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Future land use changes in a peri-urban context: Local stakeholder views

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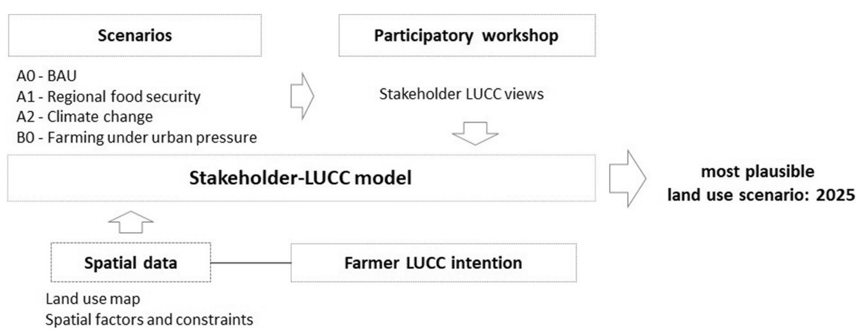
HIGHLIGHTS

- LUCC simulations in different scenarios in a peri-urban region were performed.
- Spatialization of stakeholder LUCC views by building of a hybrid model (CA-GIS).
- Land use planning could improve by engaging stakeholder participation.
- Policy guidance for decision-makers to monitor land use.

GRAPHICAL ABSTRACT



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ABSTRACT

Future land use/cover change (LUCC) analysis has been increasingly applied to spatial planning instruments in the last few years. Nevertheless, stakeholder participation in the land use modelling process and analysis is still low. This paper describes a methodology engaging stakeholders (from the land use planning, agriculture, and forest sectors) in the building and assessment of future LUCC scenarios. We selected as case study the Torres Vedras Municipality (Portugal), a peri-urban region near Lisbon. Our analysis encompasses a participatory workshop to analyse LUCC model outcomes, based on farmer LUCC intentions, for the following scenarios: A0 - current social and economic trend (Business as Usual); A1 - regional food security; A2 - climate change; and B0 - farming under urban pressure. This analysis allowed local stakeholders to develop and discuss their own views on the most plausible future LUCC for the following land use classes: artificial surfaces, non-irrigated arable land, permanently irrigated land, permanent crops and heterogeneous agricultural land, pastures, forest and semi-natural areas, and water bodies and wetlands. Subsequently, we spatialized these LUCC views into a hybrid model (Cellular Automata - Geographic Information Systems), identifying the most suitable land conversion areas. We refer to this model, implemented in NetLogo, as the stakeholder-LUCC model.

The results presented in this paper model where, when, why, and what conversions may occur in the future in regard to stakeholders' points of view. These outcomes can better enable decision-makers to perform land use planning more efficiently and develop measures to prevent undesirable futures, particularly in extreme events such as scenarios of food security, climate change, and/or farming under pressure.

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1. Introduction

Future land use and land cover change (LUCC) assessment is one of the most relevant practices in the spatial planning process. In the last few years, modelling LUCC scenarios has become a valuable technique to recognize uncertain futures and identify their impact (Holman et al., 2017; Kindu et al., 2018). Land use management requires the capacity to incorporate the various purposes and needs of the different stakeholders, who are driven by different goals – e.g. while some are driven by economic incentives, others are interested in preserving the long-term ecological functions of their land. Also, decision-makers are often motivated by economic growth and environmental protection (Bhatta, 2010; van Vliet et al., 2015).

Engaging stakeholders from different strategic sectors by using participatory workshops in the LUCC model building and assessment stages can be one step forward in the land use planning process (Hassan et al., 2011; Knapp et al., 2011). This practice can be beneficial for decision-makers on several levels: by providing an incentive to promote land use sustainability (Bartke and Schwarze, 2015; Nassauer, 2015); by reducing the complexity of the task and allowing them to make better decisions (Brits et al., 2014; Goldstein et al., 2012); by identifying LUCC uncertainties and their impact (Francis and Hamm, 2011; Jantz et al., 2010); by mitigating divergences (Gwaleba and Masum, 2018; Labiosa et al., 2013); by creating information gap tasks, and encouraging active discussion.

Stakeholder participation in the LUCC analysis has been an ongoing topic in spatial planning (Bonsu et al., 2017; Cascetta and Pagliara, 2013; Scearce, 2004). Stakeholder participation using mixed methods (quantitative and qualitative) (Schoonenboom and Johnson, 2017) mostly contributes to promote the legitimacy of future LUCC and to develop land use strategies (Brown et al. 2018; Llambí et al. 2005; McCall 2003). Finding better ways of collecting data and designing better tools to integrate stakeholder intentions and views in the decision-making process can play an essential role in public participation (Al-Kodmany, 2001).

The projection of future LUCC using models have been quite efficient and helpful since it is able to support spatial planning, and capable of answering any question about land conversion and location (Ghavami et al., 2017). These models can provide a helpful baseline, and valuable information about future demands to support strategic policies (Verburg et al., 2019). They offer an easy path to understand interface to aid planners in their analysis of spatial data and to support planning decisions on long-term policy assessment. Besides, they aim to promote efficient land use, identifying its optimal allocation and recognizing how to manage it more effectively by evaluating the impact of alternative land uses (Dunnett et al., 2018; Lambin et al., 2000).

The integration of LUCC models into the spatial planning process needs to be efficiently applied (Guzy et al., 2008). It can help to reduce the slowness of the analysis among the demographic, economic and LUCC transformations and the application of land protection tools (Wegener, 2001). In addition, it can help to analyse these LUCCs in an efficient way, finding a better balance between population needs and environmental protection.

To integrate stakeholder LUCC views into an intuitive spatial approach, different techniques have been used. One of the most widely used methods of addressing optimisation-complexity, in a complex and simultaneously simplified way, is coupling complex LUCC models and Geographical Information System (GIS) techniques. It is suitable for simulating LUCC and evaluating spatiotemporal patterns. Together, they can provide a better understanding of the spatial characteristics and complex interactions, as well as human-environment interactions (Chen, 2012).

Despite these advantages, the application of these two approaches combined is still considered somewhat challenging (Asgesen and Dragicevic, 2014) and difficult to apply to planning policies. In Portugal, this kind of approach is still scarce at the local level.

One of the most critical LUCC conversions in Portugal, particularly in peri-urban regions in the last few decades, has been the transformation from agricultural and natural land to artificial surfaces (e.g., residential, touristic, and industrial uses). Moreover, in the last few years, this phenomenon has been more intensified in the region of Lisbon, with 17% of natural and agricultural land converted to artificial land from 1995 to 2010 (Abrantes et al., 2016). The city of Lisbon has seen major changes in the housing stock. Recent political measures – such as the amendment of the housing rental law (which now facilitates the eviction of tenants), the golden visa (which allows a non-EU citizen to obtain a residence permit by purchasing a real estate property of EUR 500 k or more), the tax-free scheme for the retirement income of non-habitual residents, or the growth of tourism in recent years (which has transformed long-term rentals into short-term ones) – have led to an increase in housing prices (Rio Fernandes et al., 2019; Statistics Portugal, 2019). These steeper prices, in turn, have increased the demand for housing outside the city, which made prices soar. This is why the municipality of Torres Vedras, located roughly 50 km north, is one of the potential locations chosen by those who wish to find affordable housing near Lisbon. Accordingly, we selected this municipality as a case study for our analysis. Torres Vedras located in a peri-urban region context has had a population surge in the last few decades that has led to an increase of artificial surfaces with negative consequences, namely the loss of natural and agricultural land (DGT, 2010, 1995). This situation has led to economic and environmental imbalances, and planners need to be prepared, particularly given that agriculture is an important contributor to the local and regional economy (Statistics Portugal, 2011). More efficient policies are urgently needed to preserve natural areas and agricultural land (Abrantes et al., 2016; Gomes et al., 2018).

Studies that look into spatial LUCC models that have had stakeholder input are still scarce, but might be of great help in making better future assessments. However, some scientific research has addressed the land use assessment of specific spatial phenomena, such as watershed management (Jessel and Jacobs, 2005), sustainable environmental management (Stave, 2010), and land use allocation in a peat-meadow polder (Arciniegas et al., 2013). Nevertheless, very few studies have used this approach for future LUCC assessment in a peri-urban context, where have been proven the stage of fast and intense LUCC, with the loss of agricultural area for urbanization purposes (Foley and Scott, 2014). For instance, Gomes et al. (2019b, 2019a) evaluated land use transformations in a peri-urban context in different scenarios. However, these studies were not supported by stakeholder participation in their analysis and interpretation.

Our work aims, precisely, to explore this gap in the existing models by evaluating future LUCC maps through a participatory assessment of representative stakeholders. With this step forward we intend to answer the following research questions: 1) how stakeholder LUCC views may differ from each other and under different scenarios? 2) what are the spatiotemporal divergences in the most plausible land use scenario according to stakeholder views? and; 3) how participatory approach can help planners in the decision-making process since LUCC in peri-urban regions occurs very fast? In this process we:

(1) Assess and quantify future LUCC transformations (according to stakeholder views) for the following four scenarios: A0 - current social and economic trend (Business as Usual); A1 - regional food security; A2 - climate change; and B0 - farming under urban pressure; (2) Spatialize and identify the most suitable areas in the land conversion for the most plausible land use scenario in 2025 (chosen from stakeholder LUCC views) using a hybrid model that couple cellular automata (CA) and GIS principles, and; (3) propose the use of LUCC models to support spatial planning at the local level.

