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Land use and cover modeling as a tool for analyzing nature conservation policies – A case study of Juréia-Itatins

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ABSTRACT

Land Use and Cover Changes (LUCCs) have been a cause of great concern for socio-environmental sustainability. Applied study in this field should take into account the history of the interaction between man and nature, and the effect on the landscape that this dynamic projects. This paper's objective is to assess LUCCs with regard to the effect of a nature conservation policy and correlate such changes with the practice of shifting cultivation. For that, historical aerial photos of the study site (a protected area located in São Paulo, Brazil) were analyzed and Markov and Cellular Automata models were built and compared to simulate different scenarios, including a counterfactual one. The results showed that the policy was important to stop pressures against nature conservation and that there is a lack of correlation between shifting cultivation and reducing forest cover, highlighting the fact that the ban on shifting cultivation, justified by nature conservation, can be overestimated.

1. Introduction

Land-use and land-cover change (LUCC) in tropical rainforests is a pressing issue, of special concern for global and regional environmental governance. LUCC has been one of the main causes of deforestation, habitat degradation and climate change worldwide, but proximate and underlying causes can be complex and region-specific (Achard et al., 2002; Eddy and Gergel, 2015; Foley et al., 2005; Geist and Lambin, 2002; Van Vliet et al., 2012). Therefore, land use and land cover change do not follow a fixed pattern, and their speed and magnitude remain uncertain (Lambin and Geist, 2006).

In Brazilian tropical forests, different proximate and underlying causes influence LUCC. In the Amazon, the prevailing model of rural development since the 1970s led to increasing deforestation, forest degradation and a positive feedback with climate change (Nobre et al., 2016). Despite the reduction in deforestation rates in recent years, Lovejoy and Nobre (2018) believe that the tipping point for the Amazon system to flip to non-forest ecosystems might be reached in the near future. In the Atlantic forest, main causes of LUCC since the 1500s were sugar and coffee plantations, expansion of cattle pasture, mining and hydroelectric projects (Dean, 1997; Metzger, 2009), as well as expansion of urban areas and exotic tree plantations in recent years (Metzger, 2009; Salazar et al., 2015). This development pathway resulted in the loss of 84–89 % of its original land cover, and the remaining forest is highly fragmented in small patches (Joly et al., 2014; Ribeiro et al., 2009).

To counteract continuing deforestation and LUCC, Brazil has gradually established a complex system of protected areas (PAs) that includes several categories of parks and reserves managed by the government (de Marques and Peres, 2014). The importance of PAs for environmental conservation is unquestionable; however, following international models (Scherl et al., 2004; West et al., 2006) innumerous PAs were established on sites historically occupied by indigenous and local people, requiring their removal and affecting traditional livelihoods. As a result, conflicts have arisen between management bodies and local populations inhabiting the Atlantic forest (e.g. Adams, 2003). Most arguments for the removal of local populations are based on the impacts of livelihoods on forest ecosystems, especially of shifting cultivation (SC) systems (Adams et al., 2013). However, very few PAs were created based on the investigation of LUCC historical dynamics (forest and human occupation), despite the fact that understanding the effect of local livelihoods on the landscape where a PA is established is essential for its management, and for evaluating the PA's efficiency for conservation. One possible way to understand such dynamics is through the modeling and analysis of LUCC over time, analyzing it *vis-à-vis* public policies and legislation (Galvin et al., 2006).

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In this article, we present LUCC dynamic models constructed for a PA landscape in the Ribeira River Valley, Atlantic Forest (São Paulo, Brazil), historically occupied by traditional Caiçara populations. In the past, Caiçara's livelihood was based primarily on fishing, shifting cultivation, and extraction of timber and non-timber forest products (NTFPs), while a small surplus was traded for other goods (Adams, 2000, 2003; Ferreira, 2005; Nunes, 2003; Sanches, 2016). Our main objectives were: (1) to assess land use and land cover change by the influence of intervention/management policies on the development of spatial patterns in the landscape, and (2) to investigate the relationship between LUCC and the traditional practice of shifting cultivation.

To achieve these goals, dynamic spatial models were constructed using geoprocessing tools, Markov chains and cellular automata (CA) to simulate land use and cover change under different scenarios, and to compare trends of changes that occurred before and after the implementation of the PA in the area. We built the models in a way that can be an alternative to ready-made software packages. The innovative characteristics of this work are the incorporation of shifting cultivation as an element of dynamic modeling, the inclusion of the model code for future users, and the comparison between the performance of Markov and CA-Markov models. Lastly, there is no previous study of landscape modeling applied to the region of Juréia-Itatins.

1.1. LUCC Dynamic models and shifting cultivation system

Modeling is the process of representing reality in a simplified way. Dynamic models are applied to systems that change over time, have a specific space where the states of the system can be visualized, and have a rule of state evolution over time and space. These rules are usually derived from the knowledge about previous states (Boccara, 2010). The construction of dynamic LUCC models depends on the recognition of landscape elements at different scales (Baker, 1989a), and these elements define a particular spatial pattern resulting from natural interactions and anthropic activity. The elements can be classified according to different types of land use and cover (Baca et al., 2007).

The term "land use" refers to the ways in which land surface is transformed by people, such as agriculture, housing, and mineral extraction, while "land cover" refers to the biophysical state of the land surface (e.g. forests, exposed soil, and sea). Both are not static and may change over time (NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION, 2017). Some geoprocessing tools are extremely useful for analyzing patterns and spatial changes on a landscape (Bonham-Carter, 1994). When coupled with mathematical models, these tools can acquire dynamic characteristics and reproduce impacts from certain interventions on the landscape (Baker, 1989a; Sklar and Costanza, 1991).

Many studies apply landscape dynamic models (LDM) for LUCC analysis (Cuevas and Mas, 2008; El-Hallaq and Habboub, 2015; Fan et al., 2008; Flamenco-Sandoval et al., 2007; Garcia et al., 2007; Hendges, 2007; Mondal and Southworth, 2010; Nadoushan et al., 2015; Nouri et al., 2014; Peterson et al., 2009; Soares-Filho et al., 2006; Walsh et al., 2008; Wu et al., 2006). However, applying LDM to shifting cultivation landscapes is rare in the literature. The few authors who have constructed LUCC dynamic models for shifting cultivation landscapes either did not include it as a specific element of the model (e.g. Adanu, 2013; Amadou et al., 2018; Corona et al., 2016; Kamusoko et al., 2013; Kukkonen, 2013; Maes, 2013; Magliocca et al., 2014; Roy et al., 2015), or did incorporate SC, but in static and correlational models (e.g. Cordero-Sancho and Bergen, 2018; Cornelio, 2017; Donsavanh, 2017; Jakovac et al., 2017; Muller et al., 2013). The only exceptions are Barton et al. (2016); Iwamura et al. (2014) and López (2014). This knowledge gap can be partly attributed to the low spatial resolution of satellite images that do not allow the visualization of features that are characteristic of swidden cultivation systems, which may bias interpretation (Heinimann et al., 2017).

