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1. Introduction

Land use and land cover is the result of a set of complex systems linked by the interaction of environmental, social, and human activities and economic factors (Lambin and Reenberg 2007; Robson and Berkes 2011). Land use and land cover changes (LUCC) result from the interaction between these different factors (Geist and Lambin, 2002) in non-linear relationships, and they can take place globally or locally. In peri-urban areas, the main concern about land use/cover is related mostly to the conversion from agricultural land to urban development. The consequences can range from endangered food security (Abrantes et al. 2016; Gomes et al. 2018; Spilková and Vágner 2016) to negative impacts on the economy (Heinet et al. 2008), ecosystems (Seki et al., 2017), and climate variability (Li et al. 2009).

These areas are dynamic, and characterised by commutes to work, and heterogeneous activities (Lambin et al. 2003). The proximity to urban settlements and the urban pressure felt in these places present farmers with new challenges for the future. The literature focuses on three main challenges: (1) maintaining their farmland (Malan, 2015); (2) expanding their farmland (Deininger and Byerlee, 2011); and/or (3) selling their farmland for urban development (Curran-Cournane et al. 2016; Satterthwaite et al. 2010). Analysing and understanding how farmers would change the territory are of great importance to anticipate the uncertainties of the future.

LUCC models have been developed since the 1950s and 1960s (Yu et al., 2011). They have been performed by a multidisciplinary assessment (Agarwal et al., 2002; Verburg et al., 2006) analysing the relationship between different types of behaviour to understand complex dynamics, and artificially recognise what can happen in the real world (Macal, 2016). LUCC methods have evolved to integrate a variety of methods, coupling artificial neural networks, cellular automata, agent-based models, or multiple regressions.

Several works have been published using different methods and applied to empirical case studies, increasingly stirring interest among policymakers. For instance, Agarwal et al. (2002) present an analysis of different types of models, Boavida-Portugal et al. (2016) assess the impacts of tourism on built-up areas, Lambin et al. (2003) explore LUCC in Tropical Regions, Morgado et al. (2014) analyse contested land use visions, and Gomes et al. (2019a) and Puertas et al. (2014) simulate urban growth in a metropolitan area context.

Cellular automata (CA) are one of the most widely used methods (Macal and North, 2010). It is a powerful method for studying complex systems and exploring principles of system evolution and self-organisation (Mitchell, 1998). CA became more common and popular when, in 1970, John Conway designed the Game of Life (Huang et al. 2009), the most popular 2-D binary CA. Following successive theoretical structure improvements, CA have become a well-established method for modelling LUCC in recent decades, and have been widely used since they were introduced by Tobler (1979). CA have the ability to simulate dynamic development from a bottom-up perspective (Liu et al. 2008) based on complex spatial forms (e.g., Agarwal et al. 2002; de Almeida et al. 2003; Wang and Li 2011). CA based on Markov chains are increasingly employed in LUCC (Dezhkamet al. 2017; Sang et al. 2011), incorporating the relationships between land use and driving forces.

LUCC models are likely to become a significant tool for spatial planning (Herold et al. 2005). A better LUCC analysis can support better planning practices (Yirsaw et al. 2017), and identify the valuation of different land use options and socioeconomic settings in order to recognize desirable land uses (FAO 1993). Land use planning can shape policies to promote regulatory land use implemented by decision-makers. These policies intend to control land use activities in the future, aiming to preserve open landscapes for agriculture and nature, and encourage sustainable development. But these processes are too rigid, particularly when applied to peri-urban areas where land conversion is very fast. They are one of the major policy challenges at the moment, and more studies are needed (Abrantes et al., 2016; Gomes et al., 2019a), namely engaging stakeholders to recognize their intentions in the LUCC process. Scenarios are a good way to identify future uncertainties in endogenous and exogenous developments (Rounsevell et al., 2006) to prepare for the needs of the future (Corket al. 2000).

This paper proposes a LUCC model incorporating farmers' intentions and assessing the impacts of their intentions in agricultural, forest, and urban land. We identified how farmers' intentions may affect future land use whenever they are faced with four different scenarios, such as (a) A0 - current social and economic trend; (b) A1 - intensified agricultural production; (c) A2 - reduced agricultural production; and (d) B0 - increasing demand for urban development.

The methodology used in this study included interviews with farmers (to capture farmers' LUCC intentions), and then a combination of geographic information systems (GIS), and CA – Markov Chain – developing step-by-step guidelines towards the creation of a simulation model to predict LUCC. The main contributions of this paper are: (a) to spatially analyse and model future LUCC and their impacts on the territory, and (b) to help understand how farmers' decisions can affect the decline, preservation, or maintenance of agricultural land in peri-urban regions.

2. Data and methods

2.1. Study area

The Torres Vedras municipality, in Portugal, is located roughly 50 km north of Lisbon (covering an area of 407 sq km) and bathed by the Atlantic Ocean (Fig. 1).

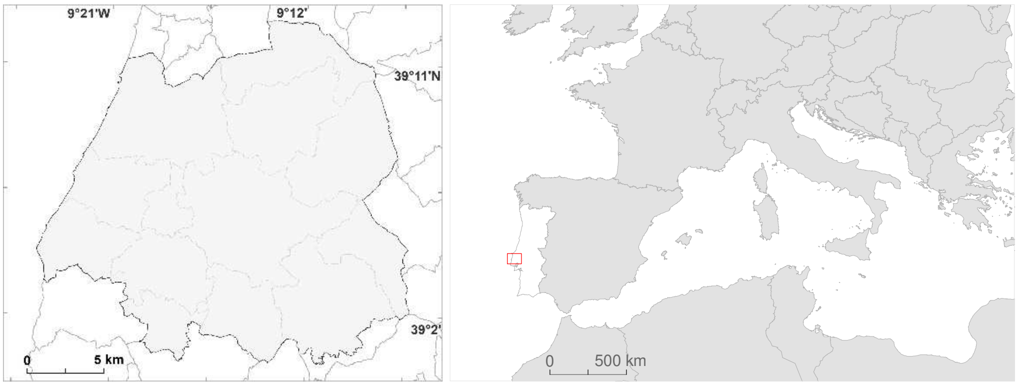


Figure 1 – Location of Torres Vedras municipality (Portugal) in Europe.

Over the past two decades, artificial surfaces have increased by 41% (1995-2010), and their population has also been increasing. In 1991, Torres Vedras had a population of 67,185 inhabitants, and in 2011, there were 79,465 inhabitants (Statistics Portugal, 2011). The population growth was around 18%. However, growth has not been the same throughout the municipality. During this period, Santa Maria do Castelo e São Miguel and A dos Cunhados parishes have had a population growth of around 47%, and 37%, respectively. Nevertheless, some other parishes have had negative population growth, such as Outeiro da Cabeça (-15%), and Matacães (-16%).

