THREE LAND CHANGE MODELS FOR URBAN DYNAMICS ANALYSIS IN SINTRA-CASCAIS AREA

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ABSTRACT

In this paper we investigate urban dynamics of Sintra-Cascais municipalities (Portugal) between years 1989 and 2025 using three different land change models: two cellular automata-based models (i, ii) and Geomod (i). Classified data of three Landsat time series satellite images (1989, 1994 and 2001) obtained after image segmentation and a texturing procedure (iii) are used as input together with suitability maps to predict urban growth scenarios with two classes (urban; not urban). Models' validation and performance are assessed comparing predicted year of 2001 against year 2001 real classification using five statistical indices and CPU processing time. Two different resolutions are tested: pixels and the objects obtained by image segmentation for the classification of image of 2001. Results indicate that one must use same level of abstraction employed in image classification to assess accuracy of models' outputs. All models' simulations increased their accuracy significantly after changing resolution from pixels to objects. Forecasts are presented and analyzed for year 2025 using the three models.

INTRODUCTION

Urban studies are becoming important tools for planners knowing that in 2015 more than half world's population will be living in cities (iv). Models are, perhaps, the best way of understanding the land change phenomenon and anticipate correct planning activities for sustainable cities. This is an important topic in current research agenda and a significant number of scientists are dedicating efforts in the study of this phenomenon (v, vi, vii).

The decision about which model to use may not be an easy task. Complexity of the phenomenon to model, data requirements and type of outputs vary significantly and one must leverage all these factors before taking the decision of choosing a model. In this study, we compare three models to study urban growth in Sintra-Cascais municipalities. Two models based on cellular automata techniques – CA_Markov model implemented in Idrisi Kilimanjaro (i) and CA_Markov model (we call it as CA_Advanced) implemented in a software developed by (ii) and Geomod also implemented in Idrisi Kilimanjaro (i). Markov type models are based on the Markov chains proposed by the Russian mathematician Andrei A. Markov in 1907. These models only became spatially explicit in early 1990s when they started integrating a cellular automata component allowing transition probabilities of one pixel to be a function of the neighbouring pixel (viii). Several urban studies have been based in the use of CA and Markov chains like (viii, ix, x) among many others. Geomod is a more recent and simpler model and was originally designed to simulate the loss of tropical forests and to estimate the resulting carbon dioxide emissions (xi, xii). This model uses the quantities specified by the user (instead of a transition matrix) and a suitability map to simulate change of a single category using a linear relationship between beginning and ending time amounts.

The most employed criterion for validating land-cover change models is based on the percentage of correct classified pixels obtained from comparison of a real map against the output of the model. However, a high number of correct classified pixels does not mean that the model has a good predictive power between two time moments due to temporal autocorrelation (xiii).

In this study, the performance of models is assessed comparing accuracy of estimated map of 2001 against the null model (i.e., no change) using five different statistical indices: percent correct, Kstandard (xiii), Kno, Klocation (xiv, xv) and Khisto (xvi). The first two indices are widely used in remote sensing studies. However, they are insufficient to compare two maps because they fail to evaluate patterns, quantities and location of change (xvi, xvii). Percent correct is a simple ratio between the numbers of correct classified pixels of the model's output and the correct pixels of a reference map. Kstandard expresses the degree to which a particular category agrees between two dates. Kno is a variation of the standard kappa index of agreement and gives the overall accuracy of a simulation run. Klocation and Khisto validate the model's ability to predict location and quantity. Kno, Klocation and Khisto are equal to 1 when the model prediction is perfect, and are equal to 0 when the model prediction is equivalent to that due to chance. The computational performance of the models was also evaluated by measuring the time necessary to run the models.

In this research, two different resolutions are employed in model validation and accuracy assessment: pixels and objects obtained by year 2001 image segmentation. Image objects validation was reasonable because image classification was performed over objects obtained by image segmentation.

STUDY AREA

The study area comprises the Sintra-Cascais municipalities with an area of 416 Km^2 (Figure 1).

