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A comparative analysis of cellular automata models for simulation of small urban areas in Galicia, NW Spain

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ABSTRACT

Urban growth models developed in the second half of the 20th century have allowed for a better understanding of the dynamics of urban growth. Among these models, cellular automata (CA) have become particularly relevant because of their ability to reproduce complex spatial and temporal dynamics at a global scale using local and simple rules. In the last three decades, many urban CA models that proved useful in the simulation of urban growth in large cities have been implemented. This paper analyzes the ability of some of the main urban CA models to simulate growth in a study area with different characteristics from those in which these models have been commonly applied, such as slow and low urban growth. The comparison of simulation results has allowed us to analyze the strengths and weaknesses of each model and to identify the models that are best suited to the characteristics of the study area. Results suggest that models which simulate several land uses can capture better land use dynamics in the study area but need more objective and reliable calibration methods.

1. Introduction

Urban growth models allow for the analysis and extrapolation of the dynamics of city growth, which is highly beneficial for researchers and planners. Among urban growth models, cellular automata (CA) are particularly relevant because of their ability to reproduce complex spatial and temporal dynamics at a global scale using local rules. These rules operate in the neighborhood of the cells of a lattice that represents the space in which the simulated processes take place. Transition rules are applied at discrete time steps and determine the state of each cell in the lattice in every iteration of the model based on the state of its neighboring cells.

One of the main advantages of CA is their ability to reproduce emergent complex dynamics such as those found in cities, based on simple rules (Silva, 2010; White & Engelen, 1993). Moreover, because CA operate on a lattice, raster-format geographic data can be incorporated into the simulation and integrated in a GIS to facilitate the visualization and interpretation of results.

Santé, García, Miranda, and Crecente (2010) reviewed the main operational urban CA models applied to real-world urban development processes and confirmed the model applied by Xie (1996) in Amherst, New York, as one of the first applications of urban CA to the simulation of real-world cases. However, the first widespread empirical applications of CA were the model of White, Engelen, and Uljee (1997) and SLEUTH (Clarke, Hoppen, & Gaydos, 1997). The first one is based on the model developed by White and Engelen (1993, 1997). A number of models based on White and Engelen's model, were applied to The Netherlands (Engelen, Geertman, Smits, & Wessels, 1999), San Diego (Kocabas & Dragicevic, 2006), Dublin (Barredo, Kasanko, McCormick, & Lavalle, 2003), Lagos (Barredo, Demichelli, Lavalle, Kasanko, & McCormick, 2004) or Tokyo (Arai & Akiyama, 2004). SLEUTH is a pattern-extrapolation model that considers four types of urban growth and has been frequently applied to North American cities such as San Francisco, Washington/Baltimore (Clarke & Gaydos, 1998), Sioux Fall (Goldstein, 2003), San Joaquin county (Dietzel & Clarke, 2006) or Phoenix (Berling-Wolff & Wu, 2004), but also to European (Silva & Clarke, 2002), South American (Leao, Bishop, & Evans, 2004) or Asiatic (Mahiny & Gholamalifard, 2007) regions.

Other well-known models are the models developed by Wu (2002), Wu and Webster (1998) and Wu and Martin (2002) focused on the calculation of the probability of development for every cell according to a number of factors, among which the neighborhood. To reduce subjectivity in the allocation of weights to factors, Wu and Webster (1998) used multicriteria evaluation techniques, whereas Wu (2002) used logistic regressions. The model built by Wu (2002) was used by other authors, who calibrated the CA using new methods such as genetic algorithms (Li, Yang, & Liu, 2007) or support vector machines (Yang, Li, & Shi, 2008). Although the aforementioned models are probably the most frequent, a wide variety of urban CA may be found in the literature based on neural-network (Li & Yeh, 2002a), statistical techniques (Li & Yeh,

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2002b), probabilistic methods (Almeida et al., 2003), optimization algorithms (Liu, Li, Liu, He, & Ai, 2008), etc.

This paper assesses the feasibility of some of the best-known examples of urban CA for the simulation of urban growth in the town of Ribadeo, located in Galicia, a region in NW Spain. Ribadeo is a small urban settlement in an intermediate functional range between Galician large urban areas and rural areas. Ribadeo has experienced a slow urban growth process in the last 30 years which took place in relatively small scattered plots. This kind of urban growth is quite different from those which are commonly simulated with urban CA models. Most examples found in literature deal with regions which are experimenting high growth rates in large urban patches, where it is relatively easier to make generalizations and extrapolate processes than in slow growth areas because there is more information on urban processes.

In this paper, the theoretical basis for the urban CA models selected to perform the comparative analysis is presented, the study area and the methods are described, and the simulation results are discussed. Finally, the conclusions drawn from the analysis of the capability of the models in simulating urban growth in Ribadeo are presented.

2. Materials and methods

2.1. Analyzed models

Three models of those inspired by R. White and G. Engelen's model, the SLEUTH model, and the model developed by Wu (2002) where chosen for the analysis. The main reason for the selection of these models is that they are the most frequently applied in real simulations of growth, in various regions and by a number of researchers different from the developers of the models. Additionally, these models have been used as a basis for the development of many others and provide great flexibility to reproduce growth patterns generated from various dynamics.

2.1.1. Family of CA models inspired by R. White and G. Engelen's model

Model developed by White et al. (1997): One of the key features of this family of models was the introduction of an extended neighborhood. By introducing a distance-decay effect, the influence of neighboring cells located at a certain distance could be considered. In addition, the model considered two types of land-use classes: fixed land uses, which affect the dynamics of the other classes but do not participate in the simulated dynamics, and active land uses, which participate in the simulated dynamics and affect the dynamics of the other land-use classes. The transition rule applied in the model developed by White et al. (1997) was based on the calculation for each cell of its potential of transition from a land use to other land uses according to following equation:

$$ {}^tP_z = {}^tRand \times S_z \times A_{zj} \times (1 + {}^tN_z)^n + {}^tH_z \quad (1) $$

where ${}^tP_z$ is the transition potential to land use z at the time step t, S_z is the suitability of the cell for land use z (which assumes values between 0 and 1), A_z is the influence of accessibility to a transportation network in the transition potential to land use z, ${}^tN_z$ is the effect of neighborhood on the transition to land use z at time t and H_z is an inertia parameter for cells that have land use z at time t, which equals zero if the land use of the cell is not z and increases its value otherwise. ${}^tRand$ is a random variable determined from following equation:

$$ {}^tRand = 1 + (-\ln \gamma)^{\alpha} \quad (2) $$

where γ is a random number between 0 and 1 and α is a parameter that scales the degree of randomness introduced in the model. Accessibility is determined from following equation:

$$ A_{zj} = \left(1 + \frac{D_j}{\delta_{zj}}\right)^{-1} \quad (3) $$

where D_j is the distance to road network j and δ_{zj} is a coefficient representing the importance of distance to network for land use z. The neighborhood effect (${}^tN_z$) is calculated according to following equation:

$$ {}^tN_z = \sum_d \sum_i w_{zkd} \, {}^tI_{di} \quad (4) $$

where ${}^tI_{di}$ is a parameter that takes on a value of 1 if cell i in distance zone d is in land use k, and 0 otherwise, and w_{zkd} is the weighting parameter applied to cells with land use k in distance zone d, that is, w_{zkd} represents how a cell with land use k at a distance d from the central cell influences the transition potential of the central cell to land use z.