Torres Vedras is one of the main suppliers of agricultural goods in Portugal (e.g., fresh fruits, vegetables, and wine) (Statistics Portugal, 2011), which is one of the most important sectors of the local economy (Statistics Portugal, 2009). The gross added-value of agricultural enterprises in Torres Vedras has increased by 63% in the last few years (2009-2016), which compares with 45% in the whole Oeste Region, and 57% nationwide.

2.2 Data

To simulate how farmers' decisions (obtained from the interviews conducted) may affect LUCC, two sets of data were needed: land use and driving forces. These data were converted into raster format (10 x 10 m pixel size).

Land use

Land use maps for the years 1995, 2007, and 2010 were used. The accuracy of the land use maps was validated at the 1:25 000 scale by Direção-Geral do Território (DGT). The land use maps contain over one hundred classes but for the purpose of this study these were regrouped into the following seven 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; and 7 – water bodies and wetlands (original data source: http://mapas.dgterritorio.pt/geoportal/catalogo.html). Artificial surfaces were grouped in the same land use class due to the urban fabric and service growth, usually accompanied by population growth (Duranton and Puga 2014; Satterthwaite et al. 2010). However, we divided agricultural land into four land use classes because the focus of this study is to provide an in-depth analysis of agricultural land use dynamics. Forest and semi-natural areas were grouped into one land use class, as well as water bodies and wetlands. Table 1 provides a detailed description of the subclasses included in each land use class (in %).

Table 1 – Land use classes and subclasses.

Land Use Class	Land use subclasses	2010 (%) - subclasses	2010 (%) - classes
(1) artificial surfaces	Urban fabric	7.09	11.40
	Industrial, commercial and transport units	2.45	
	Mines, dumps and construction sites	1.46	
	Artificial, non-agricultural vegetated areas	0.40	
(2) non-irrigated arable land	With and without dispersed vegetation	9.09	9.09
(3) permanently irrigated land	Permanently irrigated land	11	11
(4) permanent crops, and heterogeneous agricultural land	Vineyards	13.68	25.94
	Orchards	3.51	
	Olive groves	0.04	
	Complex cultivation patterns	7.18	
	Annual crops associated with permanent crops	0.95	
	Land principally occupied by agriculture	0.56	
	Agro-forestry areas	0.02	
(5) pastures	Grassland (pastures and meadows)	2.17	2.17
(6) forest and semi-natural areas	Broad-leaved forests	16.16	39.94
	Coniferous forest	0.86	
	Mixed forests	2.44	
	Scrub and/or herbaceous vegetation associations	19.89	
	Open spaces with little or no vegetation	0.60	
(7) water bodies and wetlands	Water bodies	0.15	0.46
	Wetlands	0.31	

Driving forces

A set of factors and constraints that represent the attraction and repulsion for land use conversion were used. The selected driving forces were mapped for each scenario generated by using common GIS functions, Boolean Logic (1 or 0, True or False), and fuzzy membership functions (ranging from 1 to 0, representing the attraction or repulsion for land use conversion). The Euclidean distance of each cell to urban areas, road network, agricultural land, hydrographic network, and coastline was found. These driving forces were selected following the literature and the interviews with the farmers. Table 2 identifies the list of driving forces, the hypotheses and references that support each driving force based on similar studies, and the source of these drivers used to explain LUCC.

Table 2 – Description of driving forces used to explain LUCC.

Category	Driving force	Hypotheses and references	Source
Social, economic, and physical elements	Population density	Population density has a positive effect on urban growth (Triantakonstantis, 2012)	Statistics Portugal
	Distance to urban areas	Related to costs of transport (Leão et al. 2004; Megahed et al. 2015)	DGT
	Distance to road network		OpenStreetMap
	Distance to agricultural land		DGT
	Distance to hydrographic network	Related to water availability for agricultural irrigation (Bekchanovet et al .2010)	IGeoE
	Slope	As a barrier for urban development (Leão et al. 2004) and for agricultural expansion (Li and Li 2017)	
	Distance to coastline	Related to agricultural productivity (information obtained from the interviews with farmers)	DGT
Land use regulation	RAN (National Agricultural Reserve)	Land use regulations can protect agricultural areas as well as promote urban development (Sims, 2014)	Master Plan
	Urbanizable areas (best areas for new built-up areas)		
	Non-aedificandi areas (with restrictions to urban development)		

Interviews with farmers

Face-to-face semi-structured interviews were conducted with active farmers. The questions were addressed to identify the farmers' profile, their farming practices, and their intentions for future LUCC. In order to define the farmers' profile, we asked them about their age, gender, and education. Regarding their farming practices, we asked the farmers about their farmland's size, whether they are owners or tenants, and we also asked them to identify the size of each land use class within their farmland (in ha). Finally, in order to learn about the farmers' intentions of future LUCC (for every scenario) we asked whether they intend to expand, maintain, and/or decrease their farmland (and to which land use class they intend to change); and the area (in ha) of the intended changed (expand/decrease). The interviews with farmers were then later used for the transition rules to quantify the LUCC.

2.3 Methods

2.3.1 Description of scenarios

In our study, four explorative scenarios (plus a BAU – business as usual – scenario) were developed and were run for the year 2025. The A0, A1, A2, and B0 scenarios intend to assess how farmers define their priorities for future agricultural activity. The four explorative scenarios are as follows:

A0 - current social and economic trend

The A0 scenario aims to recognize farmers' LUCC intentions, according to social, political, economic, and environmental trends. Farmers state their intentions of keeping, expanding, or selling their farmland. In the A0 scenario, population, urban land prices, and the demand for dwellings and buildings other than dwellings are stable.

A1 - intensified agricultural production

Farmers identify their motivations and priorities in a context of increasing demand for agricultural products. This demand is signalled by a population increase of 20% (in relation to the A0 scenario), as well as changing food habits (e.g., dietary pattern), and stock building. The A1 scenario also indicates increased purchasing power and the importance of the agricultural markets closest to urban centres. Some of these issues are addressed by FAO Agricultural Development Economics Division in Alexandratos and Bruinsma (2012).

A2 - reduced agricultural production

Farmers explain their intentions in a context of declining agricultural production and productivity. In this scenario, population declines by 20% (in relation to the A0 scenario), and there is also a decrease in the demand for dwellings and buildings other than dwellings. The A2 scenario recognizes decreased purchasing power and increased imports of agricultural products from regions where the final cost of agricultural products is lower. Some of these concerns are identified by Anderson (2010), and Nazzaro and Marotta (2016).

B0 - increasing demand for urban development

This scenario assesses an increase of built-up areas and increased expectations of new peri-urban residents. There is a population increase of 50% (in relation to the A0 scenario), as well as increased purchasing power, growing demand for new dwellings and buildings other than dwellings, and improved road access and public transport facilities. Moreover, in this scenario, real estate is viewed as an attractive investment, and urban land prices increase by 200% (in relation to the A0 scenario). These issues are recognized by Satterthwaite et al. (2010) and Rauws and de Roo (2011).