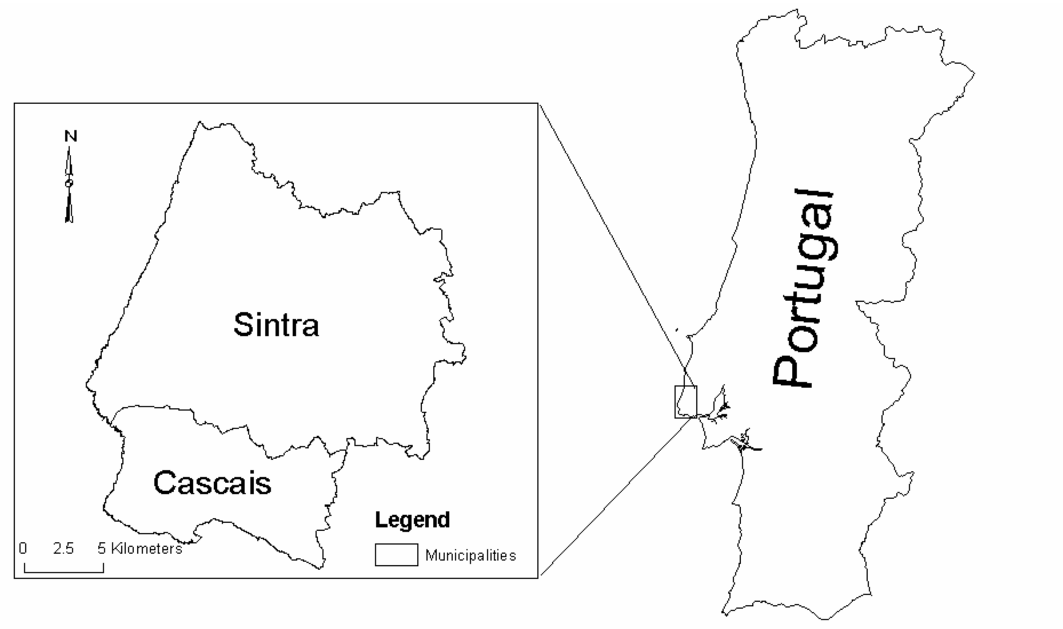

Figure 1:Study area.

This area faced high rates of demographic growth between 1990 and 2000 (29%) (xvii) which caused significant land use and land cover change. The resulting strong urban pressure in recent years is threatening natural characteristics with economic and life quality consequences. Modelling urban growth in this area may provide useful insights about the characteristics of this phenomenon.

DATA

Classified data obtained after image segmentation and a texturing procedure (iii) was used as input for modelling. This information was originally extracted from two Landsat TM and one ETM+ images. The 1989 (14-03-1989) and 2001 (8-04-2001) images were downloaded from Global Land Cover Facility of the University of Maryland (USA). The 1994 TM (8-02-1994) image was specifically acquired for the purpose of this research. The image objects obtained by image segmentation for year 2001 image were employed to assess model's validation and accuracy (Figure 2). The suitability maps were built with information derived from digital orthophotos of the Portuguese Geographical Institute (IGP) (distance to roads and urban centres maps) and NASA's Shuttle Radar Topography Mission (slope map). Administrative data from IGP was also employed in this research.