Once all the transition potentials have been calculated, each cell changes state to the land use for which it has the highest potential.

The model developed by Engelen et al. (1999): Engelen et al. (1999) modified the model developed by White et al. (1997) to simulate urban growth in a region of the Netherlands. The modified model had the same structure as the previous one, except for the fact that the modified version included zoning status as a factor, ${}^tZ_z$ (Eq. (5)) and that the inertia and accessibility parameters were not considered. Yet, accessibility was included as a factor in determining suitability:

$$ {}^tP_z = {}^tRand \times (S_z)^s \times ({}^tZ_z)^p \times ({}^tN_z)^n \quad (5) $$

Factor ${}^tZ_z$ can take on the values 0, 1, 2 or 3 according to whether a given land use is allowed (0), temporarily prohibited (1 or 2) or permanently prohibited (3). Parameters s, p, n express the importance of each element in the potential for change. This model uses binary switches that may take on the values 0 or 1.

The model developed by Engelen et al. (1999) allows cells to change only from a non-urban state to an urban state, and does not take into consideration any mechanism like the inertia parameter considered in the model developed by White et al. (1997), which takes into account the resistance to transition by some land use classes.

The MOLAND model: Within the MOLAND project (Lavalle et al., 2004), a modification of the model of White et al. was developed. In MOLAND, three types of land use classes were considered instead of two: fixed land uses, which affect the dynamics of other land use classes but do not change state; passive land uses, which affect the dynamics of the other classes and change state but are not influenced by the demands for land external to the model; and active land uses, which participate in the dynamics, change state and are influenced by the demand for land external to the model. The transition potential for each cell is calculated according to following equation:

$$ {}^tP_z = {}^tRand \times (1 + S_z) \times (1 + A_z) \times (1 + {}^tZ_z) \times ({}^tN_z) \quad (6) $$

In MOLAND, there are no inertia parameters or constraints on change from a land use class to another. Except for fixed land uses, the rest of land uses can change state freely until the amount of change simulated for each land use and iteration is satisfied. To consider the resistance to transition by some cells, the value of w_{kd} is added for the central cell of the neighborhood when $k = d$, instead of including an inertia parameter.

2.1.2. The SLEUTH model

SLEUTH is perhaps the most widespread urban CA, probably because of the availability of a free software that facilitates the implementation of the model (http://www.ncgia.ucsb.edu/projects/gig/). SLEUTH reproduces urban growth patterns, simulating four types of growth that are controlled by five parameters.

(1) Spontaneous growth reproduces random low-density growth in isolated cells. If the location has at least one urban neighbor or passes a randomized test of slope suitability, this location becomes a new urban location. Spontaneous growth occurs under the control of the slope resistance factor, which determines the maximum slope value that would allow for development.
(2) Diffusive growth reproduces the emergence of new spreading centers by creating two neighboring cells around spontaneous growth areas. The breed coefficient determines the probability of a spontaneous growth cell becoming a new spreading center.
(3) Organic growth simulates edge growth in new or existing urban centers. This type of growth occurs under the control of the spread coefficient, which determines the probability that any non-urban cell with at least three urban neighbors will generate an additional urban cell in its neighborhood.
(4) Road-influenced growth generates new spreading centers along the roads. To this end, the model randomly selects newly developed cells with a transition probability defined by the breed coefficient, and seeks the existence of a road in the neighborhood of each cell within a given maximal radius determined by the road gravity coefficient. If a road is found in the neighborhood of the selected cell, a temporary urban cell is placed at the point on the road that is closest to the selected cell. Then, this temporary urban cell seeks a permanent location along the road, in a randomly selected direction, and the maximum distance traveled is defined by the diffusion coefficient. The final location of the temporary developed cell is then considered a new urban spreading nucleus, where up to three cells can be developed along the road.

Because transition rules are not fixed, SLEUTH is a self-modifying CA model and, therefore, the coefficients that control growth may vary according to several factors. For example, an increase in urban density during the simulation may result in an increase in the slope resistance factor, such that steeper slopes can be built upon. At the same time, if areas with steeper slopes are built upon, the diffusion coefficient increases, thus promoting the expansion of the urban center into the surroundings.

SLEUTH has its own calibration method: first, the coefficients are allowed to vary randomly in increments of 25 (the parameters can take on integer values between 0 and 100) and a number of simulations are performed. The coefficient sets with the best fit are selected. The coefficient ranges that will be used for the subsequent phase of calibration are defined upon the variation of the coefficient values among the best fit coefficient sets. For the following phases of calibration, coefficient ranges are narrowed and the number of units among which the coefficients may vary decreases until the parameter set that produces the best results is obtained.

2.1.3. The model developed by Wu (2002)

The model developed by Wu (2002) considers just two land uses, urban and non-urban. Transition potential for each cell i (${}^tP_i$) is calculated from the probability of transition of each cell i (P_i), estimated through logistic regressions from a given number of variables. The probability of transition is scaled with the probability that the state of the cell is urban as a function of the number of urban cells (n) present in the 8 immediately neighboring cells.

$$ {}^tP_i = \frac{P_i \, * \, n}{8} \tag{7} $$

As shown in Eq. (7), this model does not include a random variable, because randomness is introduced using the Monte Carlo method. To this end, a random number is generated and compared with the potential for cell transition. If the potential is higher than the random number, the cell changes state. Otherwise, the cell remains unchanged.

Because transition potentials are recalculated at every iteration, the maximum potential for transition – max (${}^tP_i$) – varies. For this reason, the probability of site conversion is scaled using an exponential distance-decay function:

$$ {}^tP'_i = {}^tP_i * \exp\left[-\delta * (1 - {}^tP_i/\max({}^tP_i))\right] \tag{8} $$

where δ is a dispersion parameter that controls the shape of the distance-decay function, so that the higher is the value of δ, the steeper the distance-decay gradient and the more different the values of ${}^tP'_i$ to one another. This makes the selection of cells with higher values for transition easier for the Montecarlo method. Consequently, δ controls the degree of randomness introduced in the model (Wu & Martin, 2002).

To adjust the number of simulated transitions to the number of conversions expected at each iteration, ${}^tP'_i$ of each cell i must be scaled again using following equation:

$$ {}^tP''_i = \frac{{}^tP'_i}{\sum_i {}^tP'_i} \times N \tag{9} $$

where N is the number of conversions expected at each iteration, determined externally to the model.