Another gap in the literature is related to the methodological transparency and the publication of the modeling code (Parker et al., 2003; Rosa et al., 2014). Most LDMs are built using ready-made/closed source packages from modeling software[1], limiting the understanding of model building and the spread of its use due to financial cost. The only exception is Barton (2013), who built a LUCC dynamic model that included shifting cultivation in the model and provided the model code. However, his model uses simulated data and is not applied to a specific case study.

2. Materials and methods

In this study, the landscape was considered as a projected reflex of its social, political and ecological context, and also as a product from the history and temporal dynamics of its human and biotic communities (Balée, 2006). Therefore, our premise is that the evolution of spatial patterns in the landscape reflects political interventions and institutional changes, such as the creation of a PA. Our study site, the Itinguçu State Park, has had a history of conflicts between the state government and the traditional Caiçara communities since the 1980s, when the area was converted to a PA causing depopulation due to legal restrictions to Caiçara's traditional livelihood.

The models were built for two contexts, past (before the PA was created) and current (after the creation), and applied to perform future simulations of the landscape. Aerial photographs were used to investigate the impact of the PA on landscape dynamics and changes over time. Future simulations projected (1) the trend of changes based on the past, generating a counterfactual scenario if the PA had not been implemented, and (2) the trend found in the recent period, after the PA was implemented. Different models were constructed using Markov chains and cellular automata, which were tested and compared to evaluate their efficiency.

2.1. Study site

The Itinguçu State Park (ISP) is part of a mosaic of protected areas – the Juréia-Itatins Protected Areas Mosaic (JIPAM, approximately 97,214 ha) (Fig. 1), located in the southern coast of the state of São Paulo, Brazil. The ISP makes up approximately 5% of the total area of the JIPAM (São Paulo, 2013). The JIPAM is located in the Ribeira River Valley, one of the largest remnants of Atlantic Forest, considered one of the world's most important and threatened biomes (Myers et al., 2000; Narezi, 2018). The area is characterized by a diversity of ecosystems that provide resources for the Caiçara peoples, forming a complex socio-ecological system (Narezi, 2018).

The area of the current JIPAM became a PA in 1986, when almost the totality of its territory, including the ISP area, was declared by the state government of São Paulo as the Juréia-Itatins Ecological Station (JIEE) (São Paulo, 1986). In 2013, as a result of conflicts and the struggle undertaken by the Caiçara communities for the right to remain in their territories, the limits and categories of PAs were negotiated until the current configuration of the JIPAM was reached (Câmara, 2009; São Paulo, 2006, 2013). Basically, the JIEE was divided into different categories of PAs with smaller areas, forming a mosaic composed by two Sustainable Use PAs, four Integral Protection PAs, and two Maritime Protection Areas (São Paulo, 2013) (Fig. 1).

The ISP area was redefined as a State Park, thus remaining under the Integral Protection category as defined by the Brazilian National Protected Area System – SNUC (Brasil, 2000; Sanches, 2016). Both State Parks and Ecological Stations prohibit human occupation and use of natural resources (Brasil, 2000). The ISP was chosen as our research site

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[1] For instance: IDRISI software, used in El-Hallaq and Habboub (2015); Mondal and Southworth (2010); Nadoushan et al. (2015) and Nouri et al. (2014); DinamicaEGO software, in Cuevas and Mas (2008); Hendges (2007); Soares-Filho et al., 2001, 2004, 2006; and TerraMe software used in Flamenco-Sandoval et al. (2007).

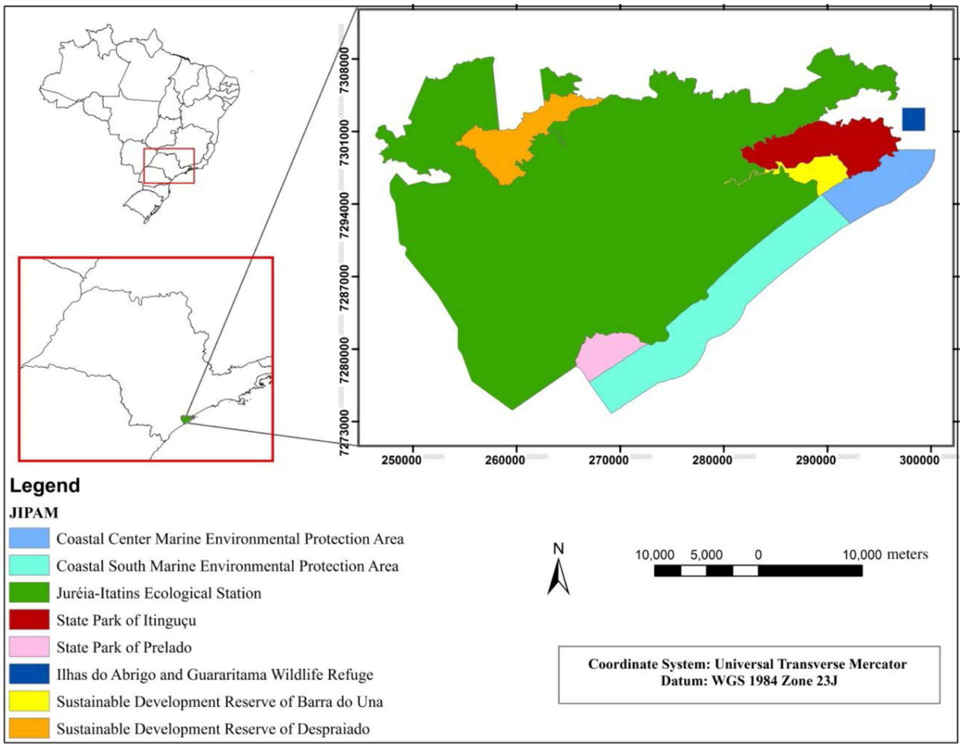

Fig. 1. The Juréia-Itatins Protected Areas Mosaic (JIPAM) and its location.

based on demand from local residents represented by the Juréia Residents Union (UMJ) and the Juréia Youth Association (AJJ). A team of local resident-researchers worked together with academic researchers.