The paper is organized as follows: after the introduction, Section 2 presents the data and methods used, which include the case study, spatial data, the design of four different scenarios, an analysis of the interviews with the farmers and the participatory workshop, and the construction of a hybrid model (CA-GIS) named 'stakeholder-LUCC model'. Section 3 presents the discussion and research findings. The conclusions are set out in Section 4.

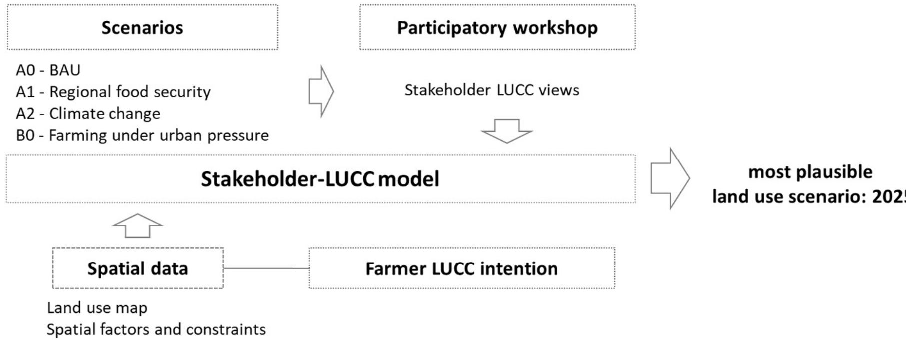

Fig. 1. Methodological flowchart.

2. Data and methods

Several methodological procedures were performed in our research. Fig. 1 shows the methodological flowchart of our paper, outlining the methodological procedures that led to the identification of the most plausible land use scenario.

2.1. Case study

The Torres Vedras Municipality (Portugal), located on the west coast of Europe, was selected as the study area (Fig. 2). Torres Vedras is 407 sq. km and it is located roughly 50 km north of Lisbon. Administratively, it is divided into 13 parishes, and the last census recorded a population of about 80,000 inhabitants (Statistics Portugal, 2011).

Located in a peri-urban region, the Torres Vedras Municipality was chosen due to an artificial surface increase of 41% between 1995 and 2010. Moreover, between 1991 and 2011, its population grew by 18%, increasing pressure on natural and agricultural land resources. From the agricultural activity point of view, Torres Vedras is one of the most relevant suppliers of fruits, vegetables, and wine in Portugal (Statistics Portugal, 2009), hence its great importance for the local and regional economy.

2.2. Spatial data

Two sets of spatial data were used to perform our analysis: (1) land use map (reference map); and (2) spatial factors and constraints. These data were converted into a raster format of 1 ha × 1 ha pixel size. This value was achieved balancing the dimension of the study area, the original data resolution, and the capabilities of the software used.

2.2.1. Land use map

The land use map for the year 2010 was accurate and validated at the 1:25000 scale by DGT (2010). This land use map represents the most updated available data, and it was aggregated in line with the goals of our study into the land use classes showed in Table 1 and Fig. 3.

2.2.2. Spatial factors and constraints

Table 2 and Fig. 4 identify the list of spatial factors and constraints (which represents the attraction to or repulsion toward LUCC conversion). These data were selected in line with the most widely cited in the literature (Chen et al., 2018; Nabiollahi et al., 2018), available data, and the characteristics of our case study (Gomes et al., 2019a, 2018).

2.3. Scenarios

Four scenarios were designed for the year 2025 (time reference for the master plan). They were the underlying narratives for stakeholder LUCC views and were described as follows: A0 - business as usual; A1 - regional food security; A2 - climate change; and B0 - farming under urban pressure. These scenarios are described in detail in Table 3, and they are in accordance with the policies of the Food and Agriculture Organization of the United Nations (FAO) and the European Union (EU).

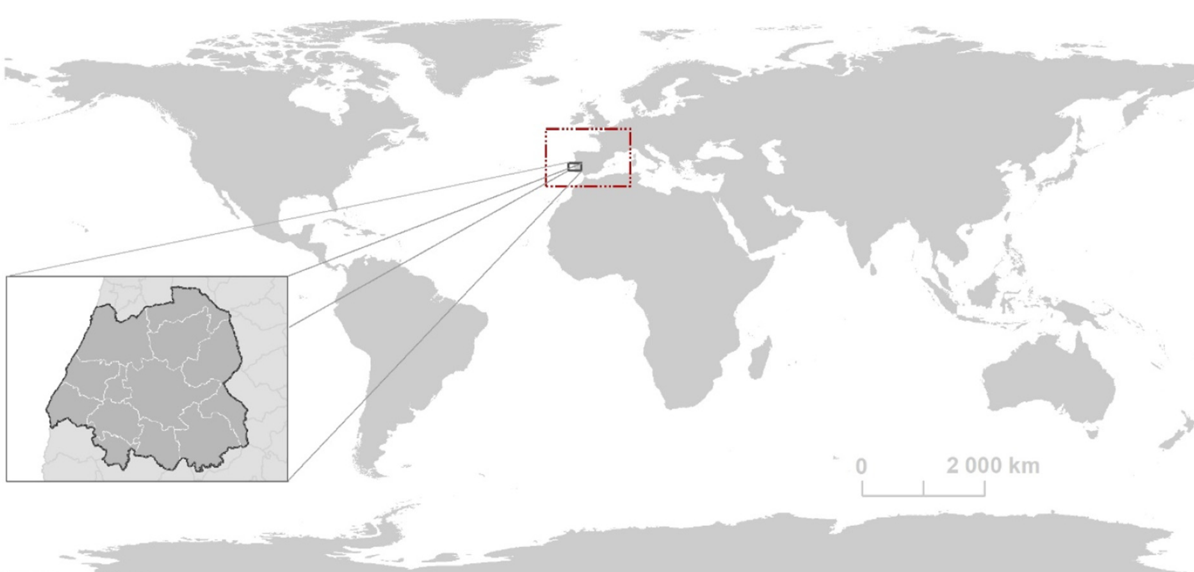

Fig. 2. Location of the Torres Vedras Municipality (Portugal).

Table 1
Land use classes.

Land use class	2010 (%)
1 - artificial surfaces (urban fabric, industrial, commercial, and transport units)	11.41
2 - non-irrigated arable land	9.09
3 - permanently irrigated land	11.00
4 - permanent crops and heterogeneous agricultural land (vineyards, orchards, olive groves, and complex cultivation patterns)	25.94
5 - pastures (grassland)	2.17
6 - forest and semi-natural areas (broad-leaved forest, coniferous forest, mixed forest, scrub, and herbaceous vegetation associations)	40.25
7 - water bodies and wetlands	0.14

Table 2
Factors and constraints.

Spatial indicators	Hypotheses	Data source
Distance to artificial surfaces	Related to the costs of building, transport, and management (Leão et al., 2004; Megahed et al., 2015). The closer urban areas and road networks are, the higher the probability of land conversion to new urban areas.	(DGT, 2010)
Distance to road network		OpenStreetMap
Distance to agricultural land	The closer an agricultural land use class is from another agricultural land use class, the higher the probability of conversion into the same agricultural land use class (Gomes et al., 2019a).	(DGT, 2010)
Slope	As a barrier for urban and agricultural expansion (Li and Li, 2017). The higher the slope is, the higher the barrier for land conversion.	Igeoe
Non-building area	Land use regulations to protect urban development (Sims, 2014). It includes groundwater, flood areas, railway station, quarries, spring water, cultural heritage, coastal planning, and Natura 2000 network.	Master plan

The selected scenarios were designed to bring up issues related to plausible futures and as a basis for decisions, which should be used for short-term planning.

2.4. Interviews with farmers

We chose to use interviews in our research to support scenario building since it is an efficient format for description and interpretation. Face-to-face interviews were the technique used to capture farmer LUCC intentions. The questions focused on the following three main points addressing the four scenarios: (1) Do farmers intend to expand and/or decrease their farmland; (2) If so, How much? Where? From/to which land use class? and according to which scenario?; and (3) Do they intend to sell their farmland for urban development? If so, Partially or totality?