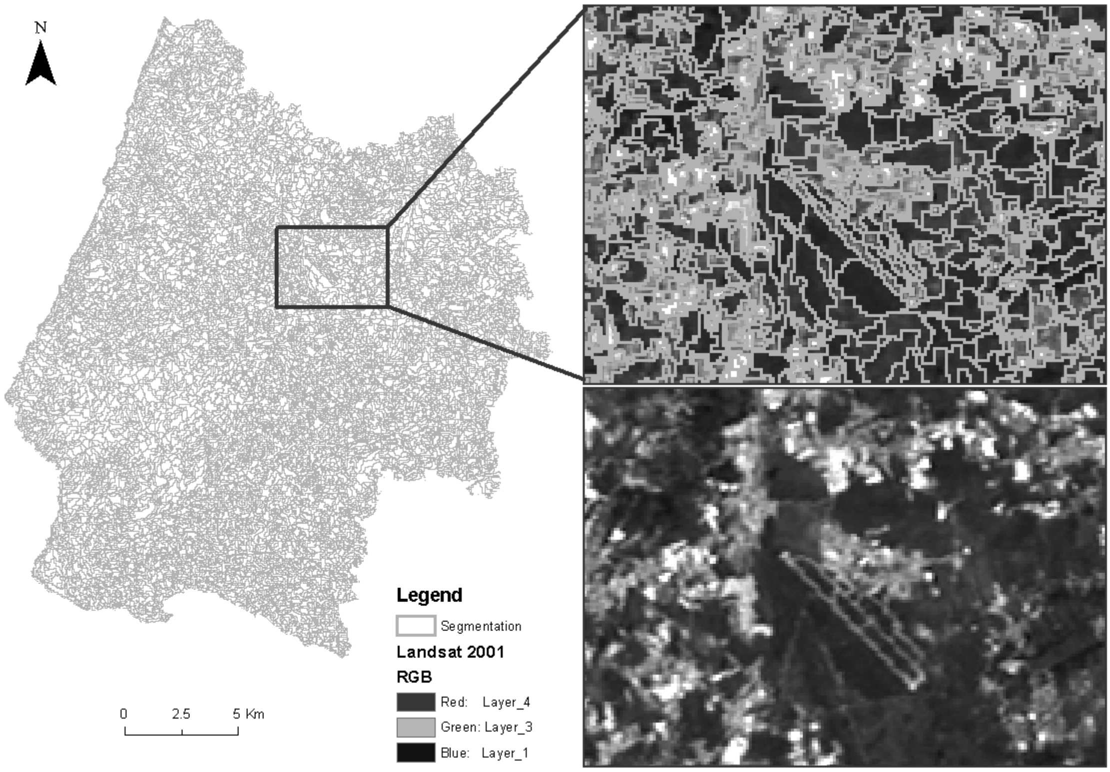

Figure 2: Image objects obtained by image segmentation employed in model's validation and accuracy assessment.

DESCRIPTION OF THE MODELS AND CALIBRATION

In this section, a short description of the three models and calibration procedure employed in this research is provided.

CA_Markov and CA_Advanced models

CA_Markov and CA_Advanced models can model the state of several categories of a pixel based on a transition matrix, suitability maps and on a contiguity filter. They enable the study of more complex phenomena than with Geomod that only allows the simulation of the transition from one category to another.

In both Markov models, the quantities of each category in time moment t_2 are obtained by estimating variations in quantities for each category in time moment t_0 and t_1. This estimation results in a non-spatial transition matrix that is calculated from variations in quantities of the categories in the data employed to calibrate the model, which are for estimating year 2001 (t_2) respectively, t_0 = 1989 and t_1 =1994 in our case study. This constitutes one of the assumptions for this type of models: transition conditional probabilities are constant over time (what is not always the case in reality!).

The location of change is determined by suitability maps, ranking and a contiguity filter. The suitability maps determine which pixels will change according to the largest suitability. These maps can be generated using a deductive approach like multi-criteria evaluation or an inductive approach like logistic regression (vi). In our study, for the modelling process of both CA_Markov and CA_Advanced models, the employed suitability maps predict the transitions of categories built and non-built up areas and were generated by the Geomod module. These suitability maps were designed for the thematic map for t1 =1994 using the following driving factors: urban areas for t0 = 1989, distance to urban centres (pixels that are closer to urban centers are more suitable for urbanization), distance to main roads (pixels that are closer to main roads are more suitable for urbanization) and slope (flatter areas are more suitable for being urbanized). Equal weights were applied to all these factors. The information employed in the generation of the suitability map was coincident wit the calibration period, i.e., roads that were built after 1994 were not included.This information was combined into a single probabilistic suitability map that aggregates all previously mentioned driving factors (Figure 3). In order to compare models' performance fairly, the same suitability map is employed in the three land cover change models.

