100m to 400m around single settlements in Europe (Bouillon et al., 2012).

In calibrating the MLP neural network, a number of driving variables have been selected and used as nodes in the input layer. Digital Elevation Model, slope and aspect (i.e. the downslope direction of the maximum rate of change in value from each cell to its neighbours measured clockwise in degrees) were downloaded from the Copernicus database of the European Environment Agency (Reference Data — Copernicus Land Monitoring Service website). Agricultural and population census data have been derived from the Portuguese National Institute of Statistics (Portal do Instituto Nacional de Estatística, n.d.). Distance from primary roads and from the cities with more than 50.000 inhabitants resulted from the Open Street Map Database (OpenStreetMap *website*). Soil thickness, ph, texture and ecological value have been derived from EPIC WebGIS (EPIC WebGIS Portugal, n.d.), an interactive spatial data infrastructure, which provides georeferenced cartography at national scale.

Other variables were derived from a change detection analysis between the inputs of CLC maps. Hence, an Evidence Likelihood function was used to evaluate the relationship among the experienced changes, the Protected Areas and the European protected sites belonging to the Natura 2000 network (derived from the Portuguese Law, 2008/142), the European statistical administrative units NUTS (*Nomenclature des unités territoriales statistiques*) of second and third level and the changes themselves. Finally, the distance from each land cover class has been considered as a dynamic variable, i.e. a variable that changes over time, depending on the intermediate stages of the simulation.

All data have been produced in raster format with a spatial resolution of 100 m × 100 m. They have then been projected in the ETRS89/ETRS-LAEA spatial reference system (EPSG: 3035). This is generally used for statistical mapping at all scales as it ensures a true area representation.

2.3. Forecasting the rural urban interface: model setting

In this paper, the use of a LULCC model is proposed to analyse and simulate the variation of RUI in time. The extent of the RUI is strictly dependent on land cover, as it represents the interface between urban and burnable vegetated rural areas. Changes in artificial surfaces, forests and non-irrigated/heterogeneous agricultural areas affect the extensions of the RUI, indeed. Therefore, a proxy to predict RUI for future scenarios is the simulation of changes in LULC and, consequently, the definition of new boundaries for the prospective RUI.

The main LULCC prediction models are based on an a priori knowledge of the study area and on the driving forces that explain changes in land use (Batty, 1997). This information is used as spatially explicit variable to calibrate the models. However, the definition of the rules to characterize the likelihood that a transition between two different land cover classes will occur is an open issue. To solve it, several transition potential models have been proposed in the literature (Eastman et al., 2005; Saeidi et al., 2017; van Vliet et al., 2016). In the present study, as highlighted before, the MLP neural network algorithm was used for the transition potential modelling. Subsequently, a Markov Chain (MC) application allowed the definition of the change demand, i.e. the quantity of changes expected among each pairwise combination of land cover classes in a certain time. Finally, a threshold procedure was used for the change allocation modelling, allowing ranking the pixels of the transition potential map starting from the assumption that the pixels experiencing a change in a specific iteration of the simulation process are those with a higher transition potential.

To correctly calibrate and validate the model, at least three land cover maps, corresponding to three different periods (i.e. T_0, T_1 and T_2) are needed. The model is then performed using the T_0 and T_1 land cover maps as input to generate a simulation at the time T_2. Therefore, the obtained map is compared with the real land cover map at the time T_2 and Kappa statistics are evaluated (Pontius, 2000). If the validation procedure confirms a good quality of the simulation, the same hyper-parameters used in this stage to calibrate the MLP are used to model T_3 by means of the T_1 and T_2 land cover input maps as input. To focus the evaluation of the calibration procedure on the validation of the MLP application and, therefore, on the quality of the transition potential maps, in the calibration stage the Markovian definition of the change demand has not been applied. Whereas, the real transition matrix measured between the T_1 and T_2 land cover maps has been used, while MC model was applied to quantify the transition between different land covers in the period T_2- T_3.

This technique gave as output a land use simulation map for T_3. Subsequently, the RUI could be identified by applying buffers to the land cover classes whose interaction defines this specific interface. However, the RUI obtained with this procedure is intensely dependent on the selection by the user of an appropriate buffer distance. Moreover, a binary logic to define the membership of a space unit to the RUI seems inappropriate. This is even truer when the RUI definition is based on the results of a previous simulation. In that case, a dichotomous identification of RUI would assume that the modelled land cover is precise, exhaustive and unambiguous (Zadeh, 1973a; Zimmermann, 2010a). Nevertheless, even a well-structured and well-calibrated LULCC model is unlikely to ensure a perfect recognition of all the structure and the patterns of the real world.

To overcome to this issue, in this study we applied fuzzy sets theory as a method to deal with uncertainty and vagueness in the definition of the boundaries of the RUI (Asadi et al., 2017; Uusitalo et al., 2015). This approach overcomes the traditional Boolean classification of spatial units, in which a cell is either belonging to RUI or not. Rather, it expresses the possibility of a pixel of belonging to the RUI set.

To model this "possibility" map, the Transition Potential Model based on MLP have been used to generate two transition probability maps for the time T_2. The first expresses the probability of having a transition from any land cover class to the urban area, while the second expresses the probability of having a transition from any land cover class to the rural surfaces. In agreement with our previous finding (Tonini et al., 2017a), CLC classes considered to define these transition maps are the following: "urban fabric" for urban area and "forest and semi-natural areas" together with "heterogeneous agricultural areas" for the rural surfaces.

The fuzzification of these two maps allowed their overlapping, giving as an output a map expressing the possibility of each cell to belong to RUI. For the tuning of the fuzzification parameters, and for the validation of the possibility map, a dataset containing points belonging to the RUI for T_2 was employed. This RUI map has been defined through the commonly-used procedure based on fixed distance buffers. Specifically, a 1 km buffer has been measured around both the urban area (i.e. "urban fabric"). Hence, the areas belonging to RUI were defined as the one belonging to the intersection of this areas with the burnable vegetated rural area (i.e. "Forest and semi-natural areas" and "Heterogeneous agricultural areas") (Tonini et al., 2017a). Specifically, the procedure was evaluated by the estimation of the Receiver Operating Characteristic (ROC) and the associated Area Under the Curve (AUC) (Hanley and McNeil, 1982; Robin et al., 2011). Once the validation confirmed the quality of the fuzzification process, the same parameters were used to create a possibility map for T_3.

Fig. 2 shows the general flowchart of the methodology proposed in this paper for the calibration, validation and simulation steps.

2.3.1. Calibration of multilayer perceptron (MLP)

The main purpose of this phase is to define proper parameters to be used to minimise the error generated through the application of the MLP. The model performances were evaluated by measuring the root mean square error (RMSE), indeed. MLP architecture is constituted by a series of processing units, named neurons after the metaphor of the biological neuroscience, able to compute and model a specific problem. MLP are extremely useful when phenomena are characterized by a strong nonlinearity or when the analysis is carried out into a high dimensional space (i.e. independent variables driving the process) (Haykin, 2008).

When used for the creation of transition potential maps, the areas that experienced a land cover change are used as training samples to analyse the relationship between input and output (Li and Yeh, 2002, 2001). The input layer is constituted by the driving variables. These are commonly considered as good explanatory variables to be used as inputs in different models (Silva et al., 2016; van Vliet et al., 2012). According to Meyfroidt (2016), driving forces in LULCC are those factors that are cause of land or environmental change and that have a marked association with the nature of the change. Besides, the output layer is defined by all the possible transitions among the different land cover classes included in the model. It also includes the possibility of having a persistence of the considered classes. As soon as the training is completed, new data are presented to the network and the activation levels are defined for all the modelled classes. As a result, the transition potential maps are generated. In our case, these represent the probability of each pixel of having a change from its starting land cover to urban cover and forests or heterogeneous agricultural areas, respectively. These maps were than used in the fuzzification process.