2.2. Study area

Ribadeo is a small coastal town with a population of 6000 inhabitants, located in the Northeastern corner of the region of Galicia, NW Spain (Fig. 1). This town is an administrative, commercial and services center because of its location at the confluence of two major roads: the road that runs along the northern coast of Spain and the road that connects the capital of the province of Lugo with the neighboring region of Asturias. Ribadeo is a representative example of a town that acts as the capital of a district or "cabeceira de comarca", which are so characteristic of Galicia (Rodríguez, 1997). In the last few years, the improvement in communications has brought about a growth process in Ribadeo, largely determined by the major road, which runs along a coastal plain. Urban land uses concentrate along the major road and along the secondary roads that converge on it because of the proximity of Ribadeo urban core. Therefore, urban land uses are established mainly in flat parcels near main roads or in Ribadeo urban core. The proximity to the shore does not exert a positive influence because of the laws that ban construction in a 100 m stripe along the coast. As a result, slope, accessibility, closeness to Ribadeo urban core and closeness to the shore constitute main drivers of urban growth in the area (García, Santé, Crecente, & Miranda, 2009).

2.3. Methods

The study area has an area of 26 km^2 and comprises the town of Ribadeo and the four surrounding parishes (administrative subdivisions of Galician municipalities): Vilaselán, Piñeira, Vilaframil and Obe. Simulation data were derived from photo interpretation of aerial photographs taken in 1978, 1995, 2003 and 2007. Aerial photo data were complemented with a land use map produced in 1995 and data from the 2000 and 2005 Surveys on Local Infrastructure and Facilities. Based on this data, raster maps of roads and land uses for 1978, 1995, 2003 and 2007 were generated at 35 m resolution, which must be representative of the average parcel size (Ménard & Marceau, 2005). Because the average parcel size is 1100 m^2, a cell size of 35 m was used. In addition, slope and hillshade maps at the same resolution were derived from a digital elevation model obtained from contour curves of the Spanish national

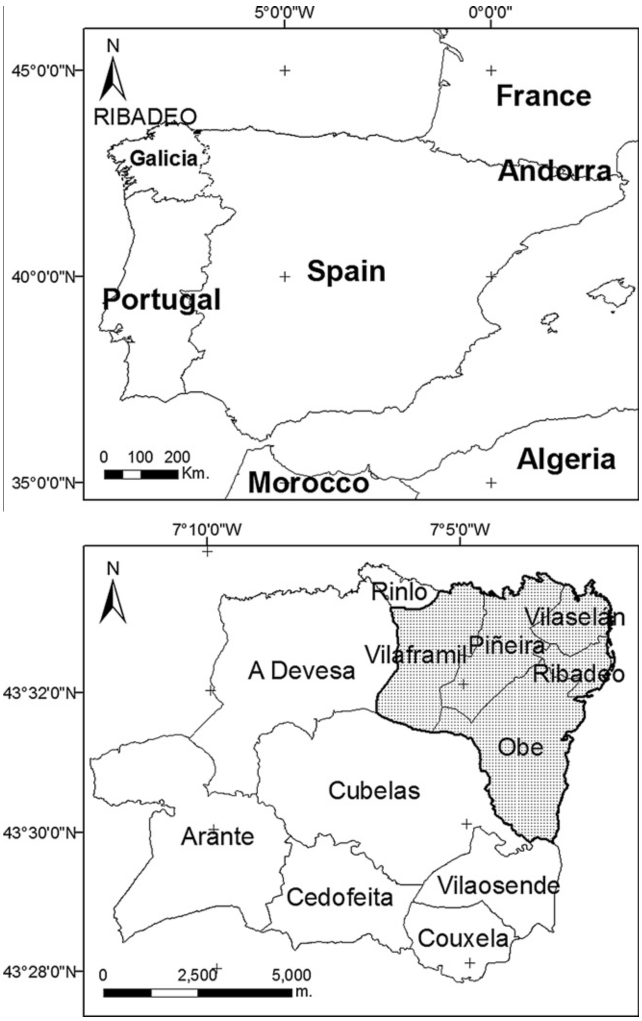

Fig. 1. Location map of Ribadeo.

topographic map (1:5000 scale). Hillshade is an input data of SLEUTH and slope is a variable used in all models. The other input variables were derived from land use and road maps for 1995. All these data were processed using ArcGis 9.2 and Idrisi Andes software.

Land use maps were classified into the following categories: agriculture, water bodies, commercial units (large shopping centers, hotels, camps, fish markets and markets), roads, excluded areas (cemeteries, churches and rocky areas), forests, industrial units (industrial plants and industrial port areas), public/institutional land uses (schools, civic organizations, day care facilities, institutional buildings or public sport facilities), parks (public gardens, green urban areas and leisure areas), residential areas and railways.

The models were calibrated using the land use maps for 1978 and 1995, except for the SLEUTH model, which required the use of maps for 3 years. For this reason, the 2003 map was included in the calibration of SLEUTH. The calibrated parameters were used to simulate urban growth between 1995 and 2007 and the land use map for 2007 was used to validate the simulation.

SLEUTH was implemented using the free software mentioned in the introduction. To implement the rest of the models, a number of independent software modules that use ASCII raster maps as input and output data were programmed in Visual Basic. ASCII raster maps can be read by most GIS software packages.

In the models inspired by White and Engelen's model, water bodies, roads, railways, institutional land uses and parks were considered as fixed land uses, and excluded areas were not candidates for change in the simulations. In MOLAND, agriculture and forests were considered passive land uses, whereas in the models developed by White et al. and Engelen et al. agricultural and forest land uses were considered idle land to be occupied by urban land uses. In SLEUTH, parks and commercial, industrial, institutional, and residential land uses were grouped into a single urban land use; excluded areas and railways were used as mask and the rest of land uses remained unchanged in order to fulfill input data requirements. Similarly, in the model of Wu, urban land uses were grouped, such that agriculture and forests were considered as non-urban land uses whereas the rest of land uses were not candidates for change in the simulation.

The total area of urban growth to simulate at each iteration was calculated by dividing the amount of growth observed for each land use between 1995 and 2007 by the number of years of this period. In SLEUTH, the total area of urban growth is controlled by two parameters which were empirically calibrated in order to obtain a total urban area close to the real one. Nevertheless, the final simulated area in the family of models of White and Engelen was overestimated by 6% due to the rounding of the divisions of the number of developed cells in the simulation period between the number of iterations. The model of Wu has underestimated the amount of growth by 2% in spite of being used the same method to determine the amount of growth in each interaction, because in this model transitions are determined by the Monte Carlo method. In the case of SLEUTH, the model parameters change depending on how the simulation evolves and therefore the amount of growth produced is very difficult to control, that is why this model has underestimated the amount of growth by 18%.

In the model of Wu, the initial probability for transition to urban is calculated using logistic regressions. The following variables were used in regressions: distance to the coast, distance to the center of Ribadeo, slope and distance to roads measured in the road map for 1995. These variables were identified as the main drivers of urban growth in the town of Ribadeo in previous studies (García et al., 2009). In order to use similar input data for all the models and to facilitate the comparison of results, the same input variables were considered. In addition, logistic regression was used to calculate the suitability for each land use in the model developed by Engelen et al. The same variables were used in the model of White et al. and in MOLAND to calculate suitability, except for 'distance to roads', which was considered in the accessibility parameter of these models (Table 1).