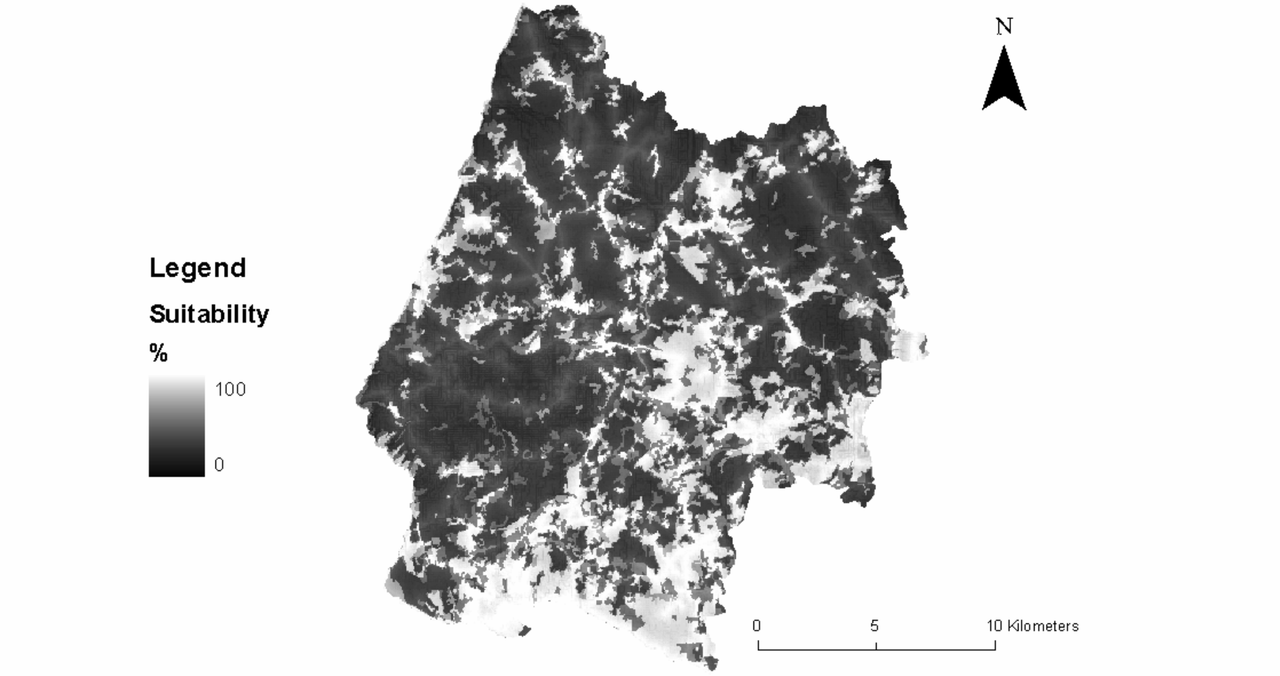

Figure 3: Suitability map employed to predict urban areas in 2001.

Markov models implement the 1st law of geography by using a contiguity rule: a pixel that is near an urban area is more likely to become an urban pixel than one pixel that is farther. The suitability value of each pixel is determined by the existence or not of pixels of the same category in a defined neighbourhood: if more pixels of the same category exist in the defined neighbourhood the suitability value for that category increases. Otherwise, the suitability value is maintained. The proximity is determined by a user-defined spatial filter. In this study both Markov models were tested with different sizes of contiguity filters (e.g., 3x3, 5x5 and 7x7).

The next important issue for both CA models is defining a rank to determine which of the pixels are going to change their category during the modelling process. In both Markov models this ranking is based on a final probabilistic value of land cover change – if a pixel refers to the highest final probability value, it needs to have the highest rank value in order to be changed. The difference between the models here is due to the final probability calculation. In the CA_Advanced model this probability calculation process is more complicated when compared to CA_Markov model (ii). CA_Advanced incorporates such components as a common probability in an analyzed neighbourhood, a spatial component based on an enrichment factor and a probability based on the suitability maps.

The final probability is based upon the transition probability matrix elements. Here the transition probability of a state ω_i to a state ω_j in an analyzed neighborhood depends not only on the probability p_{ij} but on the number of elements with the state ω_j in the neighborhood. For each state in the analyzed neighborhood, coinciding with the elements of a current cellular automaton, probability $p_{ij}^{prob} = n_j \cdot p_{ij}$, is defined, $j = 1,2,\ldots, m$, m — the number of states in the analyzed neighborhood, n_j — the number of elements with state ω_j in the neighborhood.

The spatial component of CA_Advanced transition rules is based upon spatial characteristics of each land cover type using the enrichment factor proposed in (xviii). The application of this technique is described as follows. A corresponding vector $F_i^{enr} = \{f_1, f_2,\ldots, f_M\}$ for each state ω_i is constructed, $i = 1,...,M$, M — the number of land cover types. Vector F_i^{enr} contains information about the enrichment of type ω_i on the whole image. Then for each pixel on the image the local enrichment vector F_i^{loc} is calculated. After that the probability p_{ij}^{spat} is defined for every location as $p_{ij}^{spat} \sim 1/d(F_i^{enr},F_i^{loc})$, where d — Euclidian distance between the vectors.

Thus, when all components are defined the final transition probability of the initial image elements can be represented as $p_{ij}^{fin} = f_{CA}(p) \sim (p_{ij}^{prob},p_{ij}^{spat},p_{ij}^{df})$, where p_{ij}^{df} – a probability on the basis of driving factors and suitability maps. Besides, the optimized original software of CA_Advanced model allows performing the modelling process with significant computational performance.

More detailed description of CA_Markov and CA_Advanced models, including their mathematical features, can be found in (ix) and (ii) accordingly.