2.3.2 Interviews with farmers

To identify the sample of the total farming population to be interviewed, different tests were performed to obtain the margin of error and confidence interval. Accordingly, we found a balance between the values accepted in the literature (Greenland et al., 2016), and the costs and time taken per interview. Therefore, a confidence interval of 95%, and a maximum error margin of 10% were considered. We used 2009 as the reference date for the total farming population (2201 farmers), referring to the last agricultural census conducted in Portugal. We identified a sample of 93 interviews.

2.4 Cellular Automata

In order to obtain the land use scenarios, we used IDRISI Selva software (Eastman, 2012). The simulation scenarios are composed of seven main components: multicollinearity of driving forces, cell states (fuzzy and Boolean logic), neighbourhood configuration, transition rules, time step resolution, and model assessment. The detailed steps are shown in Figure 2.

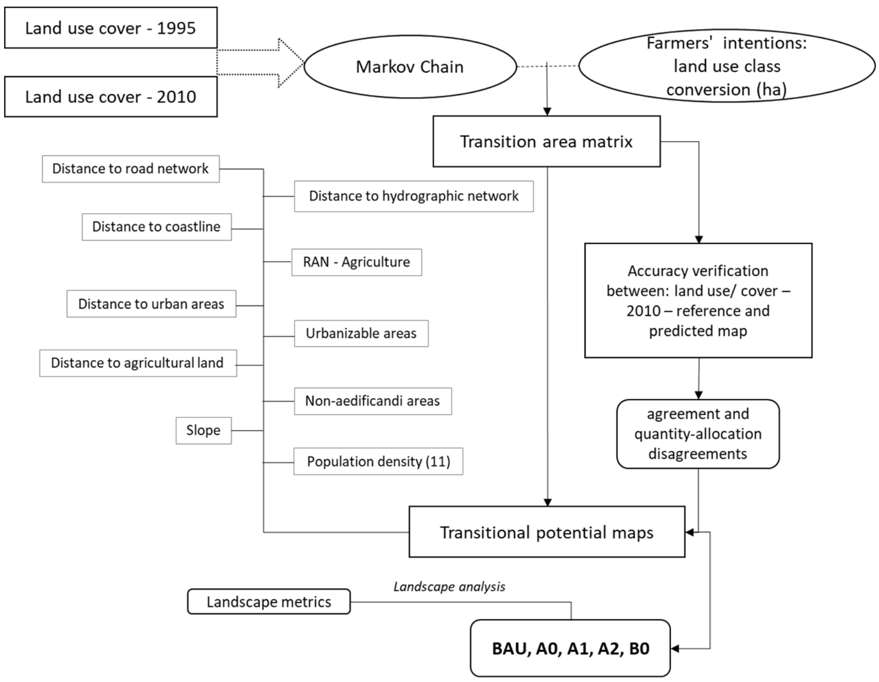


Figure 2 – Methodological framework.

Multicollinearity of driving forces

After we identified the most important driving forces that characterise the case study and the phenomena under study, we estimated explanatory variable redundancy (multicollinearity). We used the variance inflation factor (VIF) to quantify the degree of multicollinearity. The values obtained were below 2, which means that all the driving forces in the model are stable (Brien, 2007).

Cell states (fuzzy and Boolean logic)

The fuzzy analysis function was applied to demonstrate the suitability of each cell to be converted from state 1 to state 2. Fuzzy analysis corresponds to a normalisation process in which physical driving forces are transformed into a range of fixed values (Kainz, 2001). In Boolean logic, only two possible values are considered: true or false (e.g., 0 or 1) (Sui, 1992).

Neighbourhood configuration

The neighbourhood configuration chosen was the Moore neighbourhood with 5x5 cells. Neighbourhoods have adjacent cell clusters that define the distance to an individual automaton (Kocabas and Dragicevic, 2006; Verburg et al., 2004).

Transition rules to quantify land use class conversion (Markov chain and farmers' LUCC intentions)

To estimate the probability of the quantity of LUCC (in area) in 2025, two approaches were employed: Markov chain and farmers' LUCC intentions.

Markov chain is represented by a set of random driving forces (Diaconis, 2009), and has a matrix of transition probabilities expressed by $t_1 < t_2 .. t_n < t_{n+1}$. Where t_n corresponds to present time, t_{n+1} to a point in the future, and $t_1, t_2 ..., t_{n-1}$ to several points in the past (Basharinet et al. 2004; Levinet et al. 2009).

Farmers' LUCC intentions were collected from the interviews. To obtain the matrix of LUCC, the following procedures were performed:

a) We added the number of hectares of all the agricultural land use classes (non-irrigated arable land, permanently irrigated land, permanent crops and heterogeneous agricultural land, and pastures) that correspond to the current farmlands of the interviewed farmers;

b) We calculated the percentage of growth for each agricultural land use class (and for each scenario) based on farmers' LUCC intentions;

c) Afterwards, we obtained the percentage of growth and multiplied the percentage of each agricultural land use class by the corresponding land use class of the reference land use map (to obtain the area in hectares — positive or negative);

d) In order to identify the changes that will occur in the future from each land use class (transition matrix), we used the trends (in %) of past years (between 1995 and 2010) to obtain positive and negative growth (we distributed the quantity of land according to this %);

e) When the expected growth (in hectares) for a specific agricultural land use class was higher or lower than the available land (obtained in d), we used the pastures and forest and semi-natural areas as a passive land use. We added or subtracted pastures and/or forest and semi-natural areas in hectares (in the transition matrix) if the agricultural area had decreased or increased (proportion distribution between pastures and forest and semi-natural areas was based on the percentage of changes that occurred in the past (1995-2010) using the same procedure described in d);

f) For the B0 scenario, we estimated artificial surface growth as follows:

Area expected to be changed from agricultural, forest and semi-natural areas to artificial surfaces according to the farmers' intentions.

Subsequently, we multiplied the area in hectares of the farmers' intentions to transform their agricultural land into artificial surfaces by the construction index of 0.25 approved in the Torres Vedras Master Plan (Notice No. 927/2014), whose Article 31 specifies the conditions of construction. To identify passive land, we used the same technique described in d) above.

Complying with these two transition rules, we used each technique for the land use classes and scenarios mentioned in Table 3.

Table 3 – Transition rules techniques used for each land use class and scenario.