2.3.2. Validation

Validation is a crucial phase to estimate the performaces of the calibrated model. Specific procedures were implemented to assess the quality of both the LULC prediction, both the fuzzy possibility map of RUI.

The accuracy of the LULCC prediction was carried out through the measurement of *Kappa* coefficient of agreement (Pontius, 2000). Naming s the generic element of the simulation map S and a the generic element of the reference land cover map A, and assuming to have $i = 1, 2, ..c$ possible land cover classes, the evaluation of the correspondence between the two maps is given considering the observed fraction of agreement P_o, the expected fraction of agreement P_e, and the maximum fraction of agreement P_{max} (Van Vliet et al., 2011). These values are defined as

$$P_o = \sum_{i=1}^{c} [p(a = i\hat{s} = 1] \tag{1}$$

$$P_e = \sum_{i=1}^{c} [p(a = i) \cdot p(s = 1)] \tag{2}$$

$$P_{max} = \sum_{i=1}^{c} [\min p(a = i),\ p(s = i)] \tag{3}$$

where $p(a = i)$ is the fraction of cells having the land cover i in the map A and $p(s = i)$ indicates the number of cells having the land cover i in S. *Kappa* is then derived from these values through the equation

$$Kappa = \frac{P_o - P_e}{1 - P_e} \tag{4}$$

However, it is also possible to consider *Kappa* as the product of two other measures, the $Kappa_{Location}$ and the $Kappa_{Histogram}$. The mathematical formulation of the two is given by

$$Kappa_{Location} = \frac{P_o - P_e}{P_{max} - P_e} \tag{5}$$

$$Kappa_{Histogram} = \frac{P_{max} - P_e}{1 - P_e} \tag{6}$$

While the former quantifies the spatial position agreement between the categorical values of the two maps, the latter measures the quantitative agreement among their class sizes (Amato et al., 2017).

Fuzzy set theory was applied to generate a map describing the possibility of each pixel to belong to the RUI. Fuzzy sets are an extension of the conventional crisp (i.e. Boolean) sets. The latter are defined as sets in which each member matches the class concept and the class boundaries are sharp. A membership function for a crisp set can have either value 0 or 1, meaning that the generic observation z can either be or not be a part of the set (Zadeh, 1965). However, in fuzzy sets theory crisps sets are considered as a case of partial membership, while the general theory is applied to describe those situations in which the class boundaries cannot be precisely defined (Sheehan and Gough, 2016; Wieland and Mirschel, 2017; Zadeh, 2008, 1973b).

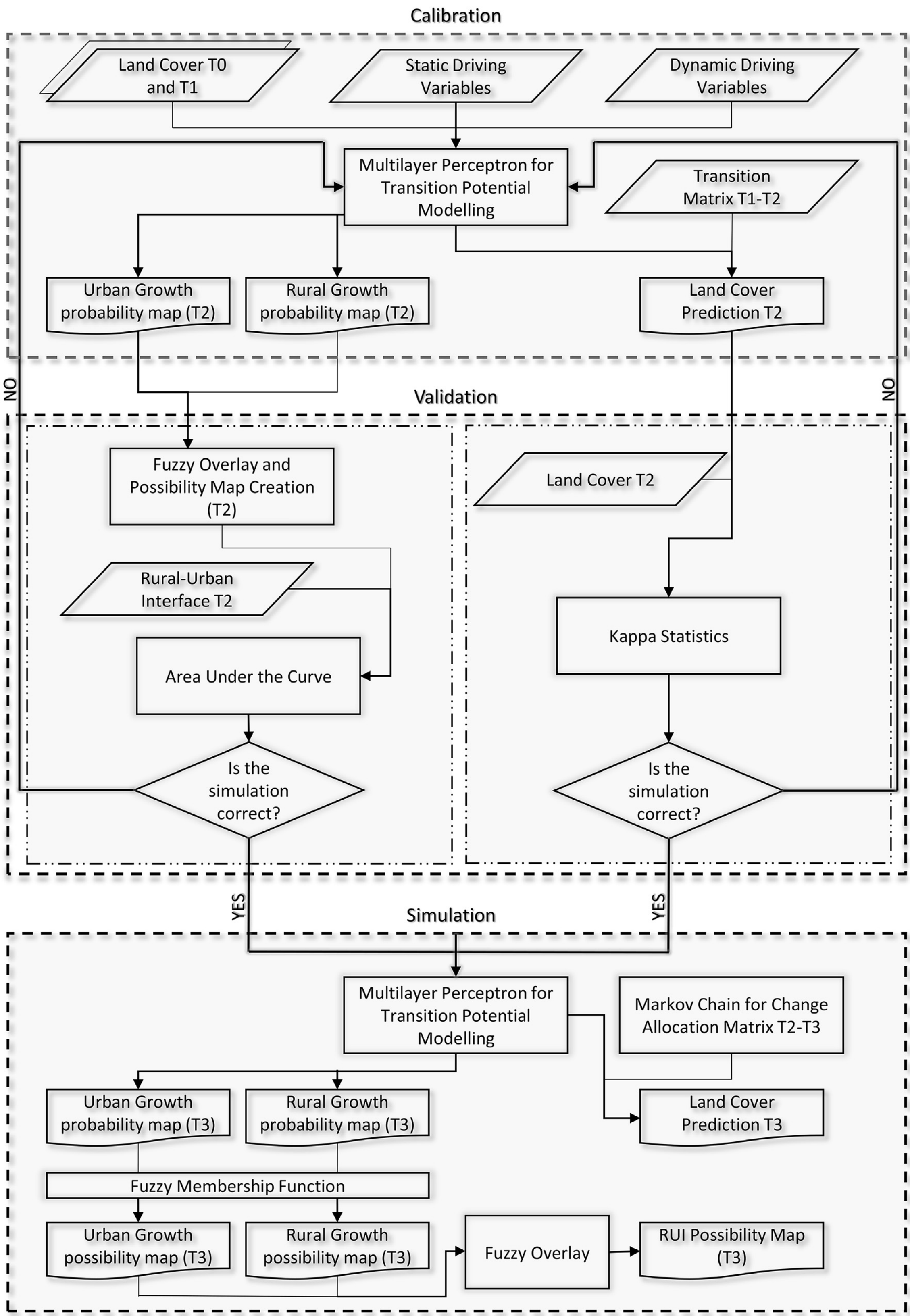

Fig. 2. Flowchart of calibration, validation and simulation procedures.

Given the space of objects Z, the fuzzy set A in Z is

$$A = \left(z, MF_A^Z(z)\right) \quad for\ all\ z \in Z \tag{7}$$

In which $MF_A^Z(z)$ is the membership function of z in A. It is crucial to comprehend how the membership function reflects a degree of belonging to a set based not on probability, but on possibility (Bai and Wang, 2006). Hence, $MF_A^Z(z)$ expresses the grade of compatibility of the predicate related to A and z with a scale that can vary continuously in the range $(0, 1)$ (Luo and Dimitrakopoulos, 2003). Authors have proposed different kinds of fuzzy membership functions (Wang and Mendel, 1992; Zimmermann, 2010b, 2001). In this work, the fuzzy near membership function and the fuzzy large membership function were implemented (Fig. 3).

Generally speaking, the near membership function is used to calculate fuzziness near to a defined intermediate value. A maximum membership value is assigned to this midpoint, while the other values decrease to 0 depending on a spread parameter. The mathematical formulation for the near membership is:

$$MF_A^Z(z)_{Near} = \frac{1}{1 + f_1 * (z - f_2)^2} \tag{8}$$

Differently, the large membership function is used to stress the tendency of high value of the object Z to have high membership in the fuzzy set. This relationship is expressed by the equation:

$$MF_A^Z(z)_{Large} = \frac{1}{1 + \left(\frac{x}{f_2}\right)^{-f_1}} \tag{9}$$

In both the fuzzy near and the fuzzy large membership functions, f_1 is the spread and f_2 is the defined intermediate value.