Geomod model

In Geomod, we can simulate the transition from one category to another. This model only needs one time moment to make an estimation based on expected time quantities, a suitability map and, optionally, a contiguity rule. One can specify predicted quantities arbitrarily but, for the sake of comparison, we will use in our study the same predicted quantities obtained with Markov transitions for the three models. Geomod assumes persistence of the phenomenon to be modelled, i.e., if a pixel was classified as urban in 1989 it will remain urban in 2001. This situation is different from Markov models and reality but, it is acceptable for this phenomenon as it very unlikely that an urban area becomes not urban for the time period in analysis. The suitability map and the optional contiguity rule work the same way as in Markov models.

Geomod, unlike the two other tested models in this study, enables the generation of suitability maps using driving factors and existing urban areas in 1989. Information of the urban areas of 1989 ensured that a pixel that was urban in 1989 remained urban in 2001 during urban growth process. Both constrained (using different sizes) and unconstrained options were tested. In the constrained mode, a user-defined filter assigns a larger suitability to the non-built pixels that are near existing built pixels. In the unconstrained mode, selection of pixels that will change to urban is based uniquely on the suitability map.

RESULTS

Models' validation was performed using five statistical indices: percent correct, Kstandard, Kno Klocation and Khisto. In table 1 are presented the best values obtained at pixel level after different combinations of filter sizes and weights used in the generation of the suitability maps.

Table 1: Best validation values obtained for model validation at pixel level (x100) and CPU time

Indices/Models	CA_Markov 5x5 filter	CA_Advanced 3x3 filter	Geomod 5x5 filter	Null model 1994 Vs 2001
% correct	**80.81**	80.24	80.51	80.00
Kstandard	58.93	58.77	**58.97**	57.35
Kno	**61.61**	60.48	61.02	59.99
Klocation	**67.75**	58.78	61.90	64.57
Khisto	86.98	**99.98**	95.26	88.82
CPU (min)	6	**≈ 1**	38	-

Both Markov models' simulations presented similar values for these indices and performed better than the null model. Only Geomod performance was slightly below the null model. CA_Markov was only exceeded by CA_Advanced in Khisto index. This latter model was the fastest of all models tested using a Pentium III, 1 Ghz with 512 Mb of RAM needing about one minute to run.

One of the case study features is that only a small land use change has taken place during the observed period. Validation values obtained were not satisfactory and were too close to the ones obtained by the null model. Other factors could also have been responsible for these results like inadequate suitability maps to model the urban phenomenon, insufficient accuracy of classification of the satellite images and/or different abstraction levels in the modelling process. The first factor is not easy to demonstrate due to the lack of data alternatives. Anyway, several strategies for building the suitability maps were tested to select the best combination of driver factors and weights. The image classification procedure was made using standard accuracy assessments for remote sensing data and was above accepted minimum levels of accuracy (iii). The third factor was investigated by using the same level of abstraction to assess models' performances. Classification of data was performed over objects obtained by image segmentation and the models simulated change over individual pixels. Models' results in pixels were converted into objects using a simple overlay rule: if object of year 2001 has its centre in a pixel classified as urban by the model output then we consider that object urban. After this procedure, the following validation statistics were obtained (Table 2).

Table 2: Best validation values obtained for model validation at object level (x100)

Indices/Models	CA_Markov 5x5 filter	CA_Advanced 3x3 filter	Geomod 5x5 filter	Null model 1994 Vs 2001
% correct	83.59	**83.95**	82.96	80.00
Kstandard	64.82	**66.28**	64.02	57.35
Kno	67.17	**67.90**	65.92	59.99
Klocation	**75.27**	68.57	68.31	64.57
Khisto	86.12	**96.66**	93.72	88.82

All models performed better than the null model using objects as the level of abstraction. The best results were obtained by CA_Advanced except for Klocation. This better performance is justified by the application of the additional spatial metric based on the enrichment factor that allows taking into account the spatial features of land use classes on the researched area more effectively. Geomod and CA_Markov also had good performances although with slightly lower results but still above the null model.

EVALUATION OF LONG-TERM FORECAST

After the calibration of all models it is interesting to investigate their behaviour in long-time forecasting provided that the recent tendencies on the investigated area will be kept. In figure 4 are presented the 26 parishes of Sintra and Cascais and the type of urban dynamics expected for year 2025 using the three models. The suitability maps employed in this forecast were similar to the ones used for estimating year 2001 and incorporated additional information about existing urban areas in year 2001.