The demographic surveys over the JIEE region are scarce and do not have a judicious temporal and methodological continuity. It is estimated that the great peak of human occupation occurred in the 18th century due to the expansion of rice cultivation (Nunes, 2003). The first demographic survey was carried out by the state government in 1991, and registered the existence of 383 families (Nunes, 2003). Another survey, completed in 2003, confirmed the sharp population decline caused by the creation of the JIEE – 137 families (Carvalho and Schmitt, 2010). Most people abandoned the area due to restrictions on habitation and subsistence activities, including shifting cultivation, hunting, fishing and extraction of NTFPs, and the lack of public infrastructure including schools and health centers. As a result of these changes, land use and cover dynamics have been altered since 1986, mainly due to a reduction in shifting cultivation.

Shifting cultivation (or swidden farming) corresponds to a rotational agricultural system, which includes cutting, clearing and burning a small area of forest (usually 1 ha), followed by the cultivation of a variety of crops and a fallow period for fertility recovery. Usually, the land is cultivated for shorter periods of time than those used for fallow (Mertz et al., 2009; Pedroso et al., 2008). The fallow period allows forest succession to occur and secondary forest occupies the site. This system can be practiced sustainably provided an adequate fallow period is observed, in situations of low population density. Shifting cultivation has been practiced for centuries by Juréia residents, but since the implementation of the JIEE it has been banned or restricted. Local residents reported that nowadays cultivation patches are smaller than in the past, and with a smaller variety of crops. Presently, the majority of the remaining ISP population still relies on traditional activities, complemented by income from jobs in the surrounding cities, tourism and handicraft (Câmara, 2009).

2.2. *Methodological design and aerial photographic sources*

The creation of the JIEE (1986) was considered the greatest underlying cause of change and a transformation vector on the spatial pattern of the local landscape, so this date was used to divide the analyzed period in Pre-PA and Post-PA. The Pre-PA period included aerial photographs of 1962, 1972 and 1980, as well as derived statistical data. The post-PA period covered the aerial photographs of 2000 and 2010, and the data derived from them. The future scenarios refer to the simulations performed to the year 2020.

Table 1 shows the aerial photographic sources used in this study. The dates were chosen based on the availability/existence of sources. The 1962, 1972, 1980 and 2000 aerial photographs were obtained in analog format. These photos were then scanned and orthorectified

Table 1
Aerial photographs used in this study.

Period	Material	Date	Scale	Source[a]	Original format	Scan resolution
Pre-PA	Aerial photograph	1962	1:25,000	The University of São Paulo (Geography Department)	Analog black and white	600 dpi
	Aerial photograph	1972	1:25,000	Forestry Institute	Analog black and white	600 dpi
	Aerial photograph	1980	1:35,000	Base Aerophotogrammetry and Projects S/A	Analog black and white	600 dpi
Post-PA	Aerial photograph	2000	1:35,000	Forestry Institute	Analog color	300 dpi
	Aerial ortho- photograph	2010	1:25,000	Metropolitan Planning State Company (Emplasa)	Digital	–

[a] Information about every source in Table 1 is given in the References Section.

based on the aerial orthophotographs of 2010 and on a Digital Surface Model (DSM), which has a compatible scale of 1:25,000. This DSM was developed by Emplasa[2] and used to orthorectify the 2010 orthophotos. The 2010 aerial orthophotographs had their positional accuracy audited by the Brazilian Institute of Geography and Statistics (IBGE).

All photos and DSM were standardized in the Universal Transverse of Mercator (UTM) coordinate system. The resampling method used in the orthorectification was a bilinear interpolation algorithm, to guarantee geometric precision and the disappearance of discontinuities in pixel gray levels (Tian and Huhns, 1986).

To clip the study area according to the specific geographical limits of the ISP, a vector file prepared by the Socio-environmental Institute (ISA)[3] was used.

The information obtained from the aerial photos was supplemented by the local team of researchers, who provided historical information about the use and occupation of the area. This team also carried out field surveys to acquire the geolocation of family units, current and previous SC spots, and other points of interest.

2.3. Thematic maps of land use and cover

The next step was to perform a visual interpretation of the photos to categorize them into different classes of land use and cover, considering the scale and the spectral responses. The classes were chosen based on previous knowledge of the study area by the resident-researchers and on the targets of this research, considering the level of detail needed for the subsequent analysis. Some of the classes were generalized and grouped, so the model could be representative of what was intended to be evaluated, as well as to rule out possible uncertainties of interpretation. Table 2 describes the final classes established to create the thematic maps of land use and cover, for each year of analysis (1962, 1972, 1980, 2000 and 2010).

For the Beach and Sea class, a mask was created and applied to all thematic maps to avoid the seasonal changes that occur throughout the year due to natural processes related to the tides. Each element classified from all photos was checked with one of the resident-researchers and corrections were made when necessary. Finally, the thematic maps of land use and cover were converted to a matrix format (or raster) of 7 m resolution. Thus, the smallest area contained in the maps was 0.0049 ha. The choice for this resolution considered the minimum size of swidden plots, characteristics of the aerial photos and computer performance.

2.4. Transition matrix, Markov model and cellular automata

Markov chain models are essentially projection models that describe the probabilistic movements of an individual element in a system comprised of discrete states. Markov models are often used in modeling changes and trends in land use and cover (Soares-Filho et al., 2002).

The mathematical representation of a Markov model is given by the transition matrix T, which is a square matrix where the number of rows and columns corresponds to the number of states in the system. Each element of the matrix is the probability of change from the index-row state to the index-column state (Karlin and Taylor, 1975).

In a first-order Markov process, the transition probability P from a given state to any other does not require the history of transitions:

$$P(w_{t+1} = s_i | w_0 = s_0,\ w_1 = s_1,\ \ldots, w_t = s_j) = P(w_{t+1} = s_i | w_t = s_j), \qquad (1)$$

w_t is a random variable which assumes the value corresponding to the state of the system at time t, in other words, w_t may be equal to one of the m possible states $(s_0,\ s_1,\ s_2,\ \ldots, s_m)$. During the simulation, a random state is drawn for each cell, which will remain in the same state or change to any other state. By repeating this operation for all cells in the target state, the final fraction changed at random will be about the same as the probability empirically found in the transition matrix for those specific states. However, the randomness implies different outcomes for each run, and for this reason running the algorithm several times and taking the average of all realizations was the strategy used to have consistent results in respect to the empirically estimated probability distribution.