The family of models of White and Engelen were calibrated by expert knowledge and tuned empirically. The coefficients δ_{zj} for the calculation of accessibility in the model of White et al. and in MOLAND were determined based on expert knowledge (Table 2). To reproduce the original models as faithfully as possible, MOLAND considered three types of roads (main, secondary and tertiary roads) in the calculation of accessibility, whereas the model of White et al. considered only one type of road. This is the reason why the coefficients δ_{zj} for both models are so different.

In MOLAND, the weights w_{kd} used to calculate the effect of neighborhood were the same as the weights used by White et al. (1997) for the simulation of urban growth in the city of Cincinnati because, as suggested by White et al. (1997), these coefficients are usually similar for every city insofar as the influence of proximity to some land uses on other land uses is governed by similar rules. Yet, in MOLAND, the coefficients w_{kd} of the central cell of the neighborhood were increased when the land use present in the central cell coincided with the land use for which the effect of neighborhood was being calculated, such that the transition of urban land uses was made more difficult.

Finally, the coefficients α that control the degree of randomness in the family of CA models inspired by White and Engelen's model

Table 1
Coefficients obtained using logistic regression for the calculation of suitability in the different models.

VARIABLES	Coefficients (Moland, White)	Coefficients (Engelen, Wu)
Suitability for commercial land use		
Slopes	0.0106	−0.8716
Distance to Ribadeo	−0.0004	0.00008
Distance to the coast	−0.0006	0.0015
Distance to roads	∅	−0.0176
Suitability for industrial land use		
Slopes	−0.0141	−0.0417
Distance to Ribadeo	−0.0001	−0.0002
Distance to the coast	−0.0004	−0.001
Distance to roads	∅	0.00006
Suitability for residential land use		
Slopes	−0.0437	−0.1061
Distance to Ribadeo	−0.0013	−0.0004
Distance to the coast	0.0007	0.0001
Distance to roads	∅	−0.0068
Suitability for agriculture		
Slopes	0.0126	∅
Distance to Ribadeo	−0.0004	∅
Distance to the coast	0.0005	∅
Distance to roads	∅	∅
Suitability for forests		
Slopes	0.0356	∅
Distance to Ribadeo	−0.0002	∅
Distance to the coast	−0.0007	∅
Distance to roads	∅	∅

Table 2
Coefficients δ_{zj} used to calculate accessibility in MOLAND and White et al.

ROADS	Coefficients (Moland)	Coefficients (White)
Commercial land use		
Main roads	4.8	10
Secondary roads	0.001	
Tertiary roads	0.0001	
Industrial land use		
Main roads	5	15
Secondary roads	0.001	
Tertiary roads	0.001	
Residential land use		
Main roads	0.75	21
Secondary roads	1.1	
Tertiary roads	0.2	
Agriculture		
Main roads	1.2	∅
Secondary roads	0.001	∅
Tertiary roads	2.5	∅
Forests		
Main roads	−0.0001	∅
Secondary roads	∅	∅
Tertiary roads	∅	∅

Table 3
Coefficients α used in the models.

	Moland	White	Engelen
Commercial	1	0.6	1
Industrial	1.2	1	1.4
Residential	1.4	3.1	2.8
Agriculture	1.8	∅	∅
Forests	1.6	∅	∅

(Table 3) were calibrated using data for the years 1978 and 1995. During the calibration, various simulations were performed using values of α in the range 0–10 with 0.1 increments because it was verified that from a value of $\alpha = 10$ the allocation of urban cells was almost random and that increments below 0.1 did not clearly affect the results.

Simulation results were validated against the 2007 land use map. To compare the performance of the models, the spatial metrics described in Table 4 were used. These spatial metrics provide a measure of the dispersion and complexity of the patches of each land use simulated in the model (O'Neill et al., 1988), because the degree of complexity and dispersion of the spatial patterns of urban land uses is related to the degree of stochasticity (Dietzel, Herold, Hemphill, & Clarke, 2005; White & Engelen, 1993; Xu et al., 2007).

3. Results and discussion

The land use maps for 2007 obtained with the five models were compared with the real 2007 land use map (Fig. 2) using the figure of merit, spatial metrics and the amount of simulated and real infill growth, edge growth and dispersed growth.

3.1. Visual comparison

As shown in Fig. 3, the cell-to-cell correspondence between the real and the map simulated using MOLAND is low. Yet, establishing the correct location of each simulated land use cell is very difficult because of path dependence and stochastic uncertainty (Brown, Page, Riolo, Zellner, & Rand, 2005). The model developed by Engelen et al. (Fig. 4) locates urban cells mainly in the center of Ribadeo and does not locate enough cells along the major road and in the south of Ribadeo. The patterns generated by the model of White et al. (Fig. 5) follow the lines of the existing roads. Because the input variables of this model do not consider different types of roads, urban cells are more or less uniformly distributed along the roads, such that cells are located where no real changes from non-urban to urban land uses took place, as in the case of the coastal area to the north of Ribadeo. Urban cells concentrate mainly in the urban settlement of the town of Ribadeo and its surroundings, as well as in the surroundings of the aerodrome, located in the northwest of the study area. As a result, urban growth along the major road and to the south of the major road is underestimated.

The analysis of the errors found in the simulations of the family of CA models inspired by White and Engelen's model reveals that most errors are caused by issues not related to the model, such as a poor classification of urban uses. As demonstrated by Yeh and Li (2006), Pontius and Li (2010) and Pontius and Petrova (2010), errors due to poor classification greatly influence the model results. Such an influence can be observed in the excessive number of urban cells located by the models of White and Engelen around the aerodrome in the northwest of the study area, caused by the classification of the aerodrome as a large industrial area, which attracted urban uses. The error was increased by the construction date of the aerodrome, between 1978 and 1995, which was the period used in logistic regressions to calibrate the suitability maps. As a result, suitability maps gave priority to this area over other areas.

The errors found in suitability maps are due to difficulties in simulating urban patterns in the study area. In Ribadeo, development processes are slow and the emergence of clearly identifiable urban patterns that can be associated to specific dynamics requires long periods. This is aggravated by the non-stationarity of the processes, because the likelihood of changes in the dynamics increases

Table 4
Spatial metrics used in the analysis of the spatial pattern of urban land uses.

Metric	Name	Description	Equation
CA_i (ha)	Total area	Total area of each land-use class	$\sum_{j=1}^{n_i} a_{ij}\left(\frac{1}{10000}\right)$
NP_i	Number of patches	Number of patches for each land-use class	n_i
LPI_i (%)	Largest patch index	Percent landscape occupied by the largest patch of land-use class i	$\frac{\max(a_{ij})}{A} \times 100$
$FRAC\_AM_i$	Area-weighted mean patch fractal dimension	This index suggests the degree of complexity of the patches. The value of the index approaches 1 for patches with simple perimeters such as squares, and 2 for patches with highly complex and space-filling perimeters. Because $FRAC\_AM_i$ is an area-weighted index, the largest patch index will be given more weight when calculating the mean.	$\frac{\sum_{j=1}^{n_i}\left(\frac{2\ln(0.25p_{ij})}{\ln a_{ij}}\right)a_{ij}}{n_i}$
ENN_AM_i (m)	Area-weighted Euclidean nearest neighbor distance	This index suggests proximity between patches. Because ENN_AM_i is an area-weighted index, the distances from the largest patches to their neighbors will be given more weight when calculating the mean.	$\sum_{j=1}^{n_i}\left[h_{ij}\cdot\left(\frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}}\right)\right]$

a_{ij} = area of each patch j of class i in m^2, n_i = number of patches for class i, A = total landscape area, p_{ij} = perimeter of each patch j of class i in m, h_{ij} = straight-line distance from patch j of class i to the nearest patch of class i measured from the center of the cells nearest to the edges of the patches.

for longer periods, which makes the identification of the urban processes more difficult (Pontius et al., 2008).