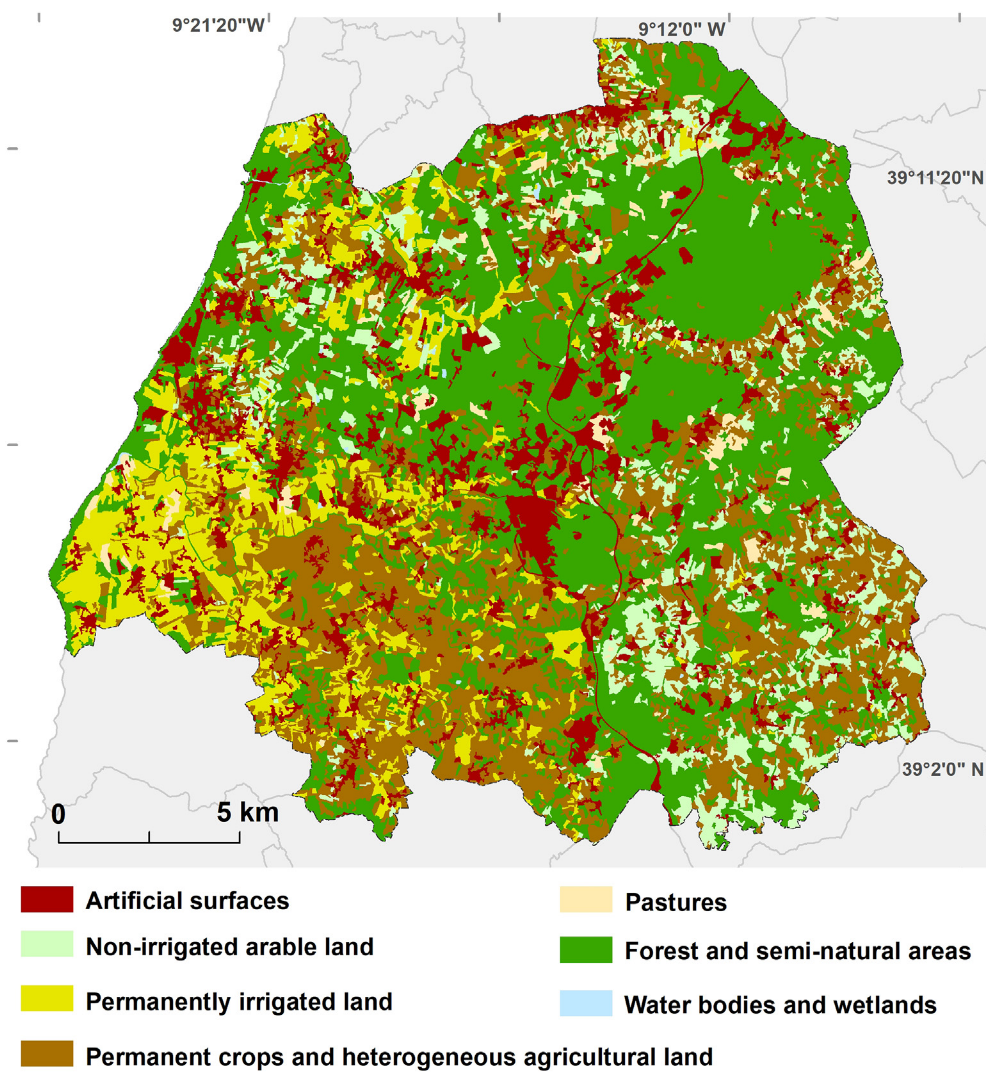

Fig. 3. Land use cover 2010.

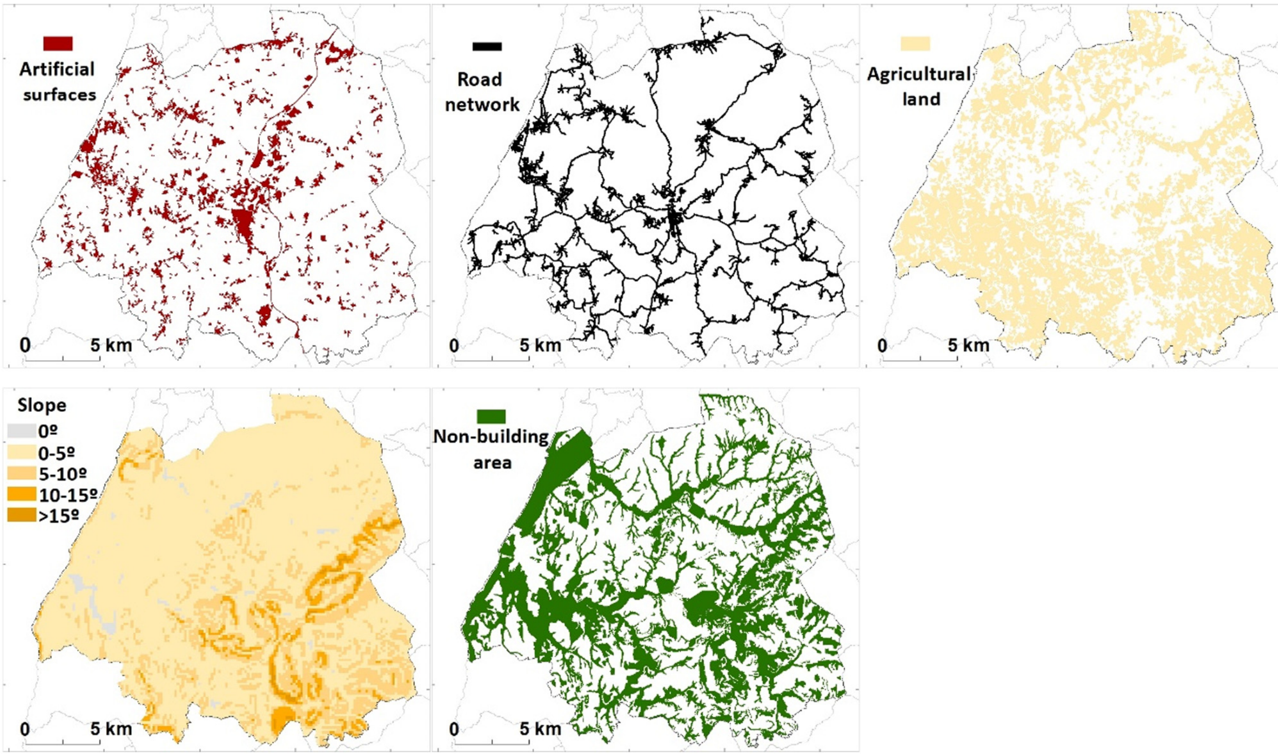

Fig. 4. Spatial factors (artificial surfaces, road network, agricultural land, and slope) and constraints (non-building areas).

2.4.1. Statistical tests

To guarantee the representativeness of the sample and estimate the sampling errors, some probability sampling types such as randomness, stratification, clustering, and systematic sampling were ensured. We used a sample of each age group (15–34, 35–64, and +65 years old) proportional to the group's size. The sample size required for the sensitivity test was assessed using different statistical tests, using different margins of error and confidence intervals (Table 4).

To choose the statistical test, two main reasons were considered: 1) the values accepted in the literature (Greenland et al., 2016); and 2) the costs per interview. Following this technique, statistical test E was chosen with a margin of error of 10% and a confidence interval of 95%. According to these parameters, we achieved a sample size of 93 farmers to interview (Fig. 5). The farmers' contact details were obtained from several institutional entities and directly on the field.

2.5. LUCC models based on farmer LUCC intentions: CA-Markov and ANN-MLP

Currently, there is a large number of spatial optimisation models able to integrate LUCC simulations. Two of the most common models due to their ability to create feasible resolutions are Cellular Automata - Markov chain (CA-Markov) and Artificial Neural Network - Multilayer perceptron (ANN-MLP) (Li and Li, 2015). They allow LUCC simulation to show the emergence of new land use patterns, and address optimisation-complexity questions.

CA-Markov and ANN-MLP models, based on farmer LUCC intentions, were used in this study. They were developed by Gomes et al. (2019a, 2019b), and they were showed and explain to stakeholders, in this research, as reference maps to analyse future LUCC.

The stakeholders evaluated and identified both models, deciding which outcome would be more plausible according to their own views. CA-Markov chain is a statistical method that integrates stochasticity in the changes between states (Macal and North, 2010), while ANN-MLP can learn using a training method called backpropagation, in which input data is displayed continually on the network (Morgado et al., 2014; Rocha et al., 2007).

These LUCC models helped stakeholders to create their own LUCC views and enabled them to learn the land use conversions that might occur under different scenarios. These models assisted stakeholders in the creation a reliable picture of future land use under different scenarios, spatially and quantitatively.

In addition, based on the knowledge acquired by looking at the LUCC models, stakeholders were able to decide and produce a consensual LUCC for 2025 (considered the most plausible scenario). This information was integrated into the stakeholder-LUCC model.

2.6. Participatory workshop

The participatory workshop provided a step forward in integrating stakeholder LUCC views in the identification of better land use and management practices. By combining multiple points of view we were able to grasp the complexity of the decisions land planners must make in order to improve land use strategies.

With this purpose in mind, we engaged seven participants with a wide range of interests. We gathered representative stakeholders who have responsibilities in four major land management fields: spatial planning, real estate development, agriculture, and forestry. We had positive responses from all the groups, except from the real estate development. Each of the selected stakeholders played an important role in the interpretation and analysis of the LUCC models and was either affected by land use management decisions, in charge of making those decisions, or intended to make LUCC (Table 5).

The participatory workshop consisted on a three-hour meeting that brought together the aforementioned stakeholders. It started with a thirty-minute presentation that laid out its purpose, followed by two and a half hours of analysis and discussion of the different outcomes of the LUCC models.

A questionnaire was answered by each stakeholder that aimed to identify (1) which LUCC model (CA-Markov or ANN-MLP) was the most plausible for them and in accordance with the chosen model;

Table 3
Scenario description: A0, A1, A2, and B0.