<table>
<tr><th>Land Use Classes</th><th>BAU</th><th>A0, A1, A2</th><th>B0</th></tr>
<tr><td>Artificial surfaces</td><td rowspan="7">BAU</td><td>BAU</td><td rowspan="5">Farmers' intentions</td></tr>
<tr><td>Non-irrigated arable land</td><td rowspan="4">Farmers' intentions</td></tr>
<tr><td>Permanently irrigated land</td></tr>
<tr><td>Permanent crops and heterogeneous agricultural land</td></tr>
<tr><td>Pastures</td></tr>
<tr><td>Forest and semi-natural areas</td><td rowspan="2">BAU</td><td rowspan="2">BAU</td></tr>
<tr><td>Water bodies and wetlands</td></tr>
</table>

Transition potential maps: logistic regression analysis

Logistic regression was used to acquire the relative weights of explanatory driving forces, which represent the very driving forces that influence LUCC (Wu 2002).

In each logistic regression analysis, we used different input driving forces to explain the dependent variable (land use/cover 2010). These driving forces depend on each land use class and scenario. Thus, we used different explanatory driving forces for artificial surfaces (land use class 1) (AS), agricultural areas (land use classes 2, 3, 4, and 5) (AA), forest and semi-natural areas (land use class 6) (FSNA), and water bodies and wetlands (land use class 7) (WBW). Table 4 shows the driving forces used for each scenario.

Table 4 – Explanatory driving forces used in logistic regression analysis for artificial surfaces, agricultural land, forest and semi-natural areas, and water bodies and wetlands for each scenario (dependent variable: land use/cover 2010)

N	Driving forces	AS (BAU, A0)	AS (A1, A2, B0)	AA (BAU, A0)	AA (A1, A2, B0)	FSNA (BAU, A0, A1, A2, B0)	WBW (BAU, A0, A1, A2, B0)
1	**Distance to road network**	○	○	○	○	○	
2	**Distance to coastline**	○	○	○	○		
3	**Distance to urban areas**	○	○				
4	**Distance to agricultural land**		○	○	○		
5	**Slope**	○	○	○	○	○	○
6	**Distance to hydrographic network**			○	○		○
7	**RAN**			○	○		
8	**Urbanizable areas**	○	○				
9	**Non-aedificandi areas**	○	○				
10	**Population density**	○					

Time step resolution

Time step resolution was 1 year, and the simulations carried out cover a time span of 15 years (or 15 time steps — from 2010 to 2025).

Model assessment

Model assessment implies using techniques to check that the simulations are satisfactorily estimated (Trucano et al., 2006). There are many techniques to validate the accuracy of predictions. Kappa index has been widely used to validate LUCC models (Kandziora et al., 2014; Pan et al., 2010; Yu et al., 2011) measuring the inter-rater agreement between categorical variables x and y, and evaluating the prediction performance of classifiers (Cohen, 1960). A kappa of 0 indicates that agreement is due to chance, while a kappa of 1 indicates a perfect agreement (Viera and Garrett, 2005). However, Pontius and Millones (2011) proposed to quantify disagreement and allocation disagreement. In this study, kappa agreement and quantity-allocation disagreements have been estimated.

Moreover, landscape metrics were used, in the discussion section, to assess the overall spatial patterns by comparing the variation and the spatial patterns between the reference map and the predicted scenarios. The mean patch size, the nearest neighbour distance, and the number of patches were estimated. The mean patch size metric relates the size of each land use class with the number of patches of each land use class (McGarigal and Marks, 1994). The mean nearest neighbour distance corresponds to the average distance of developed patches to their nearest developed neighbours, based on edge-to-edge distance (McGarigal and Marks, 1994). And the number of patches (McGarigal and Marks, 1994) corresponds to the number of spatial entities.

3. Results and discussion

3.1 Model performance

In this study, different types of kappa coefficients (measuring agreements and quantity-allocation disagreements) were applied to evaluate the simulation performance of different scenarios. We compared simulated 2010 land use with the reference map for 2010. Using the driving forces shown in Table 2 for the BAU scenario, we performed the matrix of Markov transition areas and the suitability obtained from the logistic regression analysis from 1995 to 2007. Subsequently, we computed the CA-Markov to simulate 2010 land use (Supplementary material).

We measured inter-rater agreement, i.e., we compared the actual observed agreement with the expected agreement over random allocation. Pontius (2000) refers that kappa values below 1 can be caused both by dissimilarity in sizes and by allocation of land use classes on the map, and they do not quantify disagreement and allocation disagreement (Pontius and Millones 2011). As the first step to minimize this disadvantage, a contingency table was measured (van Vliet et al. 2011). Table 5 represents the cross tabulation between the reference map and the predicted map for land use in 2010.

Table 5 – Cross tabulation between 2010 - reference map and 2010 - predicted map. Land use classes: 1 (artificial surfaces); 2 (non-irrigated land); 3 (permanently irrigated land); 4 (permanent crops and heterogeneous agricultural land); 5 (pastures); 6 (forest and semi-natural areas); and 7 (water bodies and wetlands).

predicted\ reference	1	2	3	4	5	6	7	Total
1	444478	1644	2575	8977	2664	16229	760	477327
2	1374	291476	17350	34489	7148	9932	66	361835
3	1766	2228	383055	50107	237	17007	144	454544
4	3220	21008	16353	922633	3181	40752	141	1007288
5	977	17349	10215	5180	36611	9453	0	79785
6	12378	36415	18229	34715	38446	1532960	232	1673375
7	0	8	0	0	0	12535	4803	17346
Total	464193	370128	447777	1056101	88287	1638868	6146	4071500

From this contingency table analysis we retrieve the observed and expected fraction of agreement, and the maximum fraction of agreement (van Vliet et al. 2011). To integrate these parameters into the kappa index, Hagen (2002) identifies KHistogram and KLocation, described as follows:

$$Kappa = \frac{p_o - p_e}{1 - p_e} \rightarrow \begin{Bmatrix} K_{Histo} = \dfrac{p_{Max} - p_e}{1 - p_e} \\ K_{Loc} = \dfrac{p_o - p_e}{p_{Max} - p_e} \end{Bmatrix} \rightarrow Kappa = K_{Histo} \times K_{Loc}$$

where *Po* is the correct observed proportion, *Pe* is the is the expected fraction of agreement, and *PMax* is the total number of cells taken in by each class. KHistogram ranges from 1, indicating a perfect agreement, to 0 indicating no agreement, whereas KLocation ranges from -1 to 1, in which 1 corresponds to a perfect allocation. Table 6 expresses kappa, klocation, and khistogram values obtained between 2010 (reference map) and 2010 (predicted map).

Table 6 – Kappa index, kLocation, and KHistogram between 2010 (reference map) and 2010 (predicted map). Land use classes: 1 (artificial surfaces); 2 (non-irrigated land); 3 (permanently irrigated land); 4 (permanent crops and heterogeneous agricultural land); 5 (pastures); 6 (forest and semi-natural areas); and 7 (water bodies and wetlands).