Given a number of fuzzy sets, the literature proposes several methods to use logical queries to select and combine them (An et al., 1991; Bonham-Carter and Bonham-Carter, 1994). The application of these overlay rules, which are based on a generalization of the conventional operation used in the Boolean sets, imply the computation of a new *MF* value, which is called joint membership function value (*JMF*) (Burrough, 1989; Murgante and Las Casas, 2004). To our purposes, we will only present three *JMF*: the fuzzy Or, the fuzzy Sum and the fuzzy Gamma.

The fuzzy Or operator recalls the Boolean Or logical union, as the *JMF* is dependent on the maximum value of any of the input set maps. Therefore, it is expressed as:

$$JMF_{OR} = MAX\left(MF_A^Z(z)\right)_i \tag{10}$$

Differently, the fuzzy Sum operator is matching with an algebraic product. The mathematical formulation of this operator is:

$$JMF_{SUM} = 1 - \prod_{i=1}^{n}\left(1 - \left(MF_A^Z(z)\right)_i\right) \tag{11}$$

Through this operator, the output is always larger than, or equal to, the largest contributing fuzzy membership value. This is an increasing function, used when the combination of multiple evidence is considered to be more important that any single membership function used as input.

Finally, the Gamma operator is defined as:

$$JMF_{GAMMA} = \left(1 - \prod_{i=1}^{n}\left(1 - \left(MF_A^Z(z)\right)_i\right)\right)^{\gamma} * \left(\prod_{i=1}^{n}\left(MF_A^Z(z)\right)_i\right)^{\gamma} \tag{12}$$

where γ is defined in the range $(0, 1)$. It is possible to demonstrate that the JMF_{GAMMA} includes most of the common *JMF* operators, including the JMF_{OR}, corresponding to a γ equal to 0.75, and the JMF_{SUM}, corresponding to a γ equal to 1 (Raines et al., 2010).

In this paper, the transition potential maps expressing the probability of having a change toward urban or rural coverages are fuzzified by means of the *MF* large and near function. This process of fuzzification of probability data has been already investigated (Buckley, 2004; Eslami and Buckley, 2004; Pota et al., 2013; Zadeh, 1999) and applied in geography for the creation of susceptibility maps (Hattab et al., 2013). Subsequently, *JMF* were evaluated for Or, Sum and Gamma operators. In this paper, a gamma of 0.875 was chosen as an intermediate value between the Sum and Or function. The validation of the obtained possibility maps for RUI was done via the relative operating characteristic (ROC). ROC is a quantitative measure that enables the comparison between a suitability map, which in our case represents the possibility of having RUI, and a binary variable representing the presence or the absence of the considered phenomena. To perform it, the suitability map was divided into a number of percentile groups. For each group, a two-by-two contingency table, whose entries are the hits, the misses, the false alarms and the correct rejections, was defined. The ROC metrics was evaluated by the AUC, which was computed as:

$$AUC = \sum_{i=1}^{n}[X_{i+t} - X_t][Y_i + Y_{i+1} - Y_i/2] \tag{13}$$

where, for the percentile threshold t and for n suitability group, X_t is the rate of false positive and Y_i the rate of true positive, evaluated as:

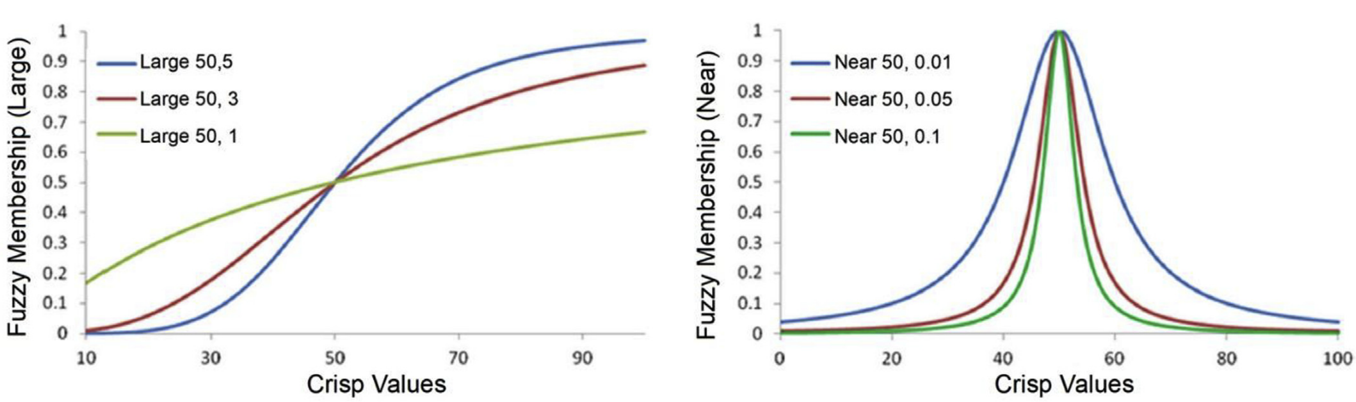

Fig. 3. Fuzzy Large and Fuzzy Near Membership functions drawed using f_1 equal to 50 and multiple values of f_2

Table 2
Multilayer perceptron (MLP) networks used to define the transition potential maps. Raster cells belonging to the output layer were halved to generate a training and a testing set. RMSE was then measured for both the sets.

Model/transition to	MLP network structure	Training RMSE	Testing RMSE	Skill Measure
Urban fabric	9-7-6	0.0813	0.0824	0.9732
Other artificial surfaces	9-8-6	0.2150	0.2198	0.7631
Irrigated agricultural areas	9-6-4	0.0833	0.0866	0.9913
Heterogeneous agricultural areas	11-7-4	0.1786	0.1812	0.9156
Forest and seminatural areas	9-7-4	0.1487	0.1514	0.9584

$$X_i = \frac{F_t}{Q}; \quad Y_i = \frac{H_t}{P} \tag{14}$$

in which P is the number of observations in the binary variable referenced as positives; Q is the number of observations referenced as negative; F_t are the fals alarms and H_t are the hits (Gil Pontius and Schneider, 2001). A perfect matching among the suitability map and the reference variable corresponds to an AUC of 1, while a 0.5 value corresponds to a random location of the values of the suitability map. Moreover, in this work both ROC and TOC (Total Operating Characteristic) were computed, as suggested by Pontius and Kangping (2014). TOC allows an easier evaluation of the size of all the entries of the two-by-two contingency table. Differently, ROC only shows the rate of true-positives on the vertical axis versus the rate of false-positives on the horizontal axis for each threshold (Pontius and Parmentier, 2014).

2.3.3. Simulations

The parameters obtained through the calibration procedures have been used to predict future transition potential maps (known as “soft prediction”) and a potential LULC map for T_3 (known as “hard prediction”). The difference between “soft” and “hard” prediction is that the first yields the entire set of simulated transitions, while the second yields only one specific transition, selected through a multi-objective land competition model. Hence, to generate a hard prediction, the change demand (i.e. the expected quantities of changes for each land cover class) have to be modelled using MC.