Such shortcomings can be observed in the evolution of the commercial land use. During the calibrated period, commercial cells along the main road are dispersed and scarce, and the commercial land use is still not concentrated at the confluence of the major road with the northern road that encircles Ribadeo, as in subsequent years.

The presence of such a low growth calls for the use of a more detailed cartography that is able to represent the urban patterns observed and, therefore, for a finer spatial resolution, which results in a greater difficulty in obtaining an accurate simulation.

The simulations performed with SLEUTH (Fig. 6) underestimate the emergence of urban cells in the south of Ribadeo. In addition, SLEUTH produces some errors caused by not considering more than two land uses. For example, in the west end of the map, the urban cells simulated by the model around two existing large urban patches do not correspond to real growth, but to a single-family detached house surrounded by a large garden and to a large industrial building with a storage area, respectively. Because the model does not consider several urban land uses, these parcels are identified as two urban cores that attract other urban uses. This limitation of the SLEUTH model was already identified by Berling-Wolff and Wu (2004).

The model developed by Wu does not locate urban cells correctly along the coastal road and overestimates growth in the south of Ribadeo (Fig. 7). Such a poor simulation along the major road is due to the fact that the model does not consider several types of road in the estimation of the suitability parameter. The main problem of the model developed by Wu is the poor simulation of dispersed patterns but, overall, the patterns generated by this model are near the real patterns.

3.2. Figure of merit

The Figure of merit is obtained from the number of hits (observed change predicted as change), misses (observed change predicted as persistence) and false alarms (observed persistence

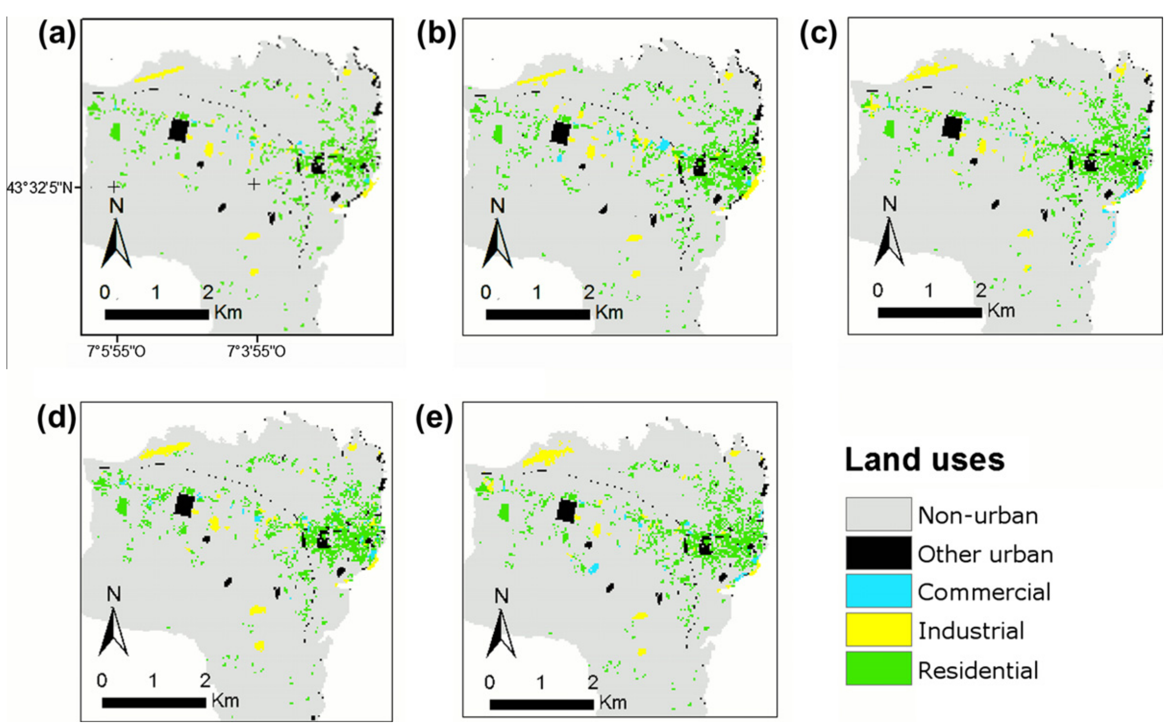

Fig. 2. Land-use maps; (a) 2007 real, (b) 1995 real, (c) 2007 simulated map using the model of White et al. (1997), (d) simulated map using the model of Engelen et al. (1999) and (e) simulated map using MOLAND.

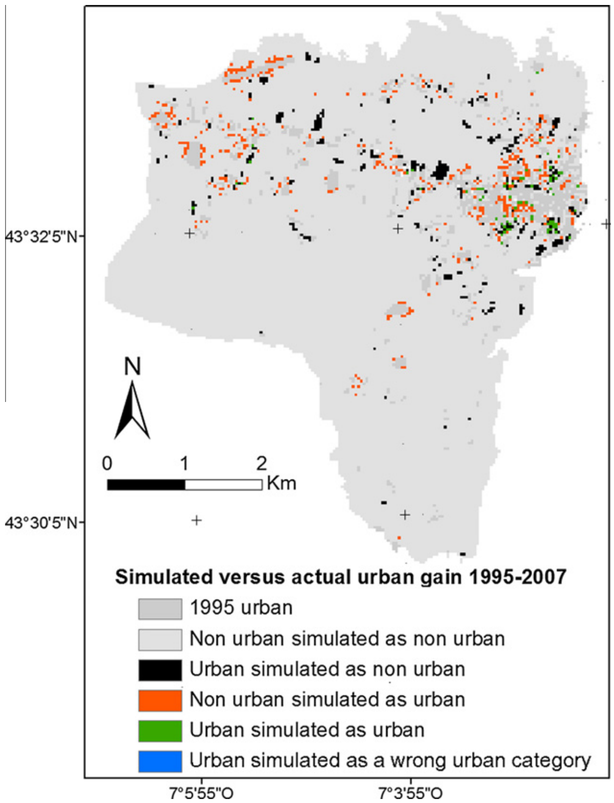

Fig. 3. Map of actual versus simulated urban gain between 1995 and 2007, using MOLAND.