Measures	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Kappa	0.93687	0.77632	0.83023	0.85844	0.42380	0.87465	0.40758
Kappa Location	0.95189	0.7861	0.83729	0.88652	0.44688	0.89028	0.78055
Kappa Histogram	0.98423	0.98755	0.99157	0.96832	0.94835	0.98244	0.52218

The results of the kappa histogram indicate similarity in all land use class sizes (except for water bodies and wetlands); hence, all dissimilarity is caused by the incorrect allocation of LUCC as expressed with Kappa Location.

The above-mentioned indexes identify the agreement between two maps. In addition, to identify the accuracy of a simulation outcome in relation to the accuracy that can be predictable given the quantity of LUCC in the simulation, three more parameters were estimated: kappa simulation, kappa transition, and kappa transloc. The values obtained are as follows: kappa simulation = 0.84805; kappa transloc = 0.86703; and KTransition = 0.97811. Since the values are close to 1, this suggests that the predicted map is very accurate. These values were obtained from the Map Comparison Kit (Visser and de Nijs, 2006).

3.2 Logistic regression

To identify LUCC factors and measure the influence of explanatory variables, logistic regression was performed. Table 7 describes the driving forces that most influence each land use class. The drivers that most influence artificial surfaces are those related to human activities (e.g., population density, and distance to urban areas), and for the cultivated land are those related to the distance to agricultural land, physical elements such as distance to coastline, slope, and agricultural land use protection (RAN). The outcomes present good explanatory capability, which means that LUCC can be explained by these driving forces.

Table 7 – Regression analysis for each land use class. Land use classes: 1 (artificial surfaces); 2 (non-irrigated land); 3 (permanently irrigated land); 4 (permanent crops and heterogeneous agricultural land); 5 (pastures); 6 (forest and semi-natural areas); and 7 (water bodies and wetlands).

Driving forces	1	2	3	4	5	6	7
Distance to road network	1.2016	0.1138	0.5740	0.3387	-0.1569	0.8147	
Distance to coastline	0.5353	-1.9153	6.4375	-0.6189	-0.0533		
Distance to urban areas	30.0381						
Distance to agricultural land		16.7638	18.9496	18.1329	25.6346		
Slope	0.1782	0.5589	-0.0018	0.2616	-0.2246	1.0069	-0.4155
Distance to hydrographic network		0.1625	0.1776	-0.6626	-0.2194		10.8896
RAN		0.2878	0.8056	0.6006	-0.0544		
Urbanizable areas	-0.8014						
Non-aedificandi areas	1.0200						
Population density	58.0011						

3.3 Land use cover changes in the different scenarios

Evolution: 1995-2010

Actual land use data from 1995 to 2010 were compared. Artificial surfaces increased by 44% from 1995 to 2010. Meanwhile, non-irrigated arable land, permanently irrigated land, permanent crops, and heterogeneous agricultural land decreased overall to 41%. In addition, according to the land use transition matrix, we observed that 11% of forest and semi-natural areas, and 10% of permanent crops, and heterogeneous agricultural land were transformed into artificial surfaces. Moreover, 37% of permanent crops and heterogeneous agricultural land were converted into non-irrigated arable land.

Evolution: 2010-2025

Every scenario shows an increase in artificial surfaces, particularly the B0. In this scenario, there is an increase by 1,918 hectares (41%) in the place of previous agricultural land, predominantly permanently irrigated land and pastures.

In the A1 scenario (intensified agricultural production), a substantial growth of permanently irrigated land (3,043 hectares) was seen, which shows the importance that farmers attribute to water availability in their farms (Fig. 3).

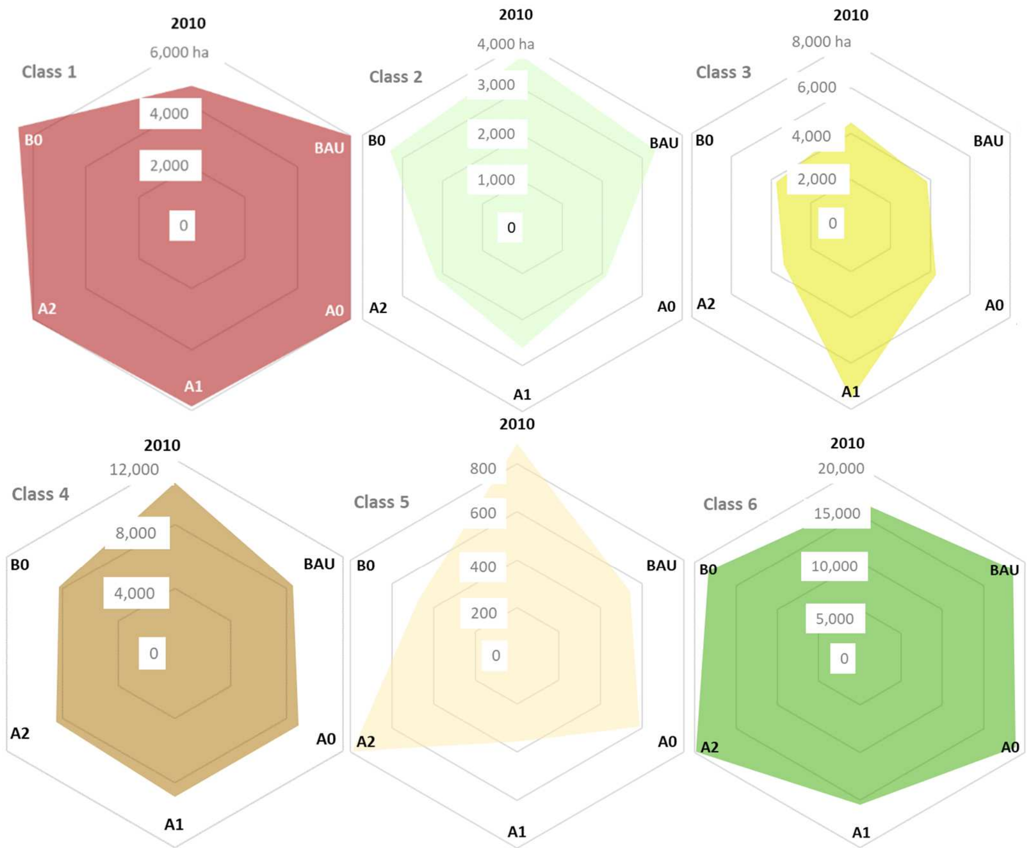


Figure 3 – LUCC for each land use class for the year 2010 and for the 2025 scenarios (1 – artificial surfaces; 2 – non-irrigated arable land; 3 – permanently irrigated land; 4 – permanent crops and heterogeneous agricultural land; 5 – pastures; 6 – forest and semi-natural areas).

According to the interviews with farmers, those in the 15-34 age group are the ones that have the greatest intentions to expand cultivated land in every scenario, because of their age, and their ambition and capacity to expand their farmland (except for the A2 scenario, in which none of them has the intention to expand cultivated land) (Fig. 4).