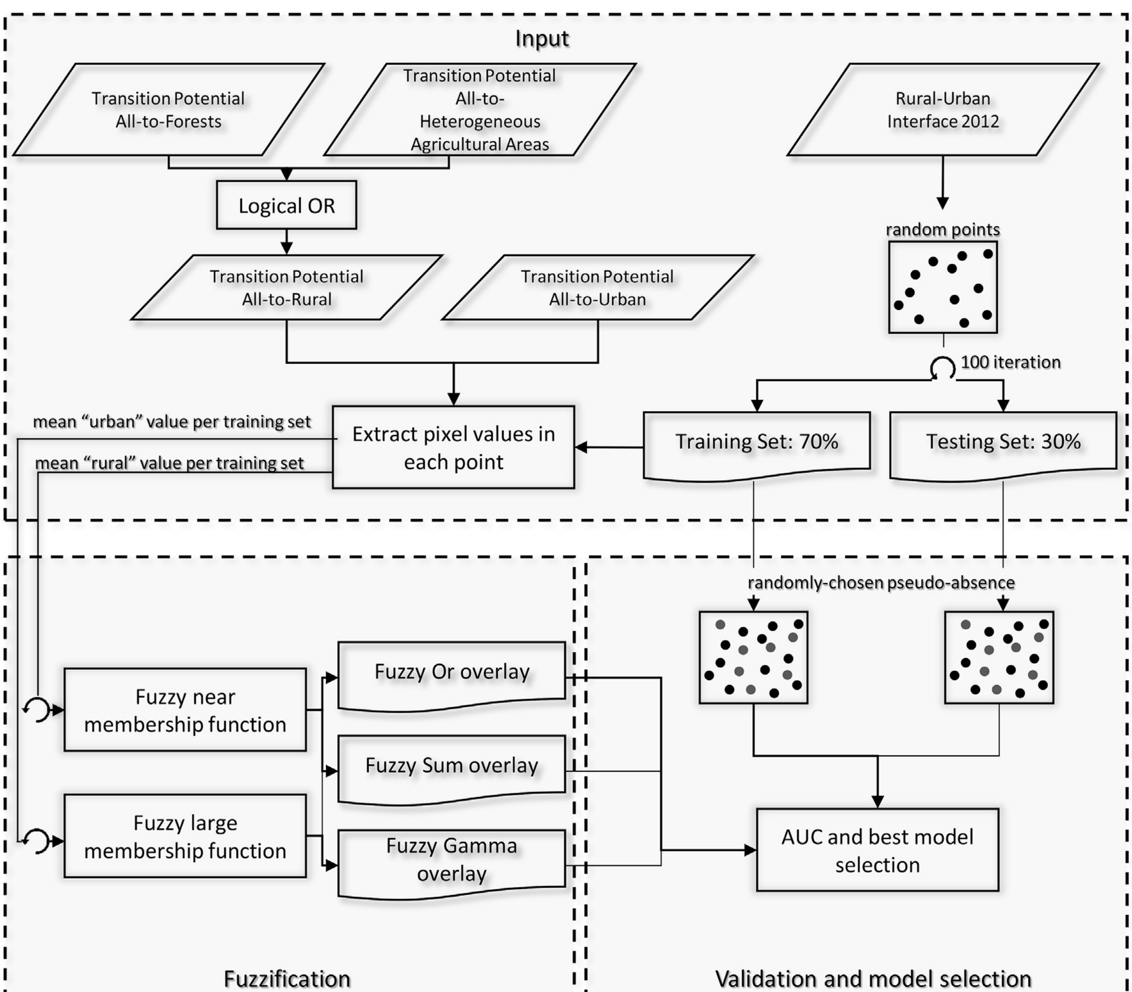

Fig. 4. Flowchart of fuzzification and sensitivity analysis processes.

MC models are based on the idea that the next step in a process depends only on the current state of the system, independently from the state measured at every previous step (Yang et al., 2012; Pontius and Cheuk, 2006; Mas et al., 2014; Pontius et al., 2008; Guan, 2008). A classical MC approach has been used (Kityuttachai et al., 2013) to predict the transition area matrix to support LULCC prediction. Hence, given the n states of the MC and called p_{ij} the probability measured from the cross tabulation of having a transition from the land cover j to the land cover i, then

$$A = \left[p_{ij}\right] \tag{15}$$

is the transition matrix of the MC and

$$X_{n+1} = AX_n \tag{16}$$

where X_{n+1} and X_n are two consecutive state vectors in which the i_{th} component represents the probability that the system is in the i_{th} state at that time.

In this study, a quadratic regression is used to interpolate transition probability matrix and model change demand for the LULCC simulation. The basic assumption is that if the frame-period $T_2 - T_3$ separating the prediction time T_3 and the previous period T_2 is an even multiple of the frame period $T_1 - T_2$ on which the transition matrix is computed, then the new transition probability matrix is derived by simply powering the starting matrix by a number given by $(T_2 - T_3)/(T_1 - T_2)$. Only if the prediction period is between even multiples of the training period, the power rule is used to generate three transition matrixes to cover the prediction period through the resolution of a simple quadratic regression (Takada et al., 2010).

Once modelled the change demand, the obtained transition matrix was used to allocate changes in the future land use map based on the transition potential output of the MLP. The output of this procedure is a land use map for T_3 on which it was possible to define multiple buffers on the urban and rural classes in order to have an evaluation of the location of the RUI through the traditional procedure. At the same time, a gamma fuzzification of the transition potential maps allowed the definition of a map expressing the possibility of belonging to RUI for T_3; this represents the main result of the analysis conducted in this paper.

3. Model calibration and results

3.1. Calibration of multilayer perceptron (MLP)

The MLP network was used to define transition potential maps. As the output layer of MLP is defined by all the possible transitions among the land cover classes, a change detection between the year 1990 and 2000 was performed. A threshold was applied to ignore the transitions affecting a total area smaller than 2500 square kilometres in the entire study area. Thus, transitions from and toward water bodies and wetlands were excluded, as they are mainly due to misclassifications in the CLC maps. The remaining transitions were divided into five groups, depending on the final coverage of the land cover shift. Each group was then used as an output layer in a different MLP neural network. It is important to highlight that the output neurons in this layer are represented both by the possible transitions detected through the change detection, and by the possibility of having a persistence of the initial land cover class.

The input layer included up to 17 driving variables selected among the ones presented in the Materials and Methods section. Each network was first trained with all the variables of interest. Subsequently, a backwards elimination stepwise analysis has been performed to reduce the complexity of the model (Derksen and Keselman, 1992; Holland and Goldberg, 1989). Hence, the least significant variables were dropped one after another and the model was refitted until only statistically significant variables remained in

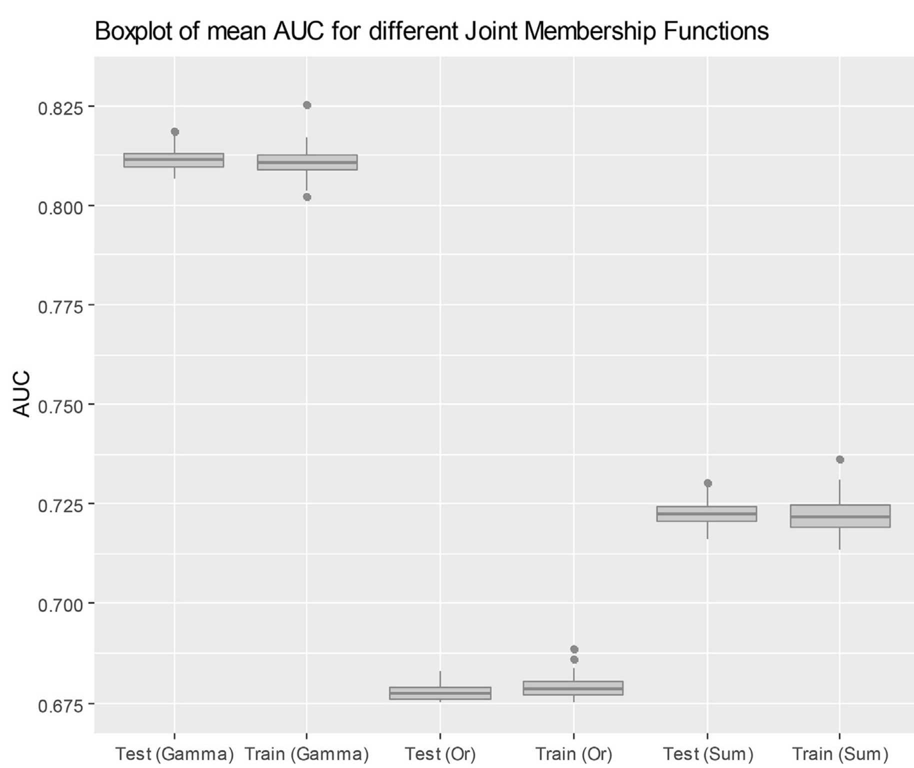

Fig. 5. Boxplot and whisker of the AUC measured on100 training and 100 testing sets for 100 Fuzzy Gamma overlay maps, 100 Fuzzy Or overlay maps and 100 Fuzzy Sum maps.