The transition matrix that was employed for both Markov models included transitional conditional areas between 1989 and 2001 because they produce a more consistent forecast for the period under analysis. We could use 1994 to 2001 transition matrix but in this case the modelling process would take after the behaviour between 1994 and 2001 excluding the tendency between 1989 and 1994. Once again, predicted quantities of Markov transitions between 1989 and 2001 were specified as end time quantities in Geomod.

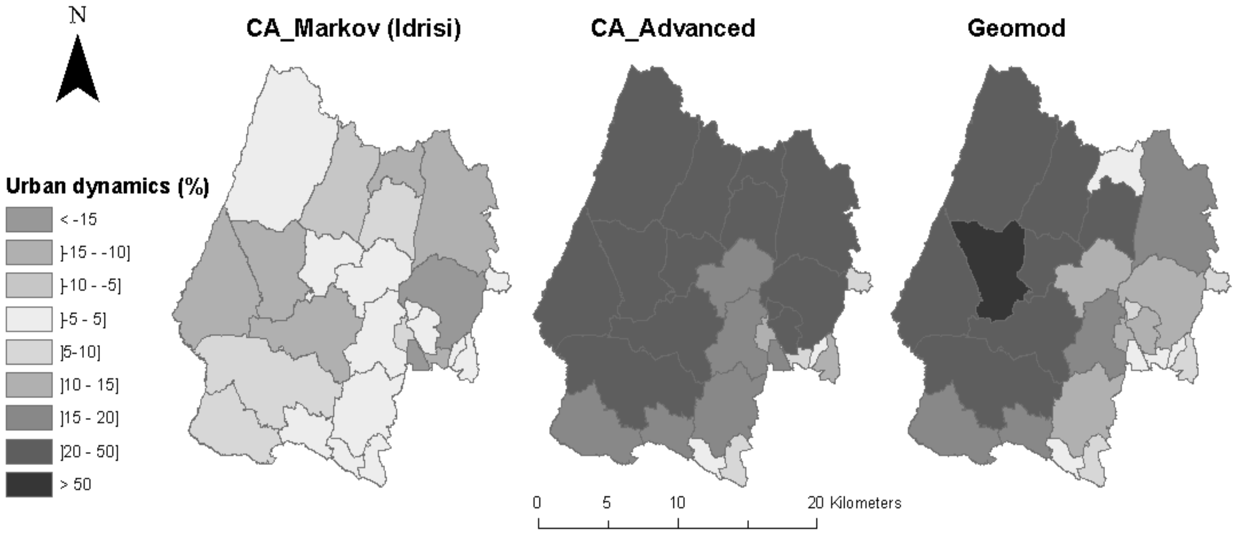

Figure 4: Estimated urban growth for year 2025 using the three models.

Results show significantly different behaviours in the estimations (Figure 4) which confirm the complexity of long-term forecasting tasks. The CA_Markov model shows some inadequacy for this case study with small land cover changes presenting urban growth with a fluctuating behaviour. The CA_Advanced and Geomod present more realistic forecasting results with different dynamics according to location.

CONCLUSIONS

This paper shows an integrated approach of remote sensing, GIS and modelling. Remote sensing was employed to obtain information about the urban phenomenon in the study area. GIS was the element that allowed the integration of this data into the models enabling us to find relations in the outputs.

Validating model's performance is a good practice for this type of studies. Validation values obtained were superior to the null model so we can, in theory, use any of these land-change models to analyze the urban phenomenon in the study area. Yet one must pay attention to their behaviour when estimating long-term forecasts. All the models applied for long-time forecast show for this case study significantly different results, which confirm the complexity of long-term forecast tasks even for up-to-date models.

Among the three models tested, CA_Advanced was the one that exhibited the best overall performance at the object level because of additional spatial component used and the original optimized software. Results further indicate that one must use the same spatial unit of analysis that was employed in the image classification procedure to achieve better modelling estimates.

There was a continued tendency for the increase of the built class (29.5%) between 1989 and 2001 in Sintra and Cascais municipalities. This tendency is to be taken seriously by local urban planners because physical space for sustainable growth is limited. The use of these models can provide useful information to detect areas where urban growth is more likely to happen. In future work, other constraints will be employed to build the suitability map like National Ecological Reserve, National Agriculture Reserve and protected areas like Natura 2000 sites. This way it will be possible to evaluate the role of these legal instruments in the urban dynamics of this area.

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