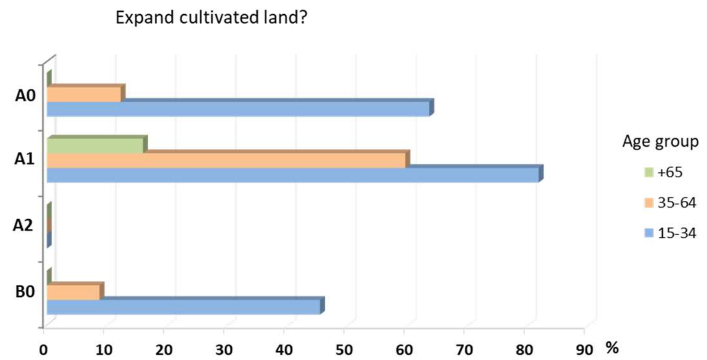


Figure 4 – Farmers' LUCC intentions to expand cultivated land (2 – non-irrigated arable land; 3 – permanently irrigated land; and 4 – permanent crops and heterogeneous agricultural land) by scenario and age group.

In Figure 5, a strong spatial correlation between new artificial surfaces, in the B0 scenario, and their proximity to existing artificial surfaces (in the reference map) can be confirmed, emphasising the relevance of the distance to urban areas driving force for this land use class.

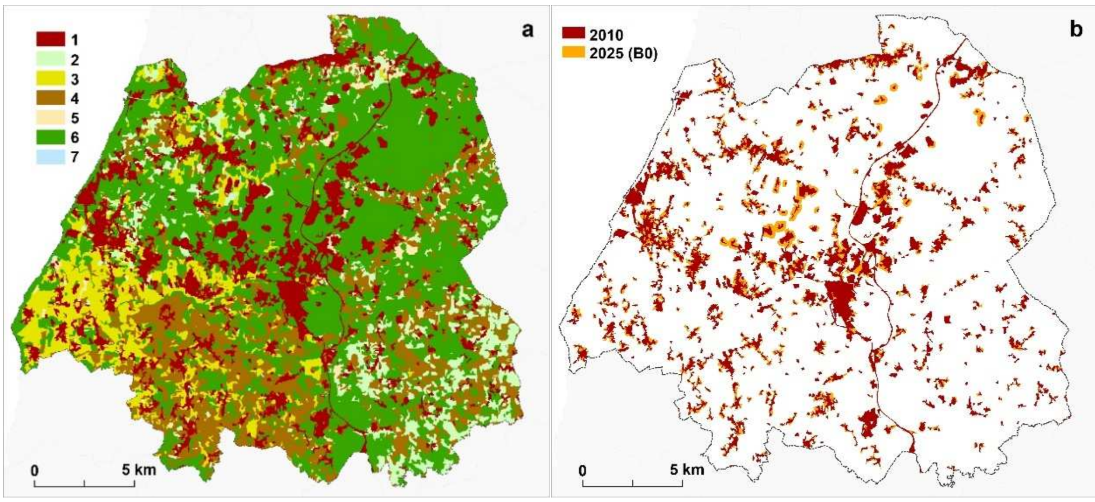


Figure 5 – (a) B0 scenario. Land use classes: 1 (artificial surfaces); 2 (non-irrigated land); 3 (permanently irrigated land); 4 (permanent crops and heterogeneous agricultural land); 5 (pastures); 6 (forest and semi-natural areas); and 7 (water bodies and wetlands); (b) B0 scenario (artificial surfaces) and reference map - 2010.

Figure 6 shows the best (A1 - intensified agricultural production) and worst case (A2 - reduced agricultural production) scenarios for agricultural productivity.

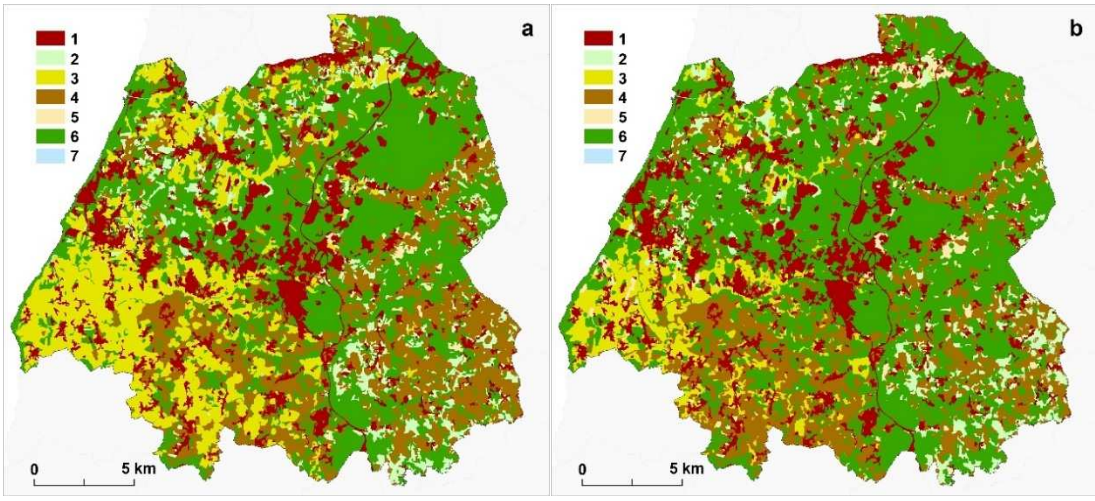
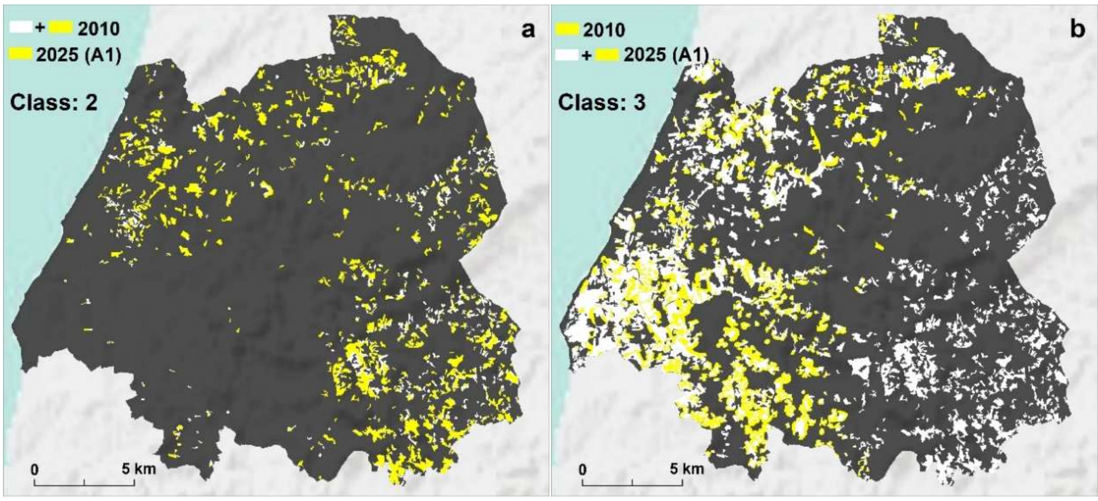


Figure 6 – (a) A1 scenario; (b) A2 scenario. Land use classes: 1 (artificial surfaces); 2 (non-irrigated land); 3 (permanently irrigated land); 4 (permanent crops and heterogeneous agricultural land); 5 (pastures); 6 (forest and semi-natural areas); and 7 (water bodies and wetlands).