Scenario	Description
A0 - BAU	The A0 scenario analyses current demographic, social, and economic trends. It is based on LUCC trends observed in more recent years.
A1 - regional food security	The A1 scenario reflects an increase in local agricultural production, innovative industries, greater use of technology, and modernisation of agricultural practices (Recanati et al., 2019). A1 scenario's key trends seek to revitalise agriculture through an increase of European funds. It is signalled by changing food habits (e.g., dietary pattern), and stock building (EC, 2011). It meets the principle of food security recognized as a priority in the rural development 2014–2020, Common Agricultural Policy programs, FAO (2012), Paris Agreement (United Nations Framework Convention on Climate Change), and Habitat III Agenda (United Nations) in which food security of peri-urban regions was identified as essential for a more sustainable development.
A2 - climate change	The A2 scenario describes a context of declining agricultural production and productivity. In a rapidly declining trajectory, the existing production systems collapse as a consequence of climate change. The Intergovernmental Panel on Climate Change (IPCC) stated in the latest report that at our case study latitude long periods of drought will be recorded (with less reliable supplies of water). This event will reduce yields in general, with direct consequences on economic agricultural viability (Günther et al., 2005; von Gunten et al., 2015). Other factors can also contribute to the production decrease, such as increased fuel costs (Lindegaard et al., 2016; Pimentel et al., 1973), ageing farming population (Recanati et al., 2019), increased production costs (Olynk, 2012), arable land decay (Stoate et al., 2001), and increased imports of agricultural products (Anderson, 2010; Nazzaro and Marotta, 2016).
B0 - farming under urban pressure	The B0 scenario records an increase of built-up areas and an increase of new peri-urban residents. The B0 scenario implies population growth; increased purchasing power; increased demand for more living space; growing market demand; and improved road access and public transport facilities (Rauws and de Roo, 2011; Satterthwaite et al., 2010).

(2) whether they consider the LUCC location plausible; and (3) whether they agree with the percentage of each land use class.

2.7. Stakeholder-LUCC model

In the literature, there are several platforms to model LUCC (Berryman, 2008), e.g., Cormas (Page et al., 2000), GAMA (Taillandier et al., 2012), MASON (Luke, 2014), SWARM (Iba, 2013), and NetLogo (Wilensky (2004). The later provides a powerful programming language (Railsback et al., 2006) and is one of the most widely used tools (Ghosh, 2015) to model natural and social phenomena, as well as complex behaviour systems (Montañola-Sales et al., 2014).

Taking into consideration the advantages mentioned above, we chose NetLogo (version 6.0) to integrate the stakeholder LUCC views into a spatial structure. We had the concern of using open-source software, and we designed it from a user-friendly perspective. The costs of our model's maintenance and data used are low. We called this model the stakeholder-LUCC model and it represents a planning decision-making approach that incorporates a built-in model using spatial data. The stakeholder-LUCC model allows spatializing future LUCC, showing the outcomes both spatially and graphically. Fig. 6 depicts its flowchart.

Table 4
Statistical tests.

Statistical test	Margin of error (%)	Confidence level (%)	Population size (n)	Response distribution (%)	Sample size (n)
A	9.58	95	2,20	50%	100
B	6.61	95			200
C	5.26	95			300
D	10.00	90			66
E	10.00	95			93
F	10.00	99			155

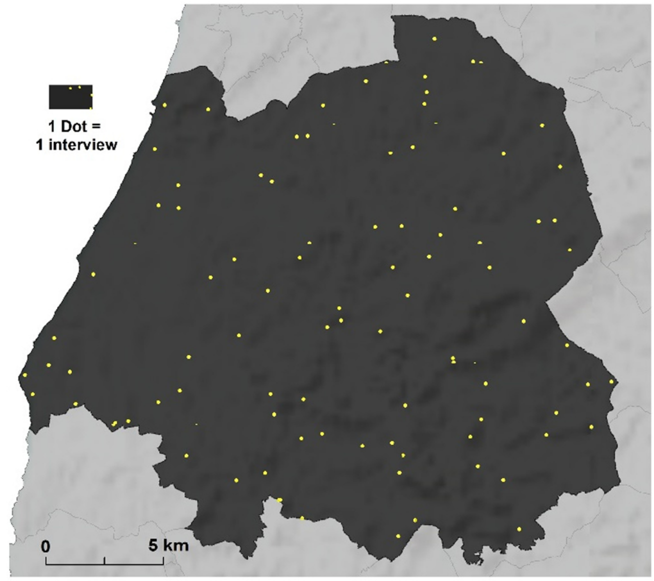

Fig. 5. Farmers interviewed.

Stakeholder-LUCC model has principles based on spatial proximity (100 m or 200 m) to some spatial elements (road network, and artificial surfaces), % of growth defined for the artificial surfaces and forest and semi natural areas (0%, 20%, and 40%), and incorporates the farmer LUCC intentions which are based in the probability of change (%) – by scenario and land use class captured from the interviews. Therefore, spatial data included in the model comprises (1) land use map (seven land use classes), (2) protected areas (and not protected areas), (3) road network (and no road network), and (4) slope (0–10° or 0–20°) (Fig. 6). Each cell can be changed (except for built-up areas, and water bodies and wetlands – these cells cannot be replaced). Farmer LUCC intentions are allocated in each cell of non-irrigated arable land, permanently irrigated land, permanent crops and heterogeneous agricultural land, pastures, and forest and semi-natural areas.

The stakeholder-LUCC model allows us to import the spatial data in *ASCII format* (raster data). The simulation started in 2010 ($t = 0$), and the projection horizon is 2025 ($t = 1$). Fig. 7 shows its interface.

The stakeholder-LUCC model was parameterised by decision rules. The outcome of each simulation and each scenario is the combination of the spatial data and parameters mentioned above, which illustrates potential LUCC maps.

Table 5
Stakeholders who participated in the workshop.

Stakeholder group	Number of participants	Function/organization
Spatial planning	1	- Urban planning technician
Agriculture	4	- Farmers Association of Torres Vedras. - LEADEROESTE - Rural Development Association. - Confederation of Farmers of Portugal (CAP-OESTE). - Farmer selected randomly from the sample of the interviewed farmers.
Forestry	2	- AFLOESTE association. - APAS Forestry association.

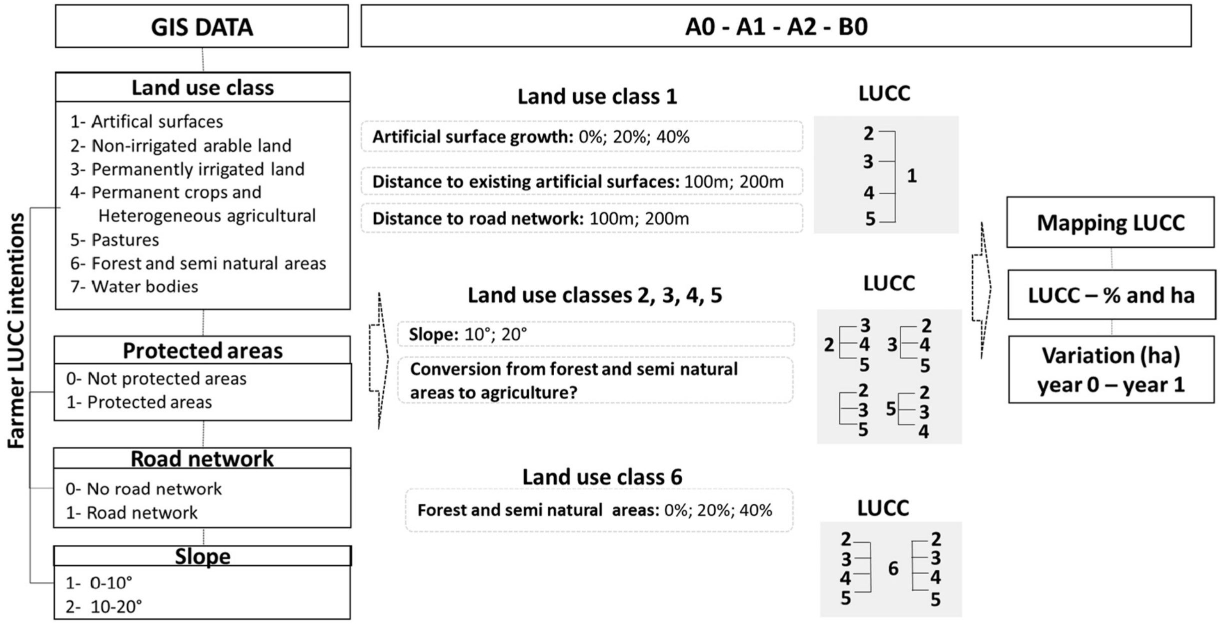

Fig. 6. Stakeholder-LUCC model flowchart.

3. Results and discussion

Our findings are divided into four subsections: the first section presents the outcome of the interviews with the farmers; the second describes the results obtained from the participatory workshop; the third is related to the integration of stakeholder LUCC views into the stakeholder-LUCC model; and the fourth depicts a discussion regarding land use strategies and advances in land use management derived from our paper.