The Markovian hypothesis means that history of visited states in the past does not account to the transitions between two subsequent periods. For this reason, probabilities have no memory, that is, the state tomorrow depends only on the state today (the Markov condition). To simplify the notation, let us denote by $T_{i,j} = P(w_{t+1} = s_i | w_t = s_j)$ the transition probability from states $j \rightarrow i$ from $t \rightarrow t + 1$ respectively.

In the present work, the map is divided into cells. There are five classes of land use/cover (which are the states of the system), so i and j range from 1 to 5 corresponding to bodies of water (BW), roads (R), forest (F), shifting cultivation (SC), and grassland (G). Based on two images captured at different times, we can estimate the transition probability matrix, which records the probability of moving from one state s_j to another state s_i. The main requirement to estimate a T from thematic maps of different dates is that they must be perfectly overlapping. The transition matrix $T_{i,j}$ is estimated from the observed data by counting the number of cells in which the state changed from j in the map on period t, to i in the next period map $(t + 1)$, that was denoted by n_{ij}. The number of occurrences of the state j in the map was denoted by N_j, measured at time t. Thus, the transition matrix reads:

$$T_{(i,j)} = \mathrm{n_{ij}}/\mathrm{N_j} \qquad (2)$$

The Markov model for prediction of land use and cover changes is:

$$L_{t+1}[(x,\ y) = i] = T_{ij} L_t[(x,\ y) = j], \qquad (3)$$

where, $L_t[(x,\ y) = j]$ is the probability to find the cell $(x,\ y)$ in the state j at time t.

There is a long debate in the literature regarding the stationarity assumption of Markov chain in the context of LUCC (e.g. Baker, 1989a; and Bell and Hinojosa, 1977), but rigorously validating it demands more data. Despite the fact that as the system evolves the process is, in general, not stationary, this technique is still used as a way to project future scenarios. The use of the Markov chain model is due to the fact that such projection is for heuristic purposes only (Baker, 1989b), and it may provide a good approximation (Weng, 2002). Markov chain modeling provides a common framework for comparing longer term trends instead of testing how well short-term transitions actually predict longer term outcomes, which requires more rigor by checking all the assumptions. To attenuate these limitations effects on the outcomes, we made successive estimates over time and computed the agreement rates to validate the quality of the transition matrices to be used in the target projection. This is the case when the amount of information in the transition matrix captures, in some extent, the underlying mechanism of the change process. If the results are not good enough, this means that breach of assumptions does not allow this technique to be used.

While Markov models are extremely useful in analyzing state changes when it is desirable to extrapolate trends over time, they lack spatial context and do not consider the neighborhood influence on each cell. Taking that into account, we complemented Markov models by using cellular automata models.

Cellular automata are discrete dynamical systems that exhibit a variety of dynamic behaviors. CA consists of a set of states, the cellular

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[2] Emplasa (Empresa Paulista de Planejamento Metropolitano S.A) is a public institution linked to the State Secretariat of Government, responsible for the regional and metropolitan planning of the State of São Paulo. Emplasa concentrates the collection and cartographic production of the state of São Paulo and coordinates the Spatial Data Infrastructure Program for the State of São Paulo (to access its cartographic products: https://www.emplasa.sp.gov.br/ProdutosCartograficos).

[3] Information about ISA is given in the References Section.

Table 2
Land Use and Cover Classes.

Classes of land use/land cover	Description
Shifting Cultivation (SC)	Area used for shifting cultivation. It includes both active areas under cultivation and those recently left to fallow.
Grassland (G)	Area predominantly covered by grasses (typically pastures); there may be a few scattered trees and shrubs and small areas of exposed soil; also used for conventional agriculture.
Forest (F)	Area densely covered by trees. It also includes features altered by rainfall erosion, areas of rocky outcrops and secondary forest.
Bodies of water (BW)	Rivers, lakes, and waterfalls.
Road (R)	Routes established for land transport. At the study site, all roads are dirt roads.
Beach and Sea	Beach: portion formed by loose particles of mineral or rock along the sea shore. Sea: body of salt water, adjacent to the beach.

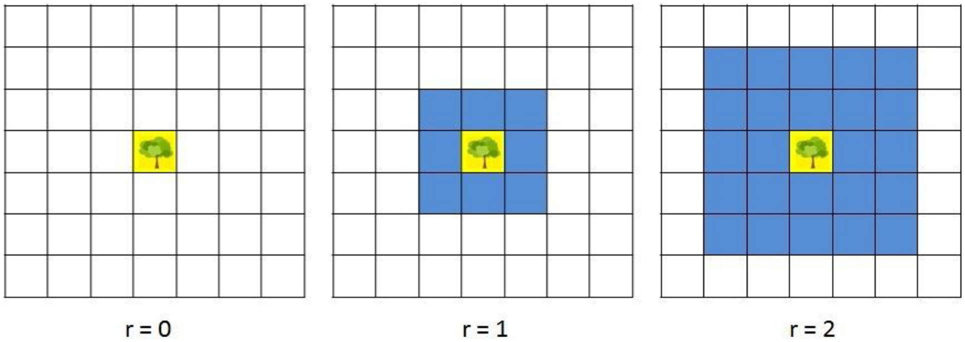

Fig. 2. Bidimensional cellular automata topology. Left panel represent the radius r = 0, the center panel is the radius r = 1, and radius = 2 is on right panel. This topology is also called Moore neighborhood.

space and the transition rule. Cellular space is a regular lattice of N cells arranged in an n-dimensional space. Each cell interacts with its neighborhood according to the transition rules, which prescribe the next state based on the cell's current state and the states of the cells in its neighborhood (Wolfram, 1983).

In Fig. 2 we see a bidimensional CA representation for three values of radius r. In this study we used the Moore neighborhood topology of radius 1, where the target cell (x,y) has eight neighbors around. This topology of radius 1 is the most common choice in CA models for LUCC (Toffoli and Margolus, 1987; Pedrosa et al., 2002). If the number of states is k (≥2), it is possible to generate k^{k^9} different transition rules, which is an extremely large number.