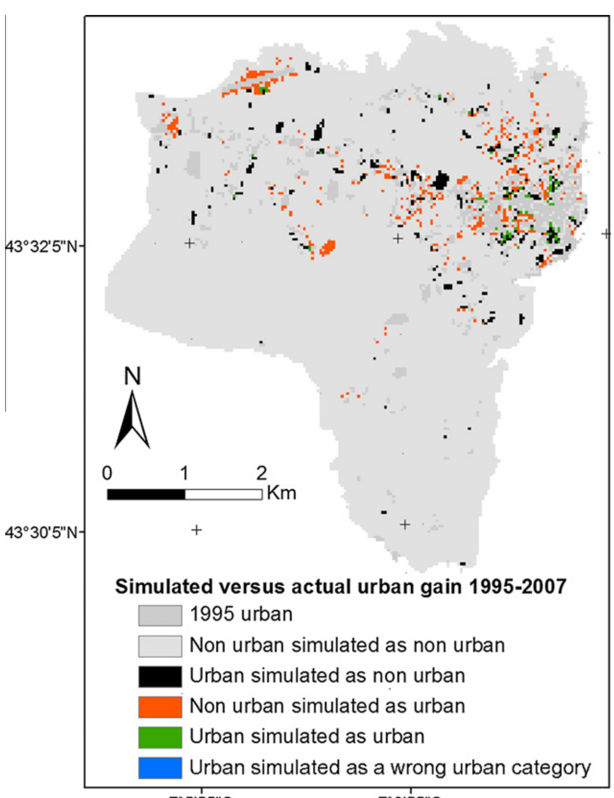

Fig. 4. Map of actual versus simulated urban gain between 1995 and 2007, using the model of Engelen et al.

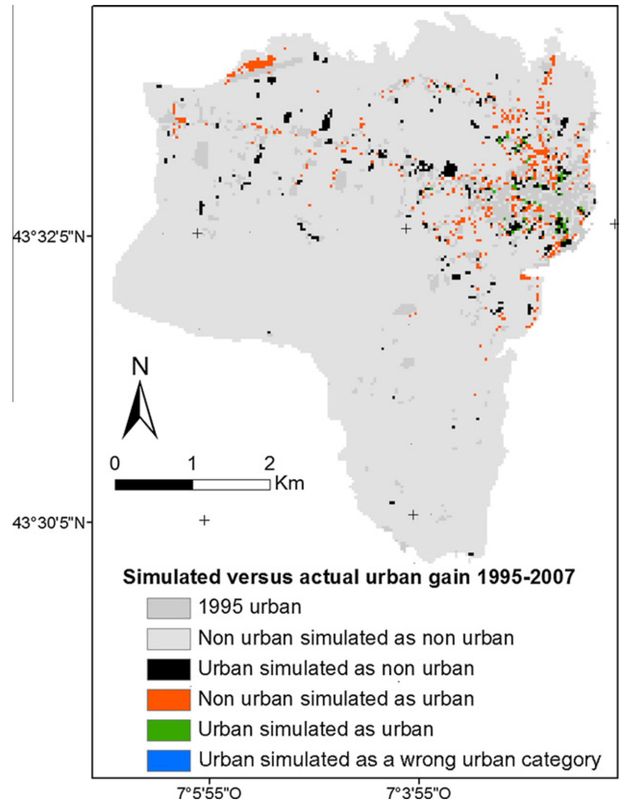

Fig. 5. Map of actual versus simulated urban gain between 1995 and 2007, using the model of White et al.

predicted as change) (Chen & Pontius, 2011) and, in the models that simulate several land use categories, from partial hits (observed change predicted as change but in a wrong land use category) (Pontius et al., 2008). The figure of merit is calculated dividing the hits between the addition of hits, misses and false alarms and, in the case of the models that simulate several categories, removing the partial hits from numerator. This measure allows to assess the cell-to-cell coincidence between simulated and real maps in a more realistic way than more common metrics as kappa index or overall accuracy which are usually calculated using the entire surface area (Santé et al., 2010). As an example, the overall accuracy of 93.1% obtained by Jantz, Goetz, and Shelley (2003) with SLEUTH was reduced to 19% when the area with fixed land use was excluded, in a study area in which the developed area accounted for a high percentage (22%) of total area. According to the figure of merit calculated with hits (Table 5), MOLAND and the model of Engelen are the models that produced more matches with the real maps. However the model of White, in which they are inspired, is the one that has produced less matches. SLEUTH and Wu fall in between. When partial hits are subtracted from hits the figure of merit diminishes between 38% and 49%.

Nevertheless, the capacity of a simulation algorithm to match the exact location of land use change is very low and even not necessary (Jantz & Goetz, 2005), since the objective of these models is to generate urban patterns similar to real urban morphologies. That is why other metrics have been used to analyze the spatial structure of model results.

3.3. Spatial metrics

Spatial metrics are used to objectively characterize the urban patterns observed in the visual analysis in order to make qualitative comparisons and to determine whether simulated patterns

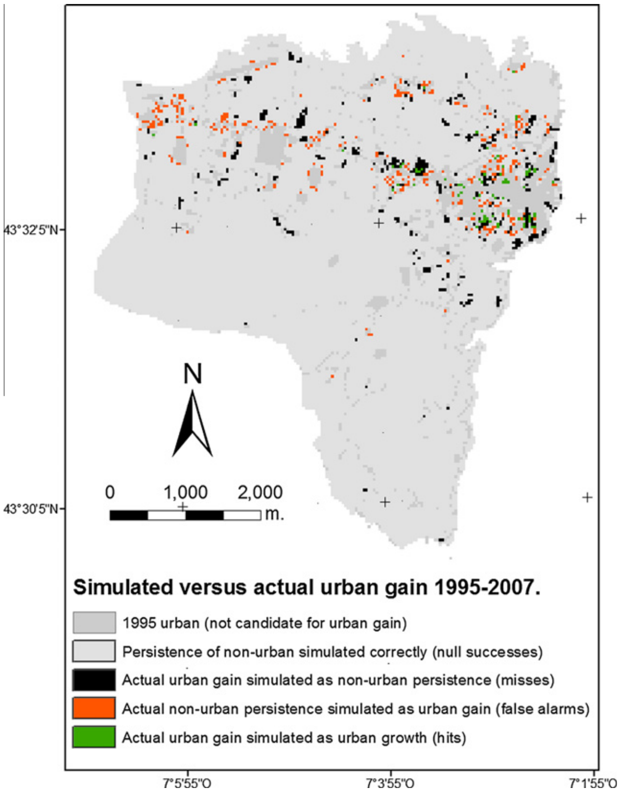

Fig. 6. Map of actual versus simulated urban gain between 1995 and 2007, using SLEUTH model.