3.1. Farmer LUCC intentions

According to the outcome of the interviews with the farmers, most farmers are landowners and represent 90% of the total farmers interviewed. The majority of respondents have between one and four years of education (36%), followed by ten and twelve years (20%), higher education (14%), seven and nine years (17%), and by the population between five and six years of school (13%). Most farmers have a small to medium-sized farm, and 47% of these farms have less than 5 ha. Farmer intentions for future land use were obtained according to the studied scenarios (Table 3). The findings revealed their intentions to expand, keep, and/or decrease their farmland. Table 6 shows the estimated probability of change for each land use class and scenario. These values were encoded in the stakeholder-LUCC model.

According to the achieved results, we highlight the following findings, comparing the size of each land use class of the farmlands of the interviewed farmers with the expected growth of each land use class in each scenario: an increase of 47.8% in artificial surfaces in the B0 scenario; a decrease of 46% in non-irrigated land in the A2 scenario; an increase of 68% in permanently irrigated land in the A1 scenario; an increase of permanent crops and heterogeneous agricultural land in the A1 scenario; and an increase of 560% in pastures in the A2 scenario.

3.2. Participatory workshop: stakeholder LUCC views

The participatory workshop helped to identify the best-suited LUCC from the point of view of the stakeholders. Thus, according to the results, five out of six participants chose the CA-Markov model as the best-fitted LUCC model in the A0 scenario; they considered the LUCC location plausible (five out of six), and two out of six did not agree with the percentage of each LUCC. In the A1 scenario, all the stakeholders elected the CA-Markov model as the best-suited model considering their views. Only one participant did not agree with the location of land conversion. However, all of them agreed with the total percentage of LUCC. In the A2 scenario, the stakeholders (four out of six) selected the CA-Markov model as the best-suited model. They agreed with the LUCC location (five out of six). Only two did not agree with the percentage of LUCC. In the B0 scenario, three stakeholders identified the ANN-MLP model, and the other three identified the CA-Markov model as the best-suited model. In addition, the majority agreed with the LUCC location (five out of six) (Table 7).

As shown, the CA-Markov model was the most elected LUCC model. One of the reasons is related to the neighbourhood principle integrated into this model. This principle defines that each cell is influenced by the nearest cell (Ilachinski, 1987; Schiff, 2011). The expansion of land use classes occurs by contiguity and reflects what the stakeholders believe that can happen in terms of land use transformations. Nevertheless, in the B0 scenario, the choice was not consensual. Three stakeholders chose the CA-Markov model and the other three chose the ANN-MLP model as the more adjusted according to their own views. The ANN-MLP model recognizes non-linear patterns (Ebrahimi et al., 2017; Mayoraz et al., 1996; Pijanowski et al., 2002), representing a closer idea of what the stakeholders believe that can happen with the behaviour of the artificial surface growth in the B0 scenario.

By analysing Table 8 and Fig. 8 and comparing them with the land use map 2010 we see an artificial surface increase in all the scenarios, especially in the B0 scenario; a decrease in non-irrigated arable land; an increase of permanently irrigated land in the A0, A1, and A2 scenarios, mainly in the A2 scenario; a decrease of permanent crops and heterogeneous agricultural land; an increase of pastures in the A0, A2, and B0 scenarios, and a decrease in the A1 scenario; a decrease of forest and semi-natural areas in the A0, A2, and B0 scenarios; and an increase of water bodies and wetlands.

3.3. The stakeholder-LUCC model

3.3.1. Model performance

Many researchers have studied the importance of testing the validity of the models (An et al., 2005; Manson, 2005). Some of these tests represent a functional verification, which should include efforts to break the model (Parker et al., 2003). They are used to control if the model is corrupted or produces entirely unreasonable results (An et al.,

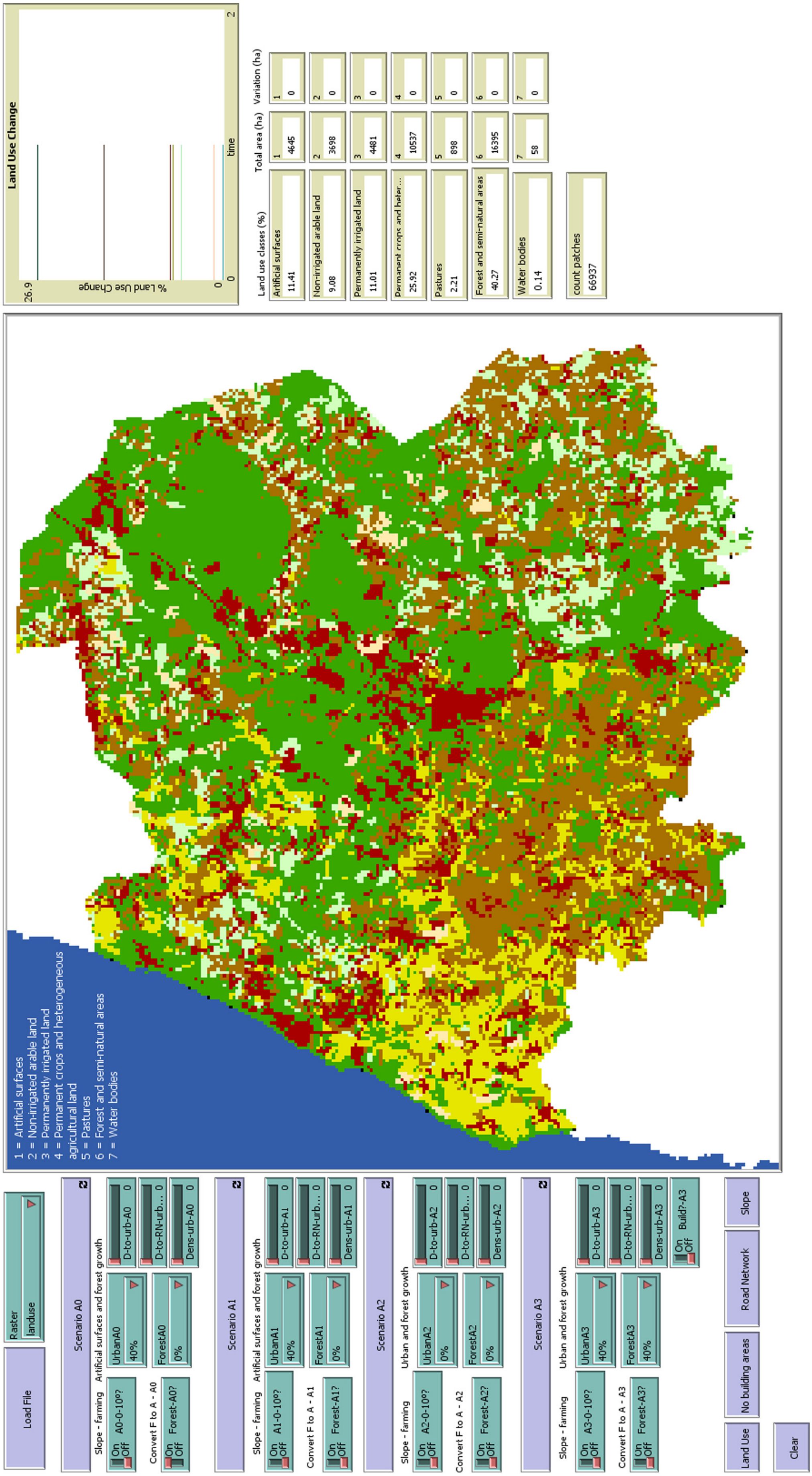

Fig. 7. The stakeholder-LUCC model interface.

Table 6
Farmer LUCC intentions – probability of change (%) – by scenario and land use class. Land use classes: LUC 1 - artificial surfaces; LUC 2 - non-irrigated land; LUC 3 - permanently irrigated land; LUC 4 - permanent crops and heterogeneous agricultural land; and LUC 5 - pastures.

Scenario	LUC 1	LUC 2	LUC 3	LUC 4	LUC 5
A0	0	0.06	20	10	−6
A1	0	3	68	71	−25
A2	0	−46	−17	−11	560
B0	47.80	0.28	−17	−1	−6

2005). The purpose is to identify the robustness of the model and recognize the inferences of any uncertainty assessment on simulation response (Helton, 2008), determining if there is a statistically significant change between simulation responses under different settings.

To identify the disturbance and influence of each parameter on each simulation response, we used a function in NetLogo called *Behaviour Space* that allowed us to perform a sweep for all potential simulations. We ran the simulation model with different settings, selecting a specific parameter in each of the following groups: artificial surfaces growth: 0%, 20%, or 40% (and according to the distance to existing artificial surfaces: 100 m or 200 m; and to the distance to road network: 100 m or 200 m); forest and semi-natural areas growth: 0%, 20%, or 40%; convert

Table 7
Stakeholder LUCC views. Land use classes: LUC 1 – artificial surfaces; LUC 2 – non-irrigated arable land; LUC 3 – permanently irrigated land; LUC 4 – permanent crops and heterogeneous agricultural land; LUC 5 – pastures; LUC 6 – forest and semi-natural areas; LUC 7 – water bodies and wetlands.