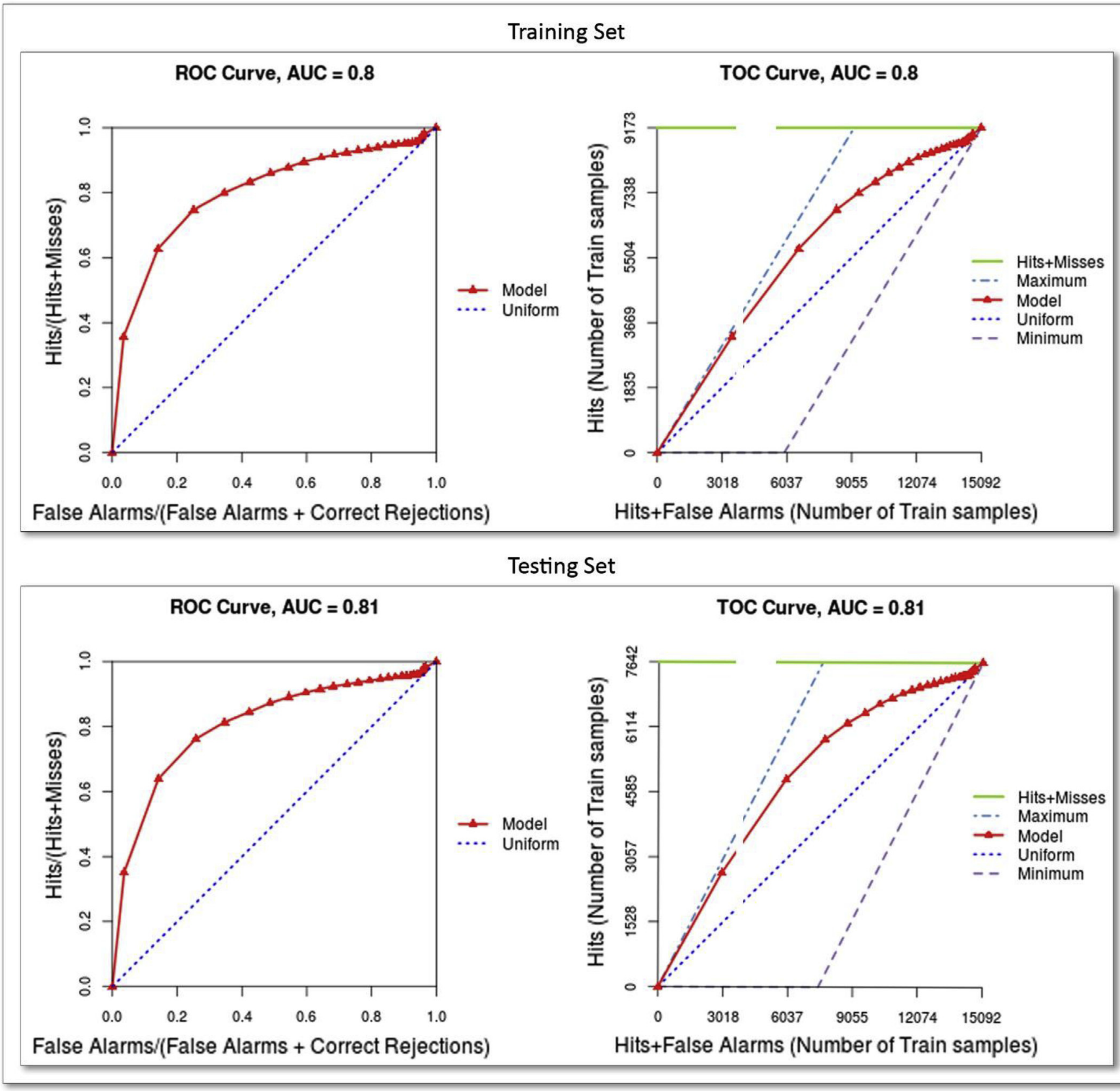

Fig. 6. Best ROC and TOC curves for the Fuzzy Gamma Overlay of both training and testing set.

the network. This methodology allows a reduction of the complexity of the network and an increase in its performances. Table 2 reports the main features of the MLP networks used to calibrate the model. Five networks were implemented based on the final class in the transition process. All the networks were set up using momentum factor equal to 0.5 and sigmoid constant 1. The skill measure represents the measured accuracy of the transition prediction minus the accuracy expected by chance.

3.2. Land change model validation

The transition potential maps obtained with the MLP were used to simulate LULCC up to 2012. The aim of this procedure was to validate the capacity of the MLP to correctly predicting the location of land cover changes. Hence, in this stage the real transition matrix measured on the CLC data for the period 2000–2012 was used to model change demand.

The result was a land cover simulation for the year 2012. A comparison with the reference map for the same year resulted into an overall *Kappa* is 0.8227. This value expresses a high capacity of the model to simulate the real-occurred land cover transition. The $Kappa_{Histogram}$ has a value of 0.9835. This very high value is not surprising at all, as it measures the quantity of changes that, in this stage of the model, was defined through the real transition matrix for the period 2000–2012. The $Kappa_{Location}$ had a value of 0.8365. Though this is a good value, it is important to highlight that the