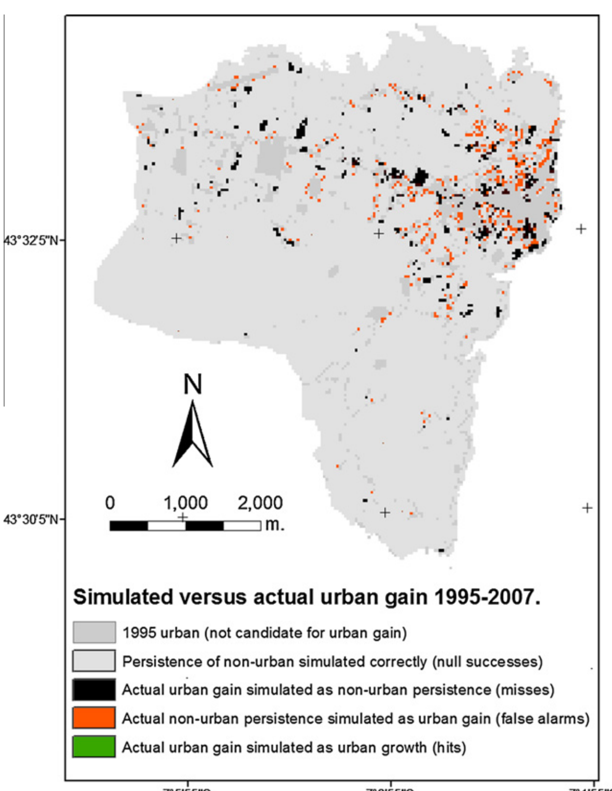

Fig. 7. Map of actual versus simulated urban gain between 1995 and 2007, using the model of Wu.

are more compact or complex than real patterns. The spatial metrics for the residential, commercial and industrial land uses of the models that considered several urban land use classes were analyzed first (Table 6). Then, the overall results obtained with all the models for the urban land use class were analyzed (Table 7).

According to the analyzed spatial metrics, the model that produces the spatial pattern of the commercial land use that comes closest to the real one is the model of Engelen et al. Yet, the model produces too many patches, which are smaller and more dispersed than real patches.

For the industrial land use class, none of the models produces a pattern clearly close to the real one. The values of spatial metrics suggest that the model by Engelen et al. produces larger and more compact patches, followed by the model of White et al. However, this situation is caused by the concentration of cells around the aerodrome generated by the models, as suggested above.

For the residential land use class, none of the models produces a pattern substantially close to the real pattern observed. The model of Engelen et al. produces the largest number of patches, as well as the smallest and most dispersed patches, while the MOLAND model produces the lowest number of patches, and the biggest and least dispersed patches.

To compare the results of all the models, the residential, commercial and industrial land use classes were grouped into a single class on which the spatial metrics were computed. Table 7 shows that, in general, the spatial pattern for the urban land use produced by the model of Engelen et al. is most similar to the real pattern. The models developed by White et al. and MOLAND produce patterns more similar to real patterns than those produced by the model of Wu and SLEUTH. The three models show values near the real values for spatial metrics.

The model developed by Wu generates the lowest number of patches, which are much larger and more clustered than those produced by the rest of models, because in this model the cells that do not have neighboring urban cells have a null transition probability, such that small new growth patches cannot be generated.

As compared to the models inspired by White and Engelen's model, the number of patches generated by SLEUTH is much lower and patches are larger and more clustered. However, SLEUTH produces more and smaller patches than in the model of Wu because SLEUTH can simulate spontaneous new growth. SLEUTH produces larger and more clustered patches than the models developed by White because, during the period used for calibration, dispersed growth occurred in patches of more than 3 cells near the roads. This pattern is similar to the growth pattern simulated by the SLEUTH model through road-influenced growth, which is controlled by the road gravity coefficient. During the calibration, the road gravity coefficient varies considerably because of the location of isolated patches, which are scattered over a wide area in the proximity of roads. Such a variation is due to the lack of a well-structured road network in this small urban area, which is essential for the good performance of SLEUTH, a model designed for cities with this kind of road network. For this reason, the calibration procedure cannot obtain a suitable value for the road gravity coefficient.

3.4. Analysis of types of growth

The types of growth (infill growth, edge growth and new growth) generated by each model was analyzed using the index proposed by Xu et al. (2007), which is determined by dividing the length of the common boundary of a newly grown urban area and the pre-growth urban patches by the total perimeter of the newly grown area. If the index takes a value above 0.5, the patch is identified as infilling growth, if it takes a value between 0 and 0.5, the patch corresponds to edge-expansion growth, and if the va-

Table 5
Figure of merit for each model.

Models	Figure of merit %	Figure of merit (without partial hits) %	Hits (cells)	Partial Hits (cells)	Misses (cells)	False alarms (cells)
MOLAND	10.7	5.49	102	25	408	438
Engelen	9.8	6.07	94	18	416	446
Wu	9	–	83	–	427	416
SLEUTH	8.8	–	75	–	435	341
White	8.1	4.22	79	19	431	461

Table 6
Simulated and real spatial metrics for the commercial, industrial and residential land use classes for 2007.

CLASSES	CA	NP	LPI	FRAC_AM	ENN_AM
Commercial Engelen	10.05	19	0.05	1.08	332.15
Commercial White	10.05	23	0.05	1.07	291.74
Commercial MOLAND	10.05	26	0.03	1.08	255.00
Commercial (2007)	9.56	13	0.06	1.05	252.12
Commercial (1995)	4.17	10	0.02	1.03	350.12
Industrial Engelen	40.79	36	0.28	1.10	215.85
Industrial White	40.79	39	0.24	1.11	247.79
Industrial MOLAND	40.79	46	0.22	1.08	335.91
Industrial (2007)	36.75	40	0.15	1.08	227.58
Industrial (1995)	23.28	31	0.06	1.06	362.55
Residential Engelen	177.63	233	1.16	1.19	85.72
Residential White	177.63	227	1.46	1.21	87.47
Residential MOLAND	177.63	222	1.32	1.20	81.33
Residential (2007)	173.58	224	0.98	1.16	88.69
Residential (1995)	129.36	218	0.43	1.11	95.32

lue of the index is 0, the patch is identified as spontaneous growth. The types of growth simulated by each model were compared with the real ones (Table 8).

The models that yield the best results for these metrics are the models inspired by White and Engelen's model, whereas the model of Wu and the SLEUTH model produce an excess underestimation of new growth and an overestimation of infill growth.

Within the family of models inspired by White and Engelen's model, slight variations between the three models are observed. Moland is the model that comes nearest to real percentages of each type of growth.

As compared to real growth and to the growth simulated by the other models, the model of Wu and the SLEUTH model produce much lower new growth and much higher infill growth, whereas the values of edge growth are similar to the values obtained from the other three models and slightly higher than real values. These results confirm the difficulties of the Wu model in simulating new growth. The results produced by SLEUTH for the analyzed types of growth are very similar to the results produced by the model of Wu, but SLEUTH has the capability to generate spontaneous growth.

Table 7
Simulated and real spatial metrics for the urban land use class for 2007.