	CA-Markov	ANN-MLP	LUCC % disagreement	LUC 1 (%)	LUC 2 (%)	LUC 3 (%)	LUC 4 (%)	LUC 5 (%)	LUC 6 (%)	LUC 7 (%)
A0	5	1	2	14.3	6.2	13.6	23.6	3.1	38.6	0.6
A1	6	0	0	14.4	6.4	18.5	21.8	0.9	37.9	0.2
A2	4	2	2	13.7	6.2	11.8	22.1	4.0	41.6	0.6
B0	3	3	1	17.9	7.6	10.5	20.6	2.9	39.7	0.6

Table 8
Selected simulations in the stakeholder-LUCC model by scenario. Land use classes: LUC 1 – artificial surfaces; LUC 2 – non-irrigated arable land; LUC 3 – permanently irrigated land; LUC 4 – permanent crops and heterogeneous agricultural land; LUC 5 – pastures; LUC 6 – forest and semi-natural areas; LUC 7 – water bodies and wetlands.

Land use classes	LUC 1	LUC 2	LUC 3	LUC 4	LUC 5	LUC 6	LUC 7
A0							
A0: selected simulation (%)	**13.96**	**7.12**	**14.14**	**23.45**	**1.76**	**39.43**	**0.14**
Deviation (stakeholder LUCC views - A0)	0.34	−0.97	−0.52	0.18	1.32	−0.83	0.49
A1							
A1: selected simulation (%)	**15.34**	**8.68**	**10.39**	**24.37**	**2.10**	**38.98**	**0.14**
Deviation (stakeholder LUCC views - A1)	−0.93	−2.24	8.08	−2.59	−1.23	−1.1	0.01
A2							
A2: selected simulation (%)	**13.31**	**8.87**	**10.74**	**25.09**	**2.17**	**39.68**	**0.14**
Deviation (stakeholder LUCC views - A2)	0.34	−2.63	1.03	−2.99	1.83	1.95	0.49
B0							
B0: selected simulation (%)	**18.41**	**8.30**	**10.01**	**23.22**	**2.05**	**37.87**	**0.14**
Deviation (stakeholder LUCC views - B0)	−0.48	−0.66	0.53	−2.62	0.89	1.86	0.49

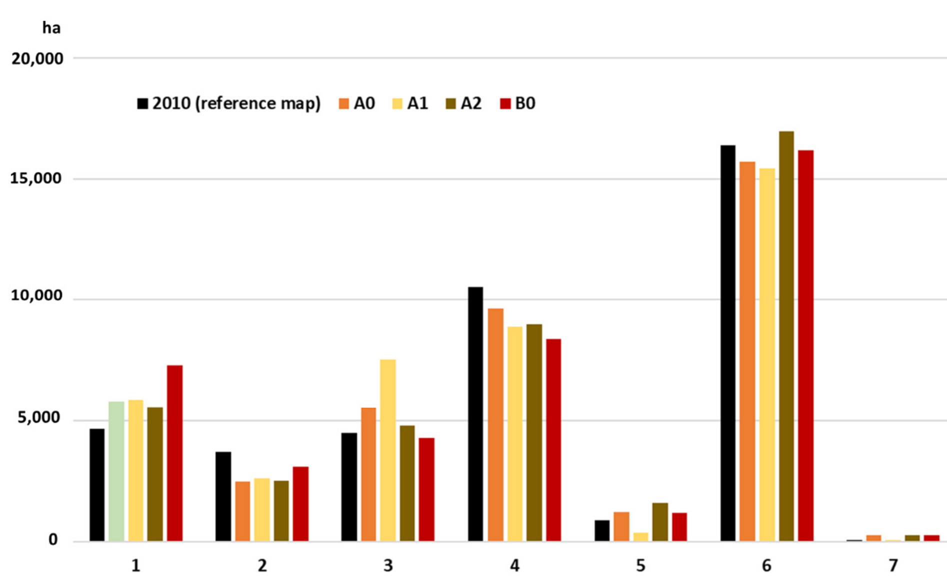

Fig. 8. Stakeholder LUCC views - A0, A1, A2, and B0 scenarios (ha). Land use classes: 1 – artificial surfaces; 2 – non-irrigated arable land; 3 – permanently irrigated land; 4 – permanent crops and heterogeneous agricultural land; 5 – pastures; 6 – forest and semi-natural areas; 7 – water bodies and wetlands.

forest and semi-natural areas to agricultural land: Yes or No; and farming in areas with the following interval slope degrees: 0–10° or 0–20°. Next, we present a radar charter showing LUCC in all the potential simulations (by scenario) performed in the stakeholder-LUCC model (Fig. 9).

Fig. 9 represents the variation in hectares of the seven land use classes analysed in the A0, A1, A2, and B0 scenario, according to the settings and parameters mentioned above. The outcomes are the result of all possible combinations (144 simulations) for each scenario.

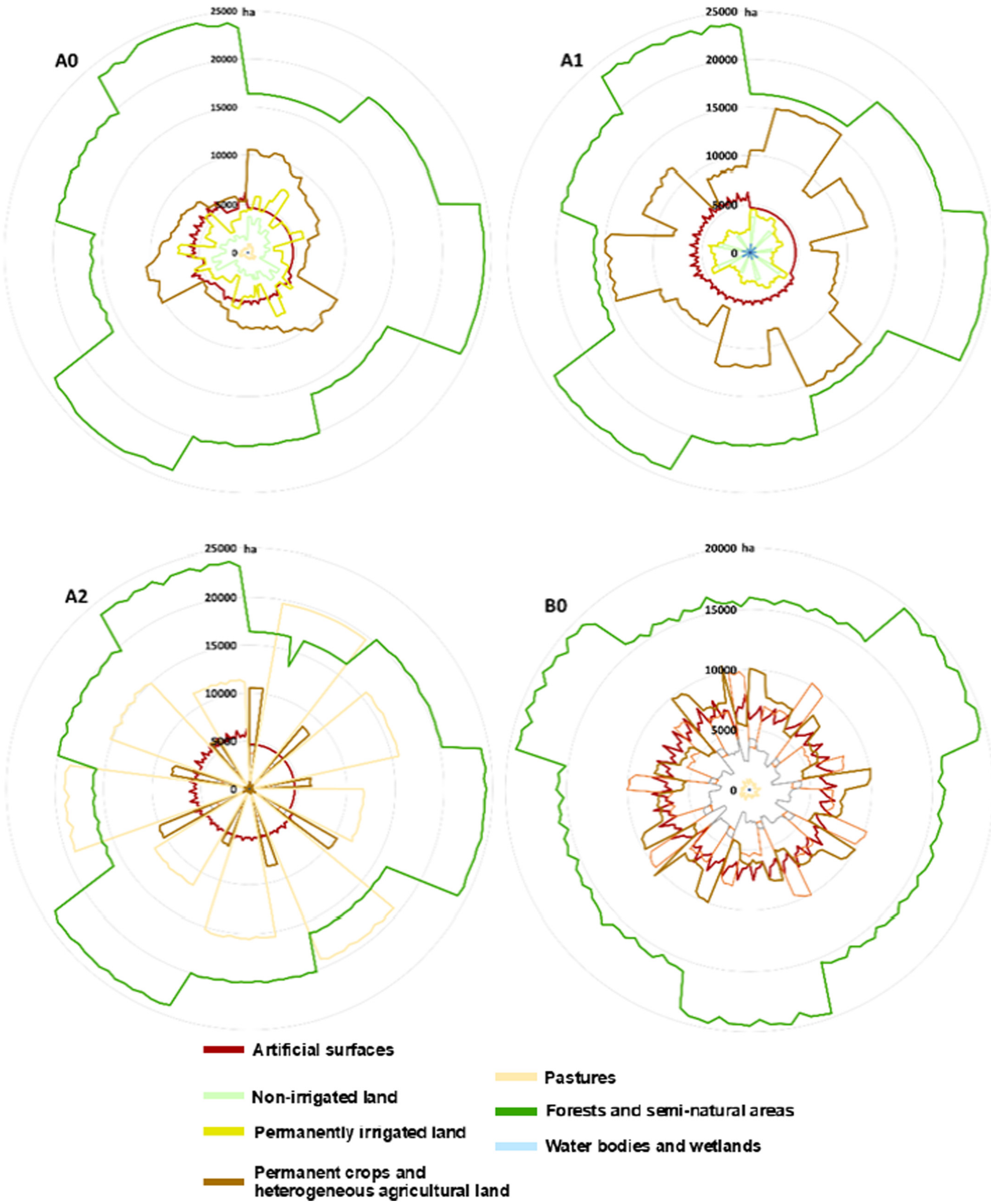

Fig. 9. The stakeholder-LUCC model simulations by scenario.

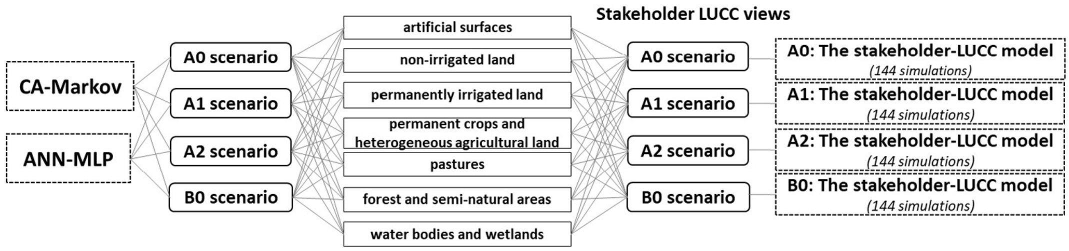

Fig. 10. Methodology flowchart representing the integration of stakeholder LUCC views into the stakeholder-LUCC model.