In the following, we will present two different ways to combine transition rules of Markov models with transition rules of cellular automata.

CA-MARKOV I: The model proposed here is divided into two stages. First of all, we applied the Markov model over all cells (x,y) as described before. After that, we applied a deterministic cellular automata (DCA) over each cell (x,y). Consider that the target cell is in the state j^* and the number of neighbors of type j is nv_j. The most frequent state around (x,y) cell is j_{max} (in the case of a tie, we choose randomly). The transition rule for the DCA is defined as:

$$\begin{aligned} \text{if} j^* &= \text{BW or R:} \\ \text{DCA}(x, y) &= \{ \begin{matrix} j^* & \text{if} nv_j^* \geq 1 \\ j_{max} & \text{otherwise} \end{matrix} \\ \text{if} j^* &= \text{F, SC or G:} \\ \text{DCA}(x, y) &= \begin{cases} j^* & \text{if} nv_j^* \geq 5 \\ j_{max} & \text{otherwise.} \end{cases} \end{aligned} \tag{4}$$

The general rule could be written as $DCA = j if nv_j \geq z \text{ or } j_{max}$ otherwise. z is the threshold value for nv_j, and to find what would be the best value for z to obtain the best fit to the model, we ranged z from 1 to 8 for each class individually and compared the results. Here we found $z = 1$ for bodies of water (BW) and roads (R), and $z = 5$ for forest (F), shifting cultivation (SC) and grassland (G). This cellular automata approach allows us to find specific rules for each state.

CA-MARKOV II: is a model inspired by the core idea of the Dinamica software, developed by Soares-Filho and his team, who were unprecedented in their method of determining the cell´s transition probability (Soares-Filho et al., 2002). Here we propose a probabilistic cellular automata (PCA), where the transition rules combine the Markovian T_{ij} with the fraction f of each state present in the neighborhood: $f_j = nv_j/8$. The PCA transition rule proposed is:

$$PCA_{ij}(x, y) = \begin{cases} T_{ij} & \text{if } f_j \geq 0.5 \\ T_{ij} f_j & \text{otherwise.} \end{cases} \tag{5}$$

Here, if there is not a majority state around the target cell, the Markov transition matrix is weighted by the fraction of states around the target cell. The general rule is to set $f_j \geq z/8$ and look for the best value of z running all over the map. Here we found the threshold $z = 4$.

The Markov, CA-Markov I and II models, as well as the performance evaluation for each model (described in Section 2.5) were constructed by developing programming algorithms in Python 2.7.2 to provide an alternative to ready-made software packages. The model´s code can be found in the supplementary material.

2.5. Models performance evaluation

Model performance evaluation consisted of comparing the simulated map with the actual map of the same date to measure their similarity (de Almeida et al., 2007). Two different techniques of performance evaluation were applied to the Markov, CA-Markov I and CA-Markov II models:

1 To check if the resulting *trend of change* from the simulated scenario remained the same as the real scenario, we computed and compared the absolute numbers of cells per class of each map to verify if they increased or decreased in the expected direction from the initial map.
2 The *spatial allocation of cells* was evaluated by running the model n times, and for each execution a cell by cell comparison was performed to check if each cell were transposed to the correct state in the correct place at the grid, thus obtaining a percentage of agreement. The percentage of agreement is the concordance between the

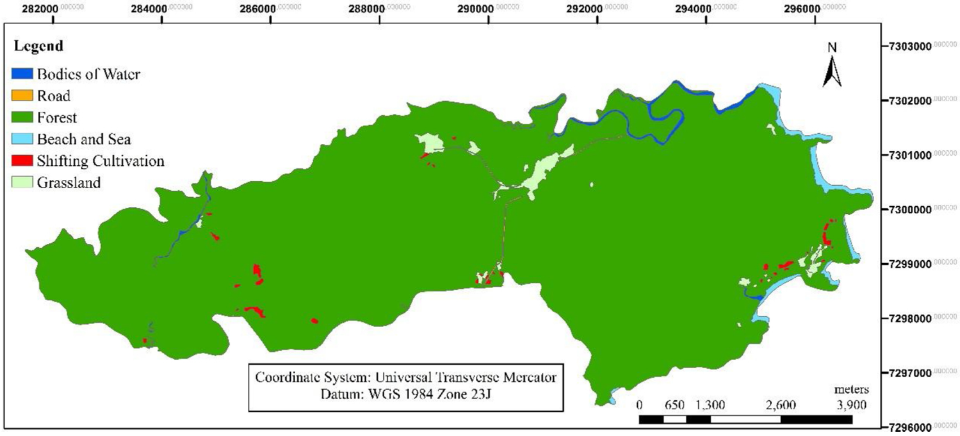

Fig. 3. Land use and cover map of 1962.

actual map and the simulated map. The Markov model was run 100 times for each projection, allowing the construction of hit frequency histograms, and its averages were calculated to compare with the results from the other models. Because the CA-Markov models required a greater computational capacity, they were executed 10 times each and thereafter the average frequency of agreement was calculated.

We executed simulations taking the year of 1980 as the initial period and projecting the year of 2000, and also taking the year of 2000 to project 2010. The simulated maps were compared with the maps generated from the interpretation of the aerial photos of the same date, considering the trend of change and the spatial allocation criteria. The simulated maps can be found in the supplementary material.

3. Results

3.1. Land use and cover maps and transition matrices

Figs. 3–7 show the land use and cover maps for each of the analyzed dates.

The year 1962 had the highest area of forest and SC, the lowest area occupied by road and low values for grassland (Fig. 3, Table 3), which agrees with the predominance of shifting cultivation as a land use. Throughout the pre-PA period (Figs. 3–5, Table 3) the road area showed an increasing trend, while SC decreased. In general, the direction of changes of forest and grassland classes was practically opposite during this period. There was a clear decrease in forest area, while grassland area increased six-fold. Variations in the area of bodies of water can be explained by variations in rainfall, especially between 1962 and 1972.

From the 1980s, we observed a drastic change in land use and cover trends, which supports the hypothesis that the creation of the PA was a transformation vector in local dynamics, reflected in the evolution of spatial patterns in the landscape. In the post-PA period the forest area shows an increasing trend, while the grassland area decreases; the road area remains practically stable. The landscape features also reflect the gradual abandonment of shifting cultivation during this period.