CLASSES	CA	NP	LPI	FRAC_AM	ENN_AM
Urban Engelen	247.33	233	1.68	1.20	86.13
Urban White	247.33	221	1.92	1.21	92.7
Urban MOLAND	247.33	214	2.03	1.21	83.64
Urban SLEUTH	247.33	179	1.87	1.19	102.27
Urban Wu	250.76	155	2.06	1.21	100.68
Urban Real (2007)	242.18	230	1.59	1.18	89.12
Urban Real (1995)	176.89	219	0.58	1.14	96.07

4. Conclusions

This paper compares some of the most widespread urban CA models to assess how these models conform to the simulation of urban land use change patterns in a study area with different characteristics from those in which these models are commonly applied. The urban expansion of the town of Ribadeo was simulated with the different models and the resulting urban patterns were analyzed by using visual inspection and spatial metrics.

The results reveal that the greatest difficulties in simulating urban growth in Ribadeo are derived from a need for great detail. This is because urban growth in the study area is low and there is not information enough to identify clearly growth dynamics, thus great level of detail is needed so as to obtain as much information as possible. In addition, the dynamics of urban expansion in Ribadeo evolve slowly and the emergence of well-defined patterns that allow the interpreter to identify these dynamics requires long periods. Because changes in urban dynamics are more probable in long periods than in short ones, the extrapolation of past trends becomes more difficult. Briefly, the simulation of the evolution of urban land uses in the study area involves a finer spatial resolution and longer time periods, which makes the assumption of stationarity by the model rules more difficult. In addition, specific events or characteristic factors of the study area may condition the evolution of global urban patterns substantially. For example, with the construction of the northern beltway that surrounds the town of Ribadeo and gives access to the Ponte dos Santos bridge, the junction of the beltway and the main road met the ideal conditions of accessibility and proximity to an urban settlement for the creation of a large shopping center that soon attracted other commercial land uses that filled an area devoted to industrial land uses. Consequently, industrial land uses searched for dispersed locations along the major road. Such specific characteristics demand models that are capable of simulating complex dynamics with a large number of influencing factors and an accurate calibration that allows for the consideration of the underlying dynamics. Taking these needs into consideration, the following conclusions can be drawn:

Because the quantity of simulated change is difficult to control in all the models, particularly in SLEUTH, it would be interesting to develop new methods to improve the control of the amount of growth.

MOLAND and the model of Engelen et al. produce higher values of the figure of merit when hits are used for its calculation. The value of the figure of merit of these models decreases significantly when partial hits are removed from hits, however this measure cannot be used for comparison with models in which this type of error does not exist. Anyway, as previously explained, a more interesting measure for model validation is the capacity of the model to capture urban growth patterns. MOLAND has produced growth patterns closer to the real ones than the other models. Overall, all the family of models inspired by White and Engelen's model produce values closer to the real ones for the spatial metrics and the types of urban growth considered. The values of these spatial metrics for the pattern produced by the model of Wu are quite

Table 8
Types of growth simulated by each model and real types of growth.

Model	Number of cells				Percentage		
	New	Edge	Infill	Total	New	Edge	Infill
Engelen et al.	170	339	32	541	31.1	62.6	5.8
White et al.	150	347	44	541	27.7	64.3	8.4
Moland	123	350	68	541	22.7	64.7	12.6
Sleuth	56	345	140	541	10.4	63.8	25.8
Wu	57	361	150	568	10.0	63.6	26.4
Real	163	317	69	549	29.7	57.7	12.6

different from the values of the real pattern, while SLEUTH produces intermediate values that slightly improve those of the model of Wu.

The model developed by Wu and SLEUTH show a common drawback: both models consider only the evolution of a general urban land use. Because none of these models consider the dynamics of multiple categories of urban land, they may produce simulation errors such as those found in the visual inspection of results, caused by the lack of differentiation between a single-family detached house with a large garden and a group of single-family detached houses. On the contrary, the models inspired by White and Engelen's model consider various urban land uses, which allows for a more complex analysis of the dynamics that generate growth patterns. These models simulated growth patterns closer to the real ones, which proves that considering the interactions between multiple land uses avoids generalizations and increases the flexibility of the model for the simulation of different situations and events, such that the specific factors and dynamics of the analyzed urban area can be more easily incorporated into the simulation. As explained in the previous paragraph, this may be particularly interesting for the simulation of the growth of areas similar to that of the study case, that is, areas with low urban growth where specific events can have a great influence on the global urban pattern.

Another drawback of Wu's model is the difficulty in simulating spontaneous growth because of the fact that the cells that do not have neighboring urban cells have null transition probability.

In contrast, the greater complexity of the models inspired by White and Engelen's model makes them more prone to introducing errors in the simulation, such as errors derived from a poor or inaccurate classification of land use classes. An example of this behavior is the large increase in the industrial land uses generated by these models around the premises of the aerodrome of Ribadeo caused by the inability of the models to differentiate these facilities from a large industrial area that attracts other industrial land uses. The greater complexity of these models results in a greater complexity of calibration, which is reflected in the large number of parameters involved in these models. In the case study analyzed in this paper, which considered only three active land uses, three variables for the calculation of suitability and one variable for the calculation of accessibility, a total of 177 coefficients were calibrated. The authors of the models determined the value of the coefficients based on expert knowledge. This approach can be useful in the simulation of areas with a high and fast urban growth analyzed at global scales, in which urban growth patterns and dynamics can be relatively easily identified. In Ribadeo, growth is low and slow, and identifying well-defined patterns and dynamics becomes more difficult. Consequently, the simulation of this area could be improved by using calibration methods based on optimization techniques that allow the user to accurately adapt the model to the characteristic dynamics of the area. Indeed, MOLAND produced more realistic urban patterns near the road network than the model of White et al. because MOLAND considered various types of roads (and, consequently, various coefficients) in the calculation of the effects of road type on the transition potential, instead of a single type of road and, consequently, a single coefficient.

Overall, in the study area, the drivers of change are not uniform across the space, whereas models assume uniformity across space in their rules. Models that consider several land uses and neighborhoods, as the models of White and Engelen, can reduce this shortcoming by means of calibration. However, these models must be provided with more objective and reliable calibration methods that allow for a more accurate capture of past trends. Some errors of the simulations generated by the model of Wu and by SLEUTH in the study area are due to not considering various urban land uses, for example, the overestimated urban growth around large low-density residential areas. Berling-Wolff and Wu (2004) and Dietzel and Clarke (2006) improved SLEUTH simulations by adding new land uses to the model and extending the neighborhood. These conclusions could be extrapolated to other areas with similar characteristics, that is to say, with slow urban dynamics, low urban growth and great influence of specific events or factors on the global urban pattern and lack of a well-structured road network.

Finally, a weakness common to all CA-based models, which are focused on the reproduction of spatial patterns, is the difficulty to model socioeconomic dynamics and decision making processes regarding land use (Irwin & Geoghegan, 2001). This shortcoming is overcome by Agent Based Models (ABM), which are process-based but have limitations for the spatial representation of these processes (Crooks, Castle, & Batty, 2008). Other models (i. e., Hunt & Abraham, 2005; Waddell et al., 2003) that analyze socioeconomic issues, require a great deal of information, such as economic or social data, which are usually difficult to obtain and disaggregate spatially. Thus, further research could be focused on the integration of CA and ABM with the aim of providing urban CA with a better developed theoretical background (Santé et al., 2010) and creating spatially explicit ABM (Torrens & Benenson, 2005).

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