In the A1 scenario, the emergence of new cultivated land is envisaged. We verified an increase by 269 hectares when compared to the reference map for 2010. This new cultivated land from previously uncultivated land was converted from pastures (67%), and from forest and semi-natural areas (33%). This increase was only seen in the permanently irrigated land (Fig. 7).



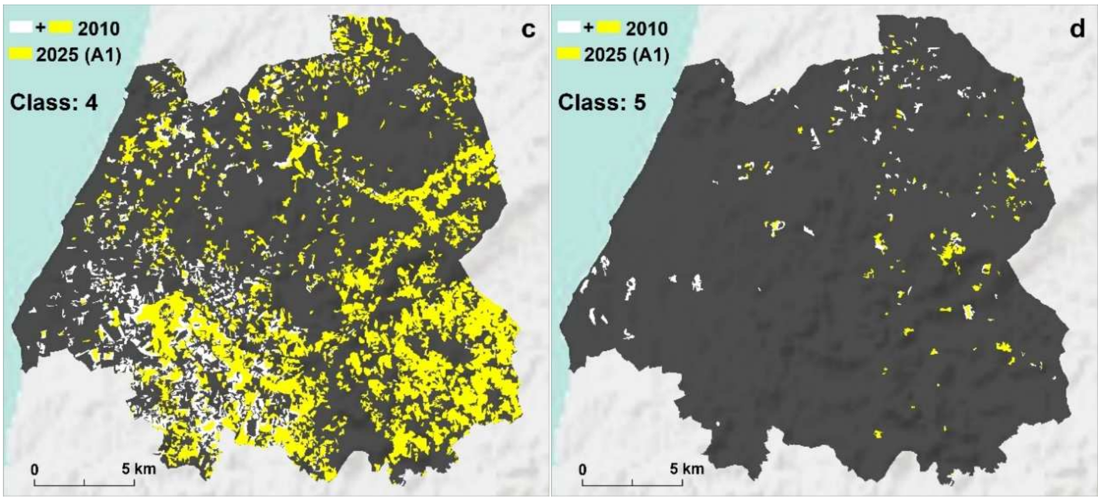


Figure 7 – Agricultural land use classes in 2010 and 2025 (A1 scenario): (a) non-irrigated land); (b) permanently irrigated land; (c) permanent crops and heterogeneous agricultural land; and (d) pastures.

In the A2 scenario, a loss of agricultural land by 4,743 hectares (from 2010) was registered. The highest losses were recognized in permanent crops and heterogeneous agricultural land, with annual mean losses of 142 hectares, followed by non-irrigated arable land (103 hectares per year), and permanently irrigated land (72 hectares per year) (Fig. 8).

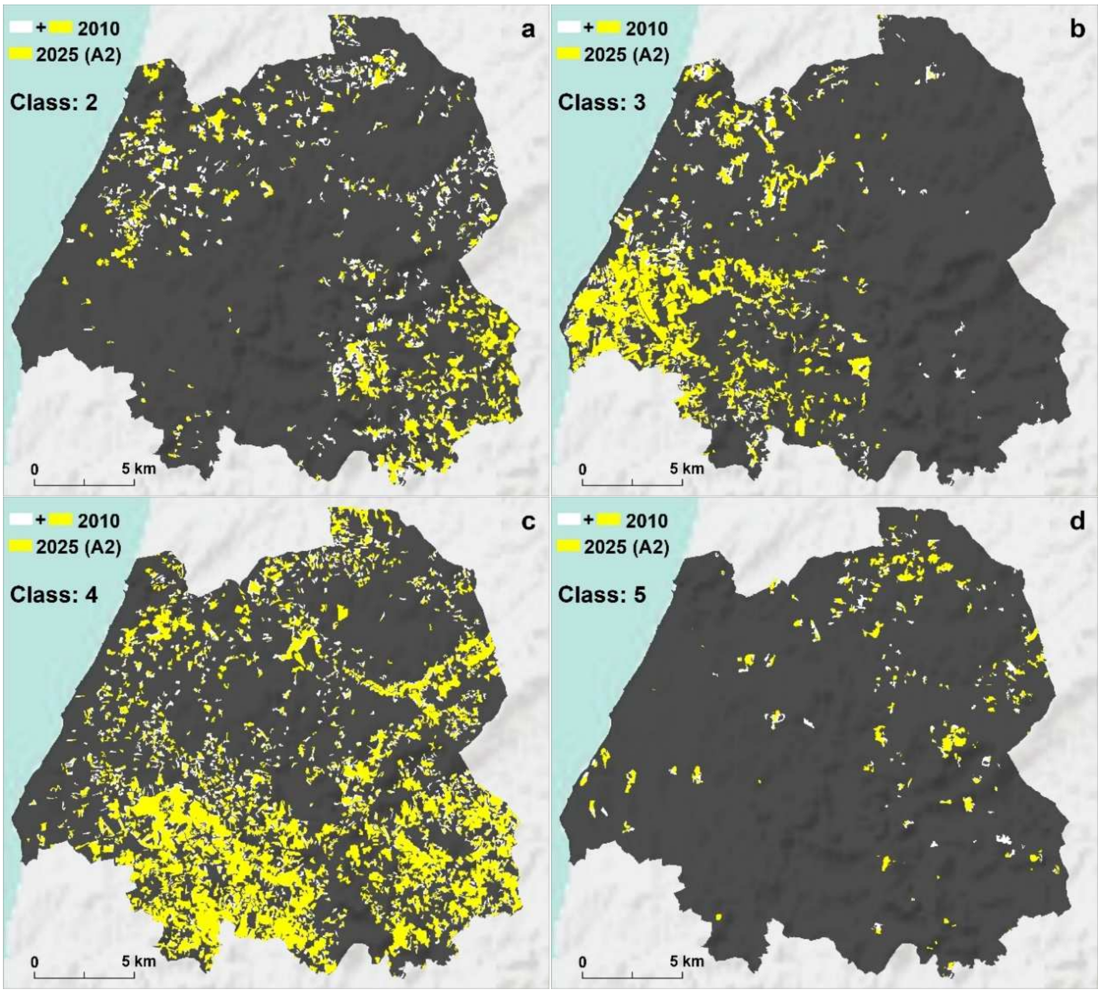


Figure 8 – Agricultural land use classes in 2010 and 2025 (A2 scenario A2): (a) non-irrigated land); (b) permanently irrigated land; (c) permanent crops and heterogeneous agricultural land; and (d) pastures.