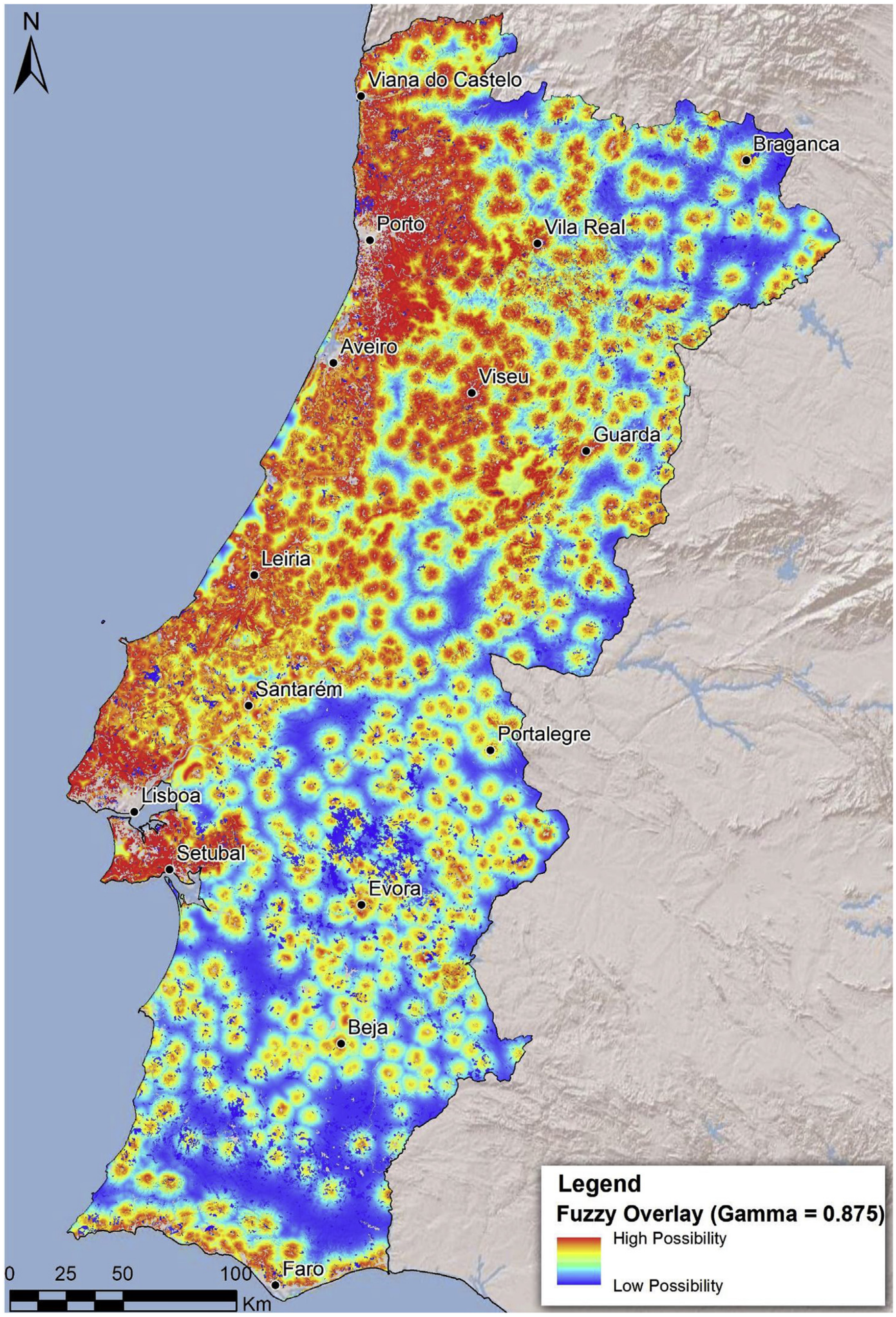

Fig. 7. Possibility RUI map for the year 2030 obtained from the fuzzy overlay using the best fitting parameters measured in the calibration phase.

error in locating the change measured by this parameter is partly due to a misclassification in the CLC map of 1990 for classes broad-leaved and agro-forestry area, corrected only in the 2000 CLC map through the standard CLC procedure. Although this error affected the correct classification in this simulation, these two classes have been reclassified in our scheme as heterogeneous agricultural area and forest and semi-natural area respectively, and both contribute to our definition of the RUI. Moreover, the 2030 simulation map was not been affected by this error, as the MLP was trained on the 2000 and 2012 CLC map, which were not reporting these misclassifications.

3.3. Fuzzification, possibilities and sensitivity analysis

The transition potential map obtained from the MLP could also be interpreted as a susceptibility map. Hence, a transition potential map can be seen as a map expressing in a range from 0 to 100 the probability for a pixel of having the right conditions to experience a land use change. Therefore, a hypothetical overlay of the transition potential maps expressing the probability of having shifts toward urban fabric, heterogeneous agricultural areas and forest and semi-natural areas could describe the tendency to generate the rural-urban interface. However, when mixing together these maps, each single pixel is considered as a target for different kinds of

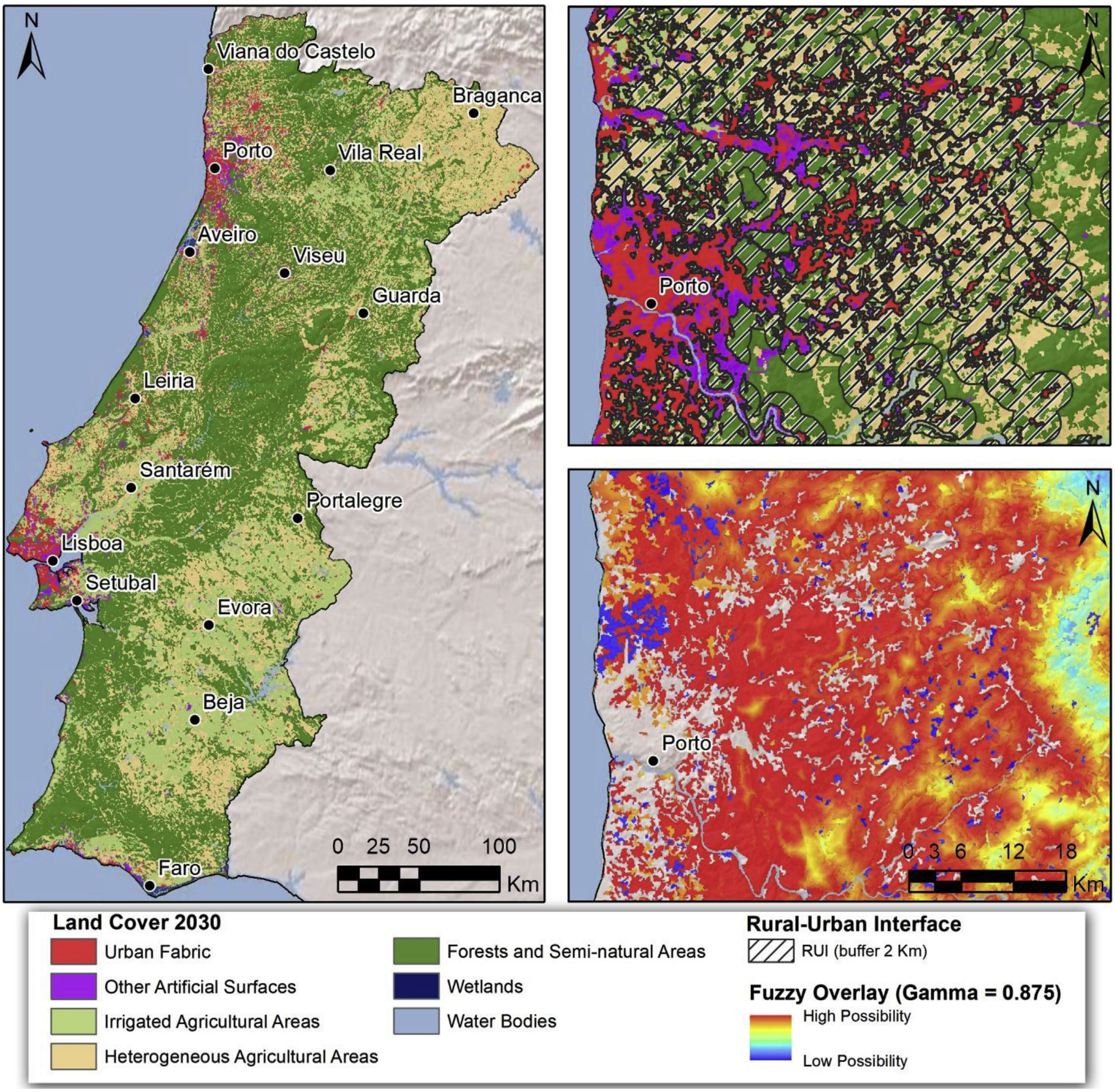

Fig. 8. Land use/Land cover hard prediction for the year 2030. Zoomed areas represent the mapped RUI (considering a buffer width of 1000m) in highly densely populated places around Porto (a) and in scattered rural-residential areas in the South (b).

possible transformations. Therefore, the use of fuzzy set theory was considered as a robust mathematical background to deal with this high level of uncertainty. To only consider the urban and the rural interaction, the transition probability maps of land cover changes toward heterogeneous agricultural areas and forests and semi-natural areas were overlapped using a logical OR function (i.e. given two maps A and B the overlay is given by $((A+B)-(A*B))$ obtaining a transition probability of having changes toward rural.

A fuzzification of the transition potential map poses two issues. Firstly, the spread f_1 has to be defined for each fuzzification. Secondly, the ability of the fuzzy overlay to identify the areas most prone to be part of the RUI has to be validated.