The transition matrices estimated for each of the four time spans (1962–1972, 1972–1980, 1980–2000 and 2000–2010) show the percentage of area that changed for each class from t to $t + 1$, and the direction of change from its original state. The transition matrices can be observed in Tables 4–7.

In the Pre-PA period, we can observe from the transition matrices an increase of road area by the conversion from grassland. This latter class experiences a considerable increase at the expense of forested area, especially between 1972 and 1980. During this period, most of the areas of SC were left to fallow, acquiring forest characteristics (93 % between 1962 and 1972; and 86 % between 1972 and 1980). In the post-PA period the forest area increased considerably due to the conversion from grassland, which diminished. The SC class followed the same pattern found in the Pre-PA period, transitioning to forest until being practically abandoned. However, the aerial photographs scale should be taken into account. Even though we worked with a fine spatial scale, we do not rule out the possibility that there may be areas of SC that could not be identified in the photos.

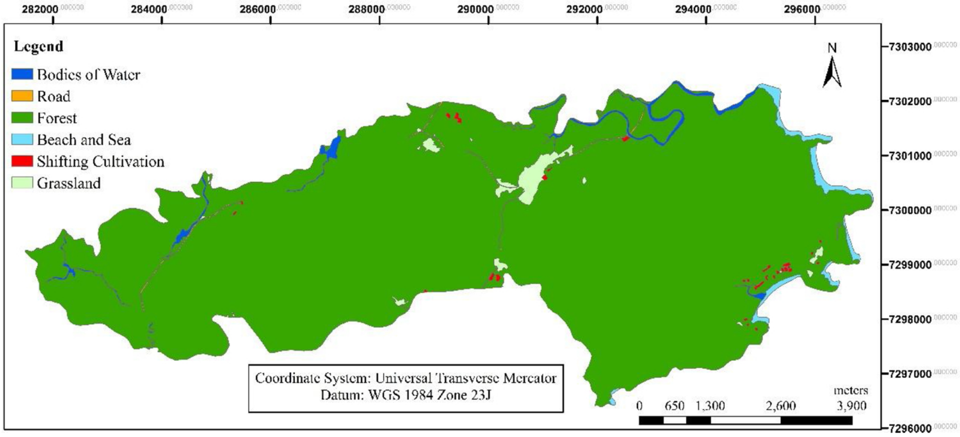

Fig. 4. Land use and cover map of 1972.

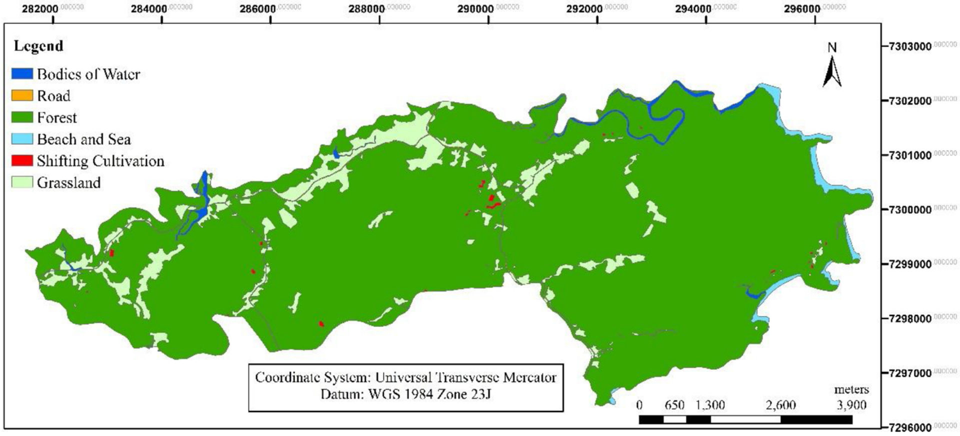

Fig. 5. Land use and cover map of 1980.

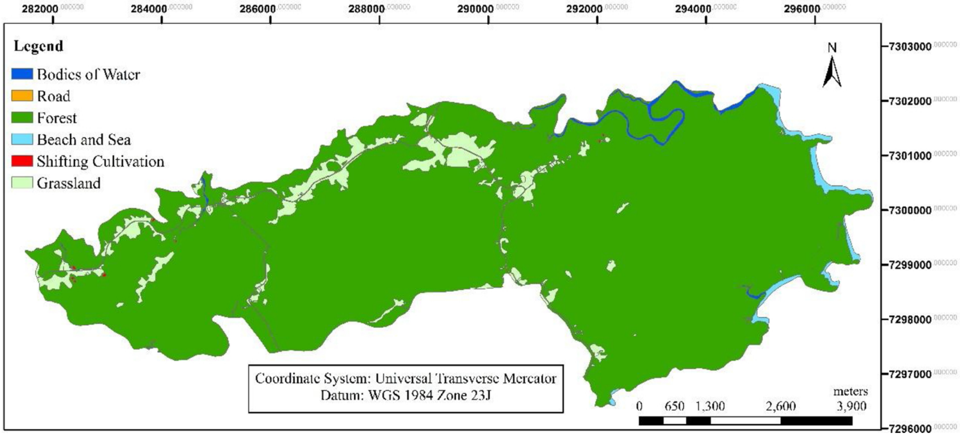

Fig. 6. Land use and cover map of 2000.

3.2. *Results of models performance evaluation*

The results of the models performance evaluation can be seen in Table 8.

In the trend of change analysis, we observed that the simulations performed by the Markov model better preserved and reproduced the transition trends found in the study area. In the CA-Markov I and CA-Markov II models a larger volume of cells did not transition to the expected class, resulting in a slightly lower percentage when compared to the Markov model. This happened because transition matrix is a good tool for reproducing trends over time, and the Markov model uses only the transition matrix as rule for state changes. On the other hand, the transition matrix does not consider neighborhood influence but only the transition probability of each class, so cells can be transitioned to a class at unlikely locations in the simulated map. By including the neighborhood dimension using CA-Markov models there is a gain in the allocation aspect, observable by the best results of frequency of agreement.