3.3.2. The stakeholder-LUCC model: integrating stakeholder LUCC views

Considering the outcomes of all the simulations, we identified which one, out of the 144 possible simulations (for each scenario), had the lowest deviations compared to the stakeholder LUCC views. Subsequently, the next step involved identifying in the model the parameters needed to achieve similar outcomes (in percentage) (Fig. 10).

This approach allowed us to reduce one of the weaknesses identified by the stakeholder-LUCC model: the multi-outcomes. This procedure helped us minimize the uncertainty of the results and aided in the choice of the simulation that best fit the views of the stakeholders. Accordingly, we searched in all the 144 simulations (for each scenario), which one had the lowest deviation (Table 8).

Therefore, according to the outcomes of each simulation, we identified the parameters needed to achieve those results. Table 10 shows those parameters to achieve the selected simulations.

As seen in Table 9, farmer LUCC intentions are the most determinant parameter responsible for the LUCC in the selected simulations, as well as the distance to artificial surfaces, distance to road network, and slope.

3.3.3. Stakeholder views: land use cover 2025

The previous analysis allowed the stakeholders to visualize and evaluate four different scenarios that may occur. This knowledge acquired by the stakeholders in the participatory workshop enabled them to develop their own views. So, at the end of the workshop, we asked them: Which LUCC do you think will be more plausible in 2025? After a dynamic discussion, they reached a LUCC consensus which is expressed as follows: artificial surfaces 16%; non-irrigated land 4.5%; permanently irrigated land 16%; permanent crops and heterogeneous agricultural land 27.94%; pastures 2%; forest and semi-natural areas 31.56%; and water bodies and wetlands 2%. Fig. 11 depicts the values in ha and percentage of each land use class of the reference land use map and the stakeholder views for 2025.

Comparing these LUCC views with the reference land use map, we can see an increase of 1869 ha in artificial surfaces (28.7%); a decrease of 1866 ha in non-irrigated arable land (−101.9%); an increase of 2033 ha in permanently irrigated land (21.2%); an increase of permanent crops and heterogeneous agricultural land of 838 ha (7.4%); a decrease of 84 ha in pastures (−10.3%); a decrease of forest and semi-natural areas of 3546 ha (−27.6%); and an upsurge of water bodies and wetlands of 756 ha (92.9%).

Subsequently, we identified in all the 576 possible simulations for all the scenarios (144*4) which one had fewer deviations in the stakeholder-LUCC model. Therefore, the selected simulation was identified as the A0 scenario (Table 10).

The last step was to spatialize this simulation that expresses the stakeholder LUCC views for the most plausible scenario in 2025 (Fig. 12).

Fig. 12 shows these transformations spatially. In the location assigned by A, we identify the site where the probability of conversion from permanent crops and heterogeneous agricultural land to permanently irrigated land is higher. In the location assigned by B, which represents artificial surfaces growth, we recognized that artificial surface expansion occurs along with the road network, and mainly infilling around existing artificial surfaces. The spatial patterns of the artificial

Table 9
Stakeholder-LUCC model parameters. Group: a - artificial surfaces; b - agricultural land; c - forest and semi-natural areas; d - water bodies and wetlands.

Group		A0	A1	A2	B0
Farmer LUCC intentions (%) - static					
a	1 - Artificial surfaces (%)	0	0	0	47.80
		Plus			
		Parameters (%)			
		40	40	40	20
	Distance to artificial surfaces (m)	100	200	200	200
	Distance to road network (m)	200	200	100	200
Farmer LUCC intentions (%) - static					
b	2 - Non-irrigated arable land	0.06	2.90	−45.61	0.28
	3 - Permanently irrigated land	20.23	67.97	−17.06	−17.00
	4 - Permanent crops and heterogeneous agricultural land	10.03	71.32	−11.00	−1
	5 - Pastures	−6.35	−25.40	560.32	−6
		Plus			
		Parameters (%)			
	Farming (slope in °)	0–10	0–20	0–20	0–20
	Convert forest and semi-natural areas to agricultural land use classes?	Yes	Yes	Yes	Yes
Farmer LUCC intentions (%) - static					
c	6 - Forest and semi-natural areas	0	0	0	0
		Plus			
		Parameters (%)			
		0	0	0	0
Farmer LUCC intentions (%) - static					
d	7 - Water bodies and wetlands	0	0	0	0

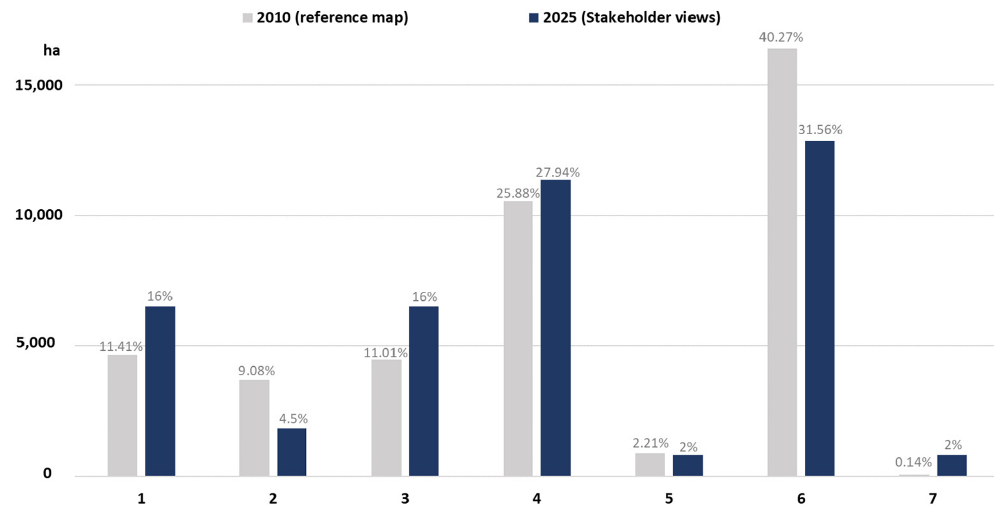

Fig. 11. Values in ha and percentage of each land use class of the reference land use map and the stakeholder views for 2025. Land use classes: 1 – artificial surfaces; 2 – non-irrigated arable land; 3 – permanently irrigated land; 4 – permanent crops and heterogeneous agricultural land; 5 – pastures; 6 – forest and semi-natural areas; 7 – water bodies and wetlands.

surface growth are categorized by linear directions, more pronounced in the south and in the west.

Moreover, the location C signals one of the highest transitions from non-irrigated arable land to permanently irrigated land, and location D from non-irrigated arable land and permanent crops and heterogeneous agricultural land to permanently irrigated land. The loss of forest and semi-natural areas occurs throughout the municipality, especially near its limits, consumed by artificial surfaces and agricultural land.

3.4. Land use strategies and advances in land use management

As mentioned above, LUCC is controlled by land use instruments, socioeconomic, and environmental indicators, topographic constraints, attraction by the proximity of some physical elements and human actions. Understanding stakeholder views was essential to assess LUCC in a peri-urban context. These views were based on future narratives in accordance with the FAO and EU policies.

This study allowed us to ascertain the reliability of analysing future LUCC as a support for decision-making to promote sustainable urban growth and agricultural land preservation. The spatial patterns of future LUCC obtained in the stakeholder-LUCC model successfully projected land use conversion and identified the most suitable areas for each conversion. According to the achieved results, policymakers can be more efficient, integrating these results into the Municipal Master Plan (PDM) and into the Inter-municipal plans (PIOT). PIOT could be a better strategy to analyse and understand land transformations at a larger scale (they are implemented in a set of municipalities). The application of PIOT in Portugal, although established by law, is not effectively visible in the Portuguese spatial planning process. Protection measures should be implemented more efficiently considering where and when land transformations may occur.

From the urban growth perspective, according to the economic and social trend in our case study in a medium-long-term period, some indicators can point to a fast LUCC transformation. An increase in housing demand has been verified in the last few years in the metropolitan region of Lisbon (Statistics Portugal, 2019). Therefore, mostly due to the amenities that Torres Vedras can offer and the lower prices of housing compared to Lisbon, this territory may be an attractive target for potential urban development. This attraction can also be driven by the evolution of information technology. In recent years, more people have been able to work from home. They can benefit from the proximity to Lisbon, but they will not need to commute daily. Additionally, we believe electric cars can increase housing demand by new residents. Although the undisputable benefits that these vehicles have in terms of greenhouse effect (zero-emission), due to the low cost of charging, they can indirectly promote the increase of extensive urbanization (Kester et al., 2020). People will be able to commute long distances at a low cost, and the demand for single-family dwellings can increase. Therefore, actions to promote urban containment growth should be implemented (Dawkins and Nelson, 2002; Fertner et al., 2016). Moreover, new built-up areas must have environmental concerns, such as high energy efficiency using renewable energies, green roofs, and environmentally friendly construction materials (Hamilton et al., 2013; Li and Yeung, 2014).