Figure 9 shows the variation of land use classes between 2010 and the 2025 scenarios. Artificial surfaces registered the highest increase in the B0 scenario, the same percentage of increase that had occurred in the past between 1995 and 2010 (41%). In the A1 scenario, permanently irrigated land increased by almost 70% when compared to 2010. Pastures decreased in every scenario — particularly in the A1 scenario — losing 60% of the area. Forest and semi-natural areas gained land in every scenario except for the A1 scenario.

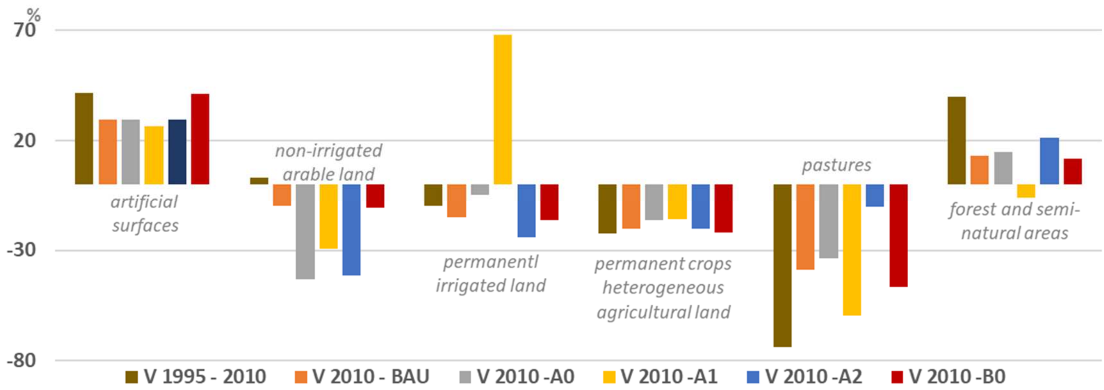


Figure 9 – Land use cover variation by land use class between 2010 (reference map) and the 2025 scenarios.

Comparing the results obtained in this study with the literature review on CA LUCC models, we can state that these results highlight the importance of competition between the various land use classes at the local level, suggesting a self-organising system. These outcomes also address complex problems, such as the evolution of LUCC developed by Hasbani et al. (2011) and Singh et al. (2015).

3.3 Competitive interactions between cells

When CA are used, cell competition arises when two cells with different characteristics oppose each other. This is related to the specific characteristics of land use classes, their capacity and availability to expand to another land use class, and existing factors and constraints. Therefore, we accordingly compared the percentages of growth that farmers showed in their LUCC intentions with what happened when we modelled these intentions in the CA approach. Table 6 shows a comparison between these two evolutions. Regarding the most similar percentages of growth, permanently irrigated land in the A1 scenario had a similar growth in both farmers' intentions and the percentage of growth between 2010 and 2025 obtained in the CA simulation (68%). The same happened in the case of non-irrigated arable land in the A2 scenario. Farmers' intentions had a similar percentage of growth for this land use class (-45.61%) as the results obtained in the CA (-41.57%).

Nevertheless, for one land use to gain land another one must lose it. In the A0 scenario, farmers intended to increase permanent crops and heterogeneous agricultural land by 10%; however, in the CA simulation, there was a decrease by -16% (for this land use class) (Table 8).

Table 8 – Comparison between the evolution of each agricultural land use class according to farmers' intentions and the outcomes obtained in the CA simulation.

Land Use Classes	Farmers – A0 (%)	CA – A0 (%)	Farmers – A1 (%)	CA – A1 (%)	Farmers – A2 (%)	CA – A2 (%)
non-irrigated arable land	0.06	-43.27	2.90	-29.21	-45.61	-41.57
permanently irrigated land	20.23	-4.72	67.97	67.96	-17.06	-24.13
permanent crops and heterogeneous agricultural land	10.03	-16.23	71.32	-16.03	-11.00	-20.11
pastures	-6.35	-33.45	-25.40	-59.67	560.32	-10.31

3.4 Land use strategies

Land use strategies should find a balance between economic growth and agricultural protection (Martín-Retortillo and Pinilla 2015; Xuezhenet et al. 2010). Several studies – e.g., Lovell (2010), Parker (2007), Vagneron (2007) – have suggested that agricultural policies should contribute to reduce human impacts on the local and regional ecosystems. A decision support system to define land use strategies should identify where, when, what, and how much land should be used for a specific purpose. To address these issues, a dynamic monitoring system of land utilisation should be implemented. According to the results obtained, a coupled analysis identifying landscape analysis and land use recommendations was performed. We analysed quantitatively and qualitatively the potential consequences of LUCC for each scenario. For the landscape analysis, some metrics were estimated assuming that landscape metrics are capable of identifying land use class morphology (Liu et al. 2008). The following landscape metrics for each class and scenario were estimated: mean patch size, mean nearest neighbour distance, and the number of patches (Fig. 10). These are the most widely used metrics in landscape analysis (McGarigal and Marks, 1994). Furthermore, a set of land use recommendations was suggested according to the literature.

Subsequently, we described this analysis focusing on the scenarios where we verified the largest spatial variations of LUCC, when compared to the reference map:

a) In the A1 scenario, the number of patches in permanently irrigated land dropped from 426 (in 2010) to 292 (Fig. 10). This reveals the compactness of this land use class and its expansion concentrated on the same land use class. Moreover, this land use class had a high increase; hence, measures to improve irrigation systems to make the farmers more efficient and competitive should be considered – e.g., Levidow et al. (2014), and Holzapfel et al. (2009);

b) In the A2 scenario, in general, agricultural land use classes showed substantial increase in the number of patches (Fig. 10) and a decrease in the covered area, revealing an increase of agricultural land fragmentation (Gomes et al., 2019b). Nevertheless, an increase of forest and semi-natural areas was seen. In this case, land use recommendations should focus on the creation of incentive programs to promote the planting of Mediterranean trees, as suggested by Brundu and Richardson (2016), and Vallejo (2005). Currently, in our case study, more than 80% of the broad-leaved forest is eucalyptus – a non-Mediterranean tree.

c) In the B0 scenario, the nearest neighbour distance for artificial surfaces was underestimated ranging from 138.86 m (in 2010) to 256.7 m. In addition, the number of patches dropped from 625 in 2010 to 477 in the BAU scenario, and 484 in the B0 scenario (Fig. 10), showing more compactness in artificial surfaces (Oueslati et al., 2015).

Urban containment and agricultural protection policies should be strengthened/applied more effectively given the major urban growth that might occur, as suggested by Bengston and Youn (2006), Cheshire (2009), and Salvati et al. (2018).