Regarding the spatial allocation of cells on the map, the CA-Markov II model presented the best result in frequency of agreement. This happened because in this model the transition matrix application is

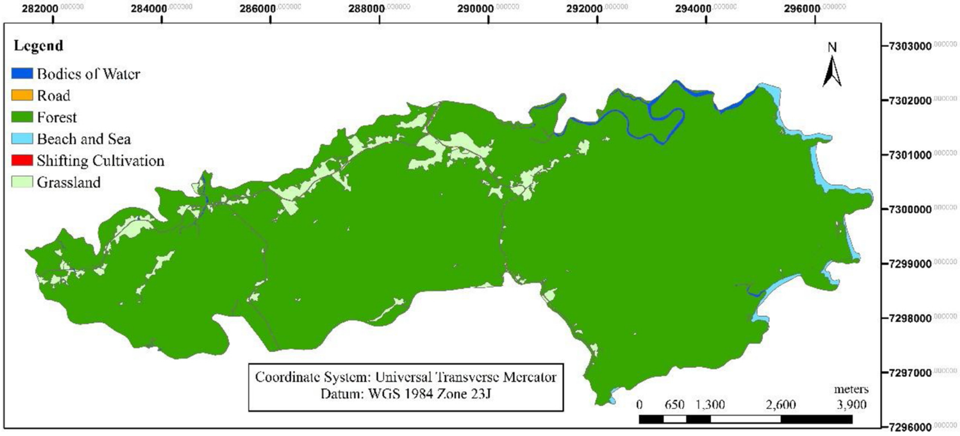

Fig. 7. Land use and cover map of 2010.

Table 3
Area (hectares) of land use or cover classes on each investigated date.

	Pre-PA			Post-PA	
Classes	1962 (ha)	1972 (ha)	1980 (ha)	2000 (ha)	2010 (ha)
BW	43.26	62.80	56.78	44.04	43.79
R	6.47	11.28	19.29	19.24	18.94
F	4,874.71	4,868.04	4,533.57	4,670.56	4,725.86
SC	21.76	12.12	7.81	1.55	0.00
G	67.06	59.02	395.81	277.87	224.67
Total	5,013.26	5,013.26	5,013.26	5,013.26	5,013.26

BW = bodies of water; R = road; F = forest; SC = shifting cultivation; G = grassland.

Table 4
Transition matrix for the 1962 to 1972 period.

From/To	BW	G	SC	R	F
BW	0.89	0.00	0.00	0.00	0.11
G	0.00	0.50	0.02	0.01	0.47
SC	0.00	0.00	0.07	0.00	0.93
R	0.00	0.06	0.00	0.48	0.46
F	0.00	0.01	0.00	0.00	0.99

BW = bodies of water; G = grassland; SC = shifting cultivation; R = road; F = forest.

Table 5
Transition matrix for the 1972 to 1980 period.

From/To	BW	G	SC	R	F
BW	0.65	0.10	0.00	0.00	0.25
G	0.00	0.59	0.00	0.02	0.38
SC	0.00	0.12	0.02	0.00	0.86
R	0.00	0.45	0.00	0.15	0.39
F	0.00	0.07	0.00	0.00	0.92

BW = bodies of water; G = grassland; SC = shifting cultivation; R = road; F = forest.

maintained for the cells that have a certain amount of neighbors belonging to the same state to which it is intended to transition, but it weighs the transition matrix by the neighborhood when this amount is smaller, avoiding transitions in unlikely places and considering the local influence of the neighborhood. The CA-Markov I model, although bringing gains in the frequency of agreement in comparison to the Markov model, presented results somewhat lower than the CA-Markov II. We believe that this is due to the fact that, although the model eliminates unlikely transitions by imposing that the cell assumes the majority state in the absence of a certain number of neighbors belonging to the same state, this is done after the application of Markov, acquiring, therefore, a deterministic character of CA (while CA-Markov II is probabilistic). Because it is deterministic, some cells of the map changed taking into account only the neighborhood, and not considering the transition matrix.

Table 6
Transition matrix for the 1980 to 2000 period.

From/To	BW	G	Sw	R	F
BW	0.74	0.06	0.00	0.00	0.20
G	0.00	0.44	0.00	0.00	0.55
SC	0.00	0.10	0.01	0.00	0.89
R	0.00	0.01	0.00	0.99	0.00
F	0.00	0.02	0.00	0.00	0.98

BW = bodies of water; G = grassland; SC = shifting cultivation; R = road; F = forest.

Table 7
Transition matrix for the 2000 to 2010 period.

From/To	BW	G	SC	R	F
BW	0.92	0.00	0.00	0.00	0.08
G	0.00	0.68	0.00	0.00	0.31
SC	0.00	0.15	0.00	0.00	0.85
R	0.00	0.01	0.00	0.97	0.02
F	0.00	0.01	0.00	0.00	0.99

BW = bodies of water; G = grassland; SC = shifting cultivation; R = road; F = forest.

Table 8
Performance comparison - simulation for years 2000 and 2010.

Analysis method	Markov	CA-Markov I	CA-Markov II
Year 2000			
Trend of change analysis	99.98 %	95.98 %	95.83 %
Spatial Allocation (average frequency of agreement)	91.64 %	93.78 %	93.85 %
Year 2010			
Trend of change analysis	99.84 %	99.37 %	98.22 %
Spatial Allocation (average frequency of agreement)	95.37 %	97.19 %	97.42 %

Due to the fact that the Markov model presented better performance in trends reproduction than both CA-Markov models, and the fact that we were more concerned about quantifying the expansion or contraction of the area of each landscape class than about where these changes may have occurred, simulations projecting future scenarios of current and counterfactual trends for 2020 were performed using the Markov model only.

3.3. Forecast simulations

Aiming to identify the future scenario for the ISP in case the current LUCC trend remains, a 2020 map was simulated using the actual map of 2010 as the initial state and the 2000–2010 transition probabilities.

For the counterfactual scenario of 2020, simulations were performed starting in 1980, using the 1971–1980 transition matrix. In both cases ten simulations were performed for each time span, and the least squares technique was used to select one of them for analysis. The simulated scenarios show an extrapolation of the trends, disregarding other variables (such as socioeconomic aspects) that could alter the course and intensity of the local LUCC.

Fig. 8 shows the evolution of the areas of each class according to the simulations. The dotted line from 1980 shows the evolution of the classes up to the year 2020 in the counterfactual scenario, and the solid line in the current trend scenario. If the trends found *a priori* were maintained (the counterfactual scenario) and the PA was not created, in 2020 the grassland area would have increased considerably due to the forest conversion, as well as road area. On the other hand, the area under SC would decrease somewhat, but would remain practically stable until 2020 instead of being eliminated due to the restrictions imposed by the PA.