From the agricultural land perspective, policies to protect and monitor it should also be employed (Gomes et al., 2019c). According to our results, the highest increase will be in permanently irrigated land. Therefore, decision-makers should contemplate some measures to improve the irrigation systems and thus make farming more efficient and competitive, e.g. Levidow et al. (2014), and Holzapfel et al. (2009). This was one of the main solutions pointed out by the stakeholders. This is more pressing because the agricultural sector must be aware of climate change. The Intergovernmental Panel on Climate Change (IPCC) projected scenarios for the latitude of our case study that show longer periods of drought and greater scarcity of water (IPCC, 2000), and measures to mitigate this effect must be implemented accordingly. Other transformations that can be seen in the agriculture sector can result from the competition of other markets, demand for new consumption patterns, or the introduction of new technology. Concerning new technology, smart farming is already a reality, and it can increase the quantity and quality of agricultural products, using unmanned tractors controlled via Global Positioning System (GPS),

Table 10
Stakeholder LUCC views (%) for 2025. Land use classes: LUC 1 – artificial surfaces; LUC 2 – non-irrigated arable land; LUC 3 – permanently irrigated land; LUC 4 – permanent crops and heterogeneous agricultural land; LUC 5 – pastures; LUC 6 – forest and semi-natural areas; LUC 7 – water bodies and wetlands.

	LUC 1	LUC 2	LUC 3	LUC 4	LUC 5	LUC 6	LUC 7
Stakeholder LUCC views (%) (2025)	16.00	4.50	16.00	27.94	2.00	31.56	2.00
A0: selected simulation (%)	15.39	5.63	16.93	21.72	1.35	38.84	0.14

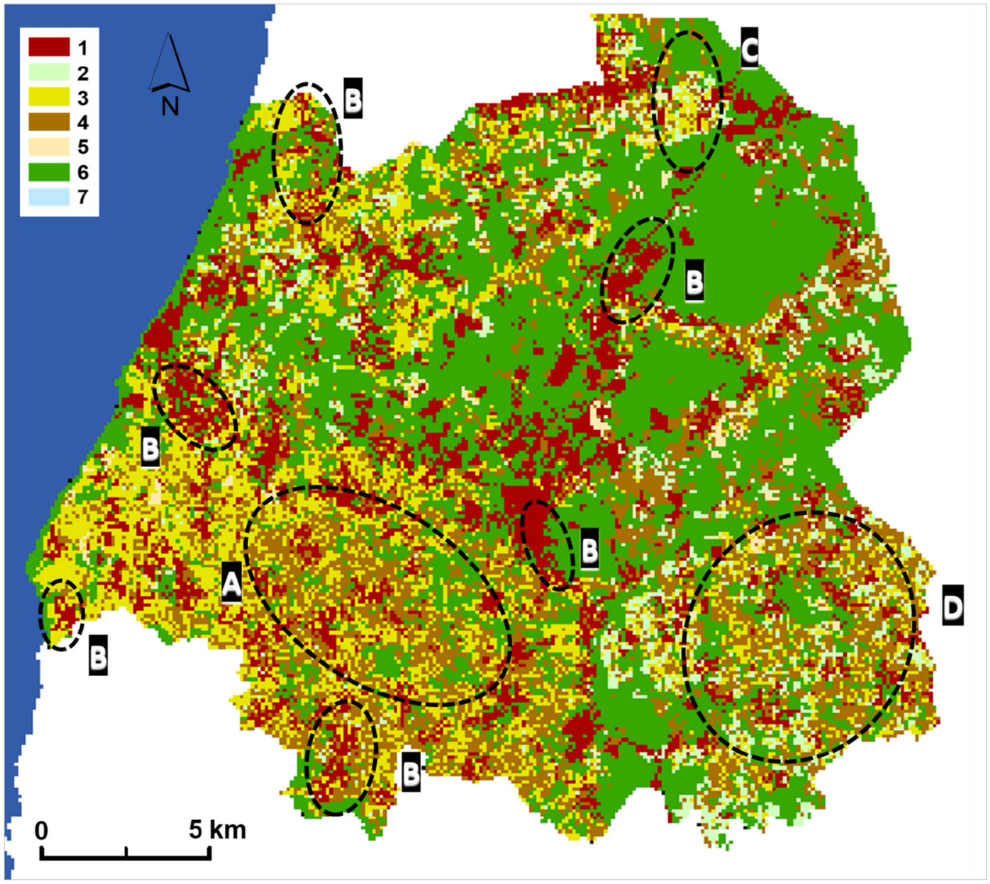

Fig. 12. Stakeholder LUCC views: 2025 (A0: selected simulation – stakeholder-LUCC model). Land use classes: 1 – artificial surfaces; 2 – non-irrigated arable land; 3 – permanently irrigated land; 4 – permanent crops and heterogeneous agricultural land; 5 – pastures; 6 – forest and semi-natural areas; 7 – water bodies and wetlands.

unmanned aerial vehicle (UAV - commonly known as drones) to kill vermin, and precision agriculture (Pivoto et al., 2018; Walter et al., 2017).

The political, environmental, demographic, social, technological and economic issues will change the current farming paradigm in peri-urban areas. This can transform LUCC quickly in the near future, forcing farmers to readapt their production according to the changes that may occur. Thus, the analysis presented in this study can be the first step to successfully examine, anticipate, and understand future land use, reducing the uncertainties to better prepare for the future.

In the context of modelling land use change for spatial planning support, this study aimed at opening up new methodological paths for further research. LUCC simulation experiments have been dealing with different categories of land use and have been conducted by Parker et al. (2003), Lambin et al. (2003), and Valbuena et al. (2010). While LUCC prediction and assessment have been developed, predictions performed in this research are based on new narratives and storylines to understand LUCC dynamics through a new approach. We presented a prospective methodology to better understand spatial and temporal land use dynamics, identifying what is more relevant in the decision process. The results achieved in this research should: (1) inform policymakers and the community, demonstrating future land use alternatives and showing its impacts; (2) show the suitable land use options to avoid undesirable future impacts (adaptive land use management); and (3) simulate LUCC to support planners, creating sustainable development strategies, and anticipating and understanding future land use uncertainties.

This paper has explored the potential for developing geospatial modelling. We integrated LUCC modelling with a GIS-based methodology to support planning decisions at the local planning level. We aimed to understand how stakeholder views can fit in the decision-making process, looking at *how*, *where*, *why*, and *what* land use conversions may occur. As the main contribution, we intend to facilitate communication and knowledge sharing between stakeholders to foster the best political options for land use, leading to an effective way of integrating expert knowledge in the evaluation of land use alternatives.

4. Conclusion

The role of human activities in controlling land use has had different effects on land use. Anticipating decisions, indicating alternative futures and their impacts, to support policy-makers is one of the biggest challenges of spatial planning. The mixed-methods (quantitative and qualitative) used in our research by means of the participatory workshop enabled us to strengthen the relations between researchers and stakeholders, and encouraged knowledge sharing and the interchange of different points of view. It allowed us to see how stakeholders can play their part in the decision-making process (local-level actors) and the interactions between spatial factors and constraints. As a result land use recommendations were put forward.

We introduced advances in the land use modelling and planning purposes, providing guidance and strategies that can be implemented in spatial planning and land management. Stakeholders recognized the collaborative participation as an efficient approach in the deliberative decision-making process, highlighting the importance of the perception of others to achieve a shared solution. They also considered this approach as very proficient to apply to the municipal planning policies and regulations. In brief, this research explored the integration of spatial planning and complexity science.

During this research, we were faced with several weaknesses in the data gathering process, as well as LUCC analysis and validation. These difficulties arise from accurate data acquisition and finding appropriate methods. Due to the limited available data, we think the calibration process was not long enough to detect satisfactory LUCC for longer predictions (a wider time-span would have been more proper). In addition, although the results presented in this study were effectively tested, several issues remain unexplored and can be addressed by future research. More analyses need to be conducted. In terms of future work, we recommend, e.g., (1) gathering detailed and updated land use data (using satellite images); (2) testing the proposed methodology for comparison in another study area to evaluate its replicability; and (3) regarding the stakeholder-LUCC model, we believe it is still only a prototype, and some progress should be made, such as to improve the usability of the model, or to allow us to add other spatial factors and constraints. These are some developments which we think could bring an advantage for the model.

Future LUCC interpretation has demonstrated to be useful for the identification of the main impacts on land conversion. However, there is still a gap between this analysis and local planning authorities when it comes to managing and reorganising land allocation priorities according to the environmental, demographic and economic needs. It can assist not only by providing spatial guidelines to monitor future trend but also to identify threats and the deterioration of agricultural land and natural areas.

In brief, the current research is entrusted with providing methodological guidance for future scientific research and may help researchers, modellers and decision-makers to better visualize and identify the most suitable areas for land conversion, and evaluate the effects of future LUCC.

CRediT authorship contribution statement

Eduardo Gomes: Conceptualization, Writing - original draft.**Arnaud Banos:** Conceptualization, Writing - original draft.**Patrícia Abrantes:** Conceptualization, Writing - original draft.**Jorge Rocha:** Conceptualization, Writing - original draft.**Markus Schläpfer:** Conceptualization, Writing - original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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