To overcome these issues, a dataset of about 15,000 points was created. Points were chosen based on the RUI measured for the year 2012, in which hard boundaries were mapped as explained in section 2.2.1, ensuring a homogeneous distribution within the RUI and imposing a minimum distance among them of 1 km. This dataset was then used to create 100 training/testing subsets, always having 70% of the points in the training set. They are considered as positive observations, i.e. points detecting the presence of the RUI. All the points were associated with the value of the corresponding pixel in both the maps of transition potential all-to-rural and all-to urban (Fig. 4). The mean values for each of the training sets for both urban and rural maps were then measured. These parameters were used as spread f_1 in creating 100 fuzzifications of the all-to-rural transition potential and 100 fuzzifications of the all-to-urban transition potential.

The fuzzy large membership function was used for the fuzzification of the all-to-urban map. In this way, the higher tendency of the pixel nearest to the urban area to influence the RUI has been considered. To the contrary, the use of the fuzzy near function in fuzzifying the all-to-rural map highlighted the higher propensity of the points in a distance between 500 m and 1 km from the rural coverages of influencing the shape of the RUI. The result of this process were 100 fuzzy maps expressing the possibility of the pixels of experiencing a transition toward rural coverages and being included in the RUI, and 100 fuzzy maps expressing the possibility of the pixels of being with a given distance from urban areas such as to be considered as part of the RUI. These maps were overlaid through three different *JMF* functions. This enabled an evaluation of the best *JMF* in describing RUI between the fuzzy Or, the fuzzy Sum and the fuzzy Gamma overlay rule.

To compare the overlay maps, randomly chosen pseudo-absence points were added to both the training and testing sets as negative observations, i.e. adding information about the absence of RUI. The resulting sets were used to verify the capability of the *JMF* maps of predicting the presence of the RUI. ROC and TOC curves were calculated for all the training and testing sets for all the fuzzy maps

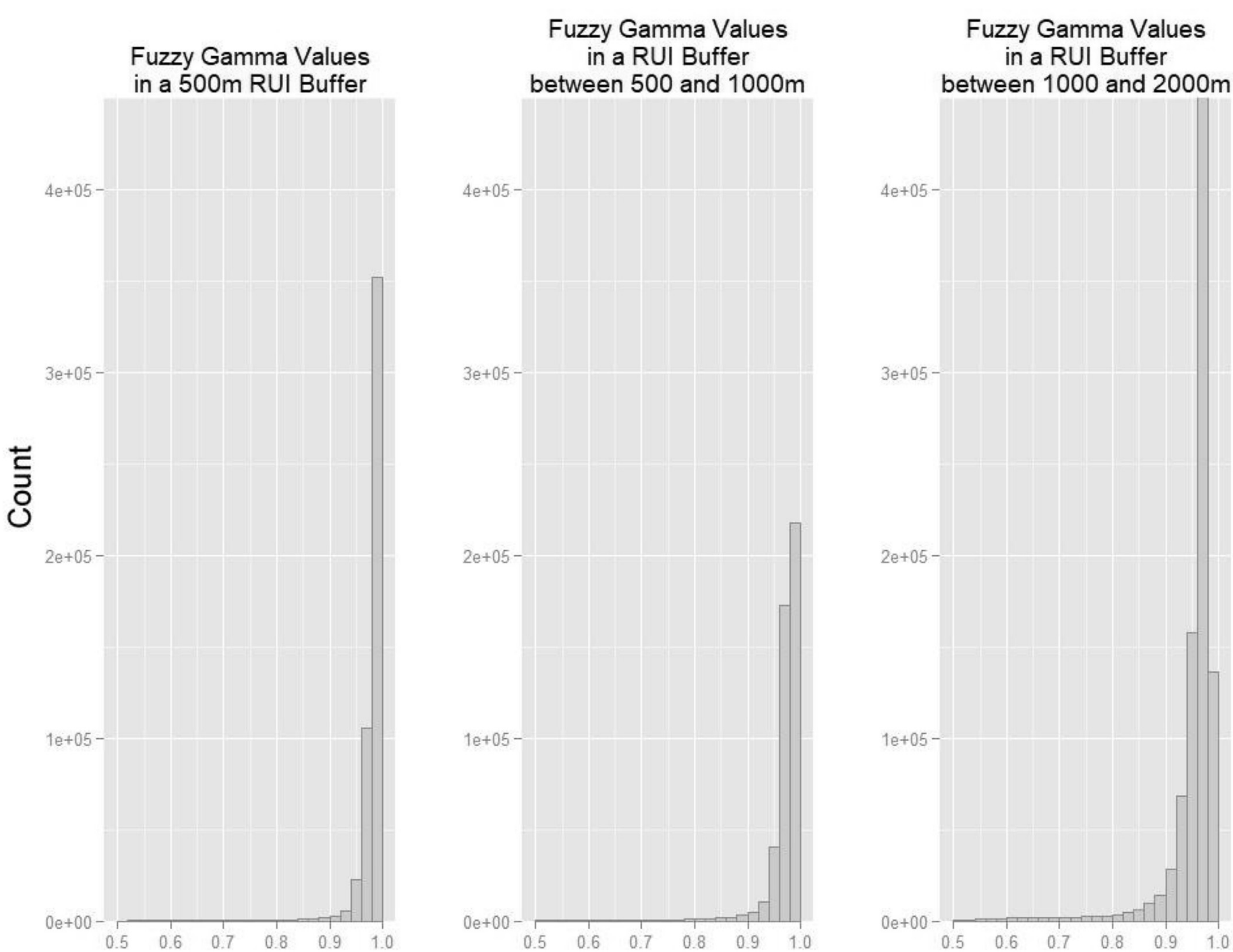

Fig. 9. Histograms of the Fuzzy Gamma Overlay functions for the year 2030 measured in the different buffer zones of the RUI.

using the R package *"TOC"*. Fig. 5 summarises the mean values of the AUC measured for all the maps.

The fuzzy gamma overlay function was found to be the best model in identifying the presence of RUI with a mean AUC value of 0.811 (and standard deviation of 0.003) for the training dataset and of 0.811 (and standard deviation of 0.002) with the testing dataset. Fig. 6 shows ROC and TOC curves for both training and testing sets measured for the best fitting combination of parameters in the fuzzification process and in the gamma overlay operation.

Specifically, the curves in Fig. 6 were obtained by using a spread of 0.6215 in the fuzzification of the all-to-urban potential map and a value of 0.6618 in the fuzzification of the all-to-rural map. Therefore, these parameters were also used in the simulation stage before performing a fuzzy gamma overlay.

3.4. Change prediction maps

The parameters obtained through the calibration and verified in the validation stage have been used to simulate LULCC in Portugal for the year 2030. Transition potential maps for 2030 obtained applying MLP have been used to identify the RUI through the procedure proposed in this paper. Fig. 7 shows the predicted RUI for the year 2030 obtained through the Fuzzy Gamma Overlay. The visual inspection of this map reveals that the areas where the RUI has the highest possibility to extend in 2030 are found around the most populated cities, driven by the growing peri-urban fringes of urban areas. Specifically, they are located in the area enclosed by Braga-Porto-Aveiro-Vila Real (in the northwestern area) with a spatial contiguity along the coast up to the city of Lisbon and the peninsula of Setubal, and crossing the city of Coimbra. Another highly predisposed area in the onrthern part of the country is located around the city of Viseu, in the Centro Region, while in the southern part clusters are visible along the coastline in the Faro Region, this last probably due to the expansion of tourism-led development. In the e northeastern mountainous region towards the interior and in the sothern part of the country, characterized by rolling plains, hotspots for RUI are scattered in the area, probably driven by the abandonment of agricultural activities and the consequent spreading of the forest.

To validate this fuzzy RUI map, the hard prediction for LULC 2030 was considered (Fig. 8). Following the standard procedure to map the RUI (Tonini et al., 2017a), which considers the intersection between the enhanced surface surrounding urban areas and the overlapping burnable vegetated rural areas, three different buffer widths of 500, 1000 and 2000 m were applied. An overlay between the different buffers and the fuzzy possibility RUI map allowed an evaluation of the capability of the latter to identify as most fire-prone areas all those pixels included in the buffers.

Fig. 9 shows the histograms corresponding to the values of the pixels included in the different buffer widths. Noticeably, even in the buffer range between 1000 and 2000 m, 88.84% of the pixels have a possibility value higher than 90, while 72.10% have a value higher than 95. These values corresponded respectively to 92.11% and 85.96% for the buffer distance between 500 and 1000 m and to 93.29% and 90.54% for the buffer distance between 0 and 500 m.

4. Discussion

Several studies highlighted how land use changes are among the primary fire ignition causes (Ganteaume et al., 2013). The rapid urbanization of the European Mediterranean countries over the last decades, principally due to the development of tourism and the huge growth of metropolitan areas, implicates a higher range of possible fire causes due to the presence of human-rural interactions (Hill et al., 2008; Lasaponara et al., 2006). Specifically, human activities influence the spatio-temporal characterisation of forest fires occurrence (Bar Massada et al., 2009). RUI evolves under the pressure of anthropogenic and environmental factors, such as urban growth and fragmentation, abandonment of rural areas, deforestation, and its mapping is closely related to LULCC. RUI has been deeply investigated by researchers and fire managers in the last decades, and several geospatial models for defining and mapping its extension have been developed. RUI mapping is indeed a fundamental tool for decision-makers in order to design their policies with regard to forest fires protection and prevention. In the present research, authors propose an innovative approach to assess the spatio-temporal variability of RUI, related to LULCC, with the final goal of elaborating a future scenario of this interface for Portugal. On the one hand, the proposed fuzzy RUI map can be modelled for different temporal horizons and different socio-economic scenarios, so to consider the dynamic nature of land use over time. On the other hand, compared with the classical approaches used in RUI mapping, the information given by the fuzzy RUI map are richer and account for uncertainty. Hence, depending on the sensibility of decision-makers and on the available resources, different thresholds or defuzzification procedures can be applied to the map to identify the areas to be considered as RUI and in which implementing concrete and effective policies to reduce the exposure of the artificial surfaces to fire risks.

Concerning the methodology discussed in this paper, results shown in previous sections highlight the effectiveness of the proposed framework in identifying the RUI through a flexible approach. The main aim of the study was avoiding the rigid definition of boundaries rising from the classical binary classification methods. In this sense, fuzzy set theory offers a solid mathematical background on which solve the issue of labelling each pixel as belonging or not to the RUI through the assignation to each pixel of a degree of possibility of belonging to the RUI set.

Nevertheless, fuzzy set theory is not the only possible approach to deal with uncertainty. Recent studies have tested the effectiveness of multi-label classification in LULCC simulations (Omrani et al., 2015). Conventionally, LULCC simulation maps, such as the 2030 land cover map proposed in this paper, are the result of a mono-label classification where a single specific class is assigned to each pixel. However, to take into account the uncertainty deriving from a long-term prediction, multi-label approaches can be used to associate spatial unit with a set of multiple classes. Multi-label classifications have substantial differences with the fuzzy set theory (Boutell et al., 2004). Fuzzy membership functions are generally used to deal with ambiguity in the classification of an object, but their overall purpose is its precise classification (Malczewski, 2006). This is usually obtained through a defuzzification procedure, which derives a crisp set from a fuzzy one (Power et al., 2001). Differently, multi-label classifications are used to assign multiple classes to each object, and are based on the assumption that the different labels are not mutually exclusive (Omrani et al., 2017). Hence, multi-label classifications would not be effective in defining RUI, as a pixel can either be considered as belonging to the interface or not, and the two options are mutually exclusive.

5. Conclusions

The present paper introduces a new approach for elaborating a fuzzy map of the Rural Urban Interface, expressing the possibility of a pixel of belonging to the RUI set. The procedure, allowing to make a prediction, is based on Land Use/Land Cover simulation models. The study area includes the entire mainland Portugal, one of the most fire prone country in Europe.

A future scenario for LULCC was computed for the year 2030, based on the Corine Land Cover (CLC) maps representing observed land cover for the years 1990, 2000 and 2012. In this study, we adopted a spatially explicit inductive method, allowing to estimate the change transition potential between CLC1990 and CLC2000. Therefore, statistical functions and algorithms accounting for explanatory spatial variables (e.g. road network, population density, agricultural census, altitude, slope, etc.), based in our case on artificial neural network, and specifically Multilayer Perceptron (MLP) algorithm, were used for the transition potential modelling. Then, a Markov Chain procedure was applied to allocate the transition among different land covers in the period 2000–2012. A backpropagation algorithm was used to correctly train the MLP model. After the validation of the model, performed via Kappa statistics by comparing the simulated and the observed land cover maps for the year 2012, the transition potential was allocated from the CLC2012 to obtain the future land cover map for the year 2030. Despite its complexity, this procedure is extremely robust, especially considering how the application of a non-linear model is perfectly appropriate f to investigate phenomenon like land use/ land cover changes which are naturally non-linear. Moreover, it does not rely on expert knowledge inputs and provides a high goodness of fit value.

Once the LULCC scenario for the year 2030 has been created and validated, it was used to evaluate the possibility of each pixel to belong to the RUI set, by applying a fuzzification procedure. The fuzzy membership function was used for the fuzzification of the all-classes-to-urban and all-classes-to-rural map. The results of this process are fuzzy maps expressing at once the possibility of each pixel of experiencing a transition toward rural coverages and of being in a distance from urban areas. These maps were then overlapped through joint membership fuzzy functions, which overlays probability map of having shifts for the year 2030 toward the urban and the vegetated burnable rural areas. The resulting map well describe a future scenario of RUI in Portugal.

Actually in this country it does not exist jet a specific legislation about RUI (or WUI), but only one general mention at this regard in the National Plan to Protect the Forests against Wildfires, in the Portuguese Law 16/2009. In this Plan it is suggested the need of maintaining an external buffer strips around population clusters, especially in those with the highest fire vulnerability, in order to protect urban-forest interface. The fuzzy RUI map resulting from the present study represents in this context a key tool for policy makers. Indeed, it expresses with a different degree of certitude the possibility of an area to belong to the RUI, allowing to take actions where these possibility is higher. More in general, RUI maps represent a fundamental tool to give practical indications in term of land and fire management. For local interventions, and for land use policy purposes, it is necessary to define spatial limits. Moreover, when planning for future strategies, it is crucial to develop models for land change prediction. The method developed in this paper can be generalised to the investigation of the spatio-temporal evolution of urban-interface vulnerable areas different that the RUI: in all these cases, a map representing the tendency towards relevant land cover/use classes identified on a prospective map provides a much more realistic, useful and unbiased result than crisp maps.

Software availability

Name of the software Land Change Modeler for ArcGIS Software Extension
Version 2.0
Developers Clark Labs, Clark University
System requirements Microsoft Windows 7 or above, ESRI® ArcGIS® 12.2 or later
Program size 500 MB
Contact address Clark Labs, Clark University, 950 Main Street Worcester, MA, 01610-1477 USA
Telephone +1.508.793.7526
Fax +1.508.793.8842
Web www.clarklabs.org

Name of the software TOC
Version 0.0-4
Developers Robert G. Pontius, Alí Santacruz, Amin Tayyebi, Benoit Parmentier, Kangping Si
Maintainers Alì Santacruz
System requirements R 2.14.0 or later
Contact email amasantac@unal.edu.co
License GPL-2 | GPL-3
Web https://CRAN.R-project.org/package=TOC

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