4. Discussion

The results of the different simulations carried out pointed to the absence of a correlation between shifting cultivation and deforestation/reforestation. Whether in the pre-PA or in the post-PA period, in the current or in the counterfactual scenario, the evolution of SC, grassland and forest classes indicated that deforestation and reforestation occurred on a greater or lesser scale regardless of the variation of the SC area.

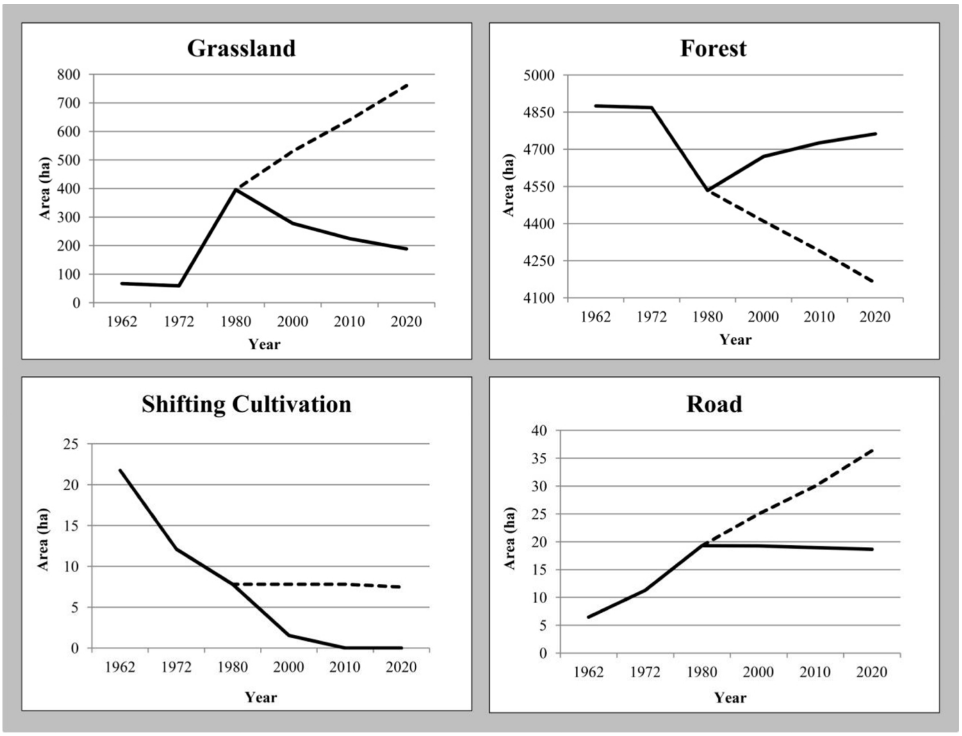

Fig. 8. Evolution of areas (hectares) of land use and cover classes, and projections for 2020. Dotted line: counterfactual scenario; solid line: current trend scenario.

It should also be emphasized that in our case study the area used for shifting cultivation in 1962 corresponded to a very small part of the territory (0.43 %), even at a time when the population density was higher in the Juréia region and families were more dependent on SC for their subsistence. The same pattern was observed by Adams et al. (2013) and Munari (2010) in the Ribeira Valley. In 1962 we observed the largest area of SC compared to the other studied years, but at the same time the largest forest cover area. In addition to this, transition matrices have shown that, in all periods, over 85 % of the SC area was converted into forest from one date to the next, suggesting that the ban on shifting cultivation as a premise for environmental conservation has been overestimated, and would not compensate for the conflicts caused by the implementation of the JIEE (considering maintenance of traditional characteristics of the shifting cultivation system).

Therefore, we could assume that the government's main concern in creating the PAs should be to prevent LUCC trends observed in other parts of the state of São Paulo coast (urban expansion, tourism infrastructure, oil pipes and drilling infrastructure, thermoelectric power plants and motorways), and not to impose restrictions on SC. It is a fact that the PA brought favorable changes to the local landscape dynamics in order to hinder those pressures on land use. However, the way in which this PA was implemented (expelling traditional residents, restraining the practice of SC and not involving the community in the decision-making process) may not have been the most socially and environmentally appropriate policy.

However, it is important to notice that restrictions to SC are only part of the social conflicts observed at the JIPAM, that include constraints to other subsistence activities (e.g. fishing, collecting non-timber forest products), housing, and lack of public services of health and education. Our results are intended to serve only as parameters for the "shifting cultivation versus forest preservation" socio-environmental debate, providing subsidies for further research and contributing to the dialogue between the managing bodies of the JIPAM and local residents, who are still struggling to maintain their traditional rights.

Related to our methodology, working with aerial images is useful in building models with applicable results in which the visualization of LUCCs becomes simpler and dynamic. However, the existence, availability, and often the cost of aerial images at an adequate scale becomes a limiting factor, especially when it comes to gathering data from the past. Socioeconomic data may also carry the same problem, and it is necessary to look for modeling alternatives that suit the amount of data available for a study area. The methodology presented here is an alternative for modeling in situations of data scarcity. Building counterfactual scenarios is an alternative that provides a comprehensive understanding of the response of landscape to changes, and brings insights into the relative contribution of human interventions to local dynamics (Barton et al., 2016). Nevertheless, LUCC is also affected by different socioeconomic variables that were not controlled during our modeling process, which is a limiting factor of this study.

5. Conclusions

The main objectives of this study were to assess the influence of environmental intervention/management policies on the development of spatial patterns in an Atlantic forest landscape, and to investigate the relationship between LUCC and the traditional practice of shifting cultivation in the Atlantic Forest. Dynamic spatial models were built using geoprocessing tools, Markov chains and cellular automata and the performance of the models was compared.

The results showed that the PA has restricted the practice of shifting cultivation and guaranteed forest recovery. However, our simulations demonstrated that variations in the area under shifting cultivation showed independence from deforestation/reforestation trends. The models were built as alternatives to ready-made software packages, and we hope that the programming code can be taken and improved for the analysis of trends in LUCC, subsidizing new and open access modeling methodologies, and contributing to the planning and management of protected areas.

CRediT authorship contribution statement

Camila Assaf: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Cristina Adams:** Conceptualization, Methodology, Validation, Investigation, Resources, Writing - original draft, Writing - review & editing, Project administration. **Fernando Fagundes Ferreira:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Writing - original draft, Writing - review & editing. **Helena França:** Methodology, Resources, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

None.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.landusepol.2020.104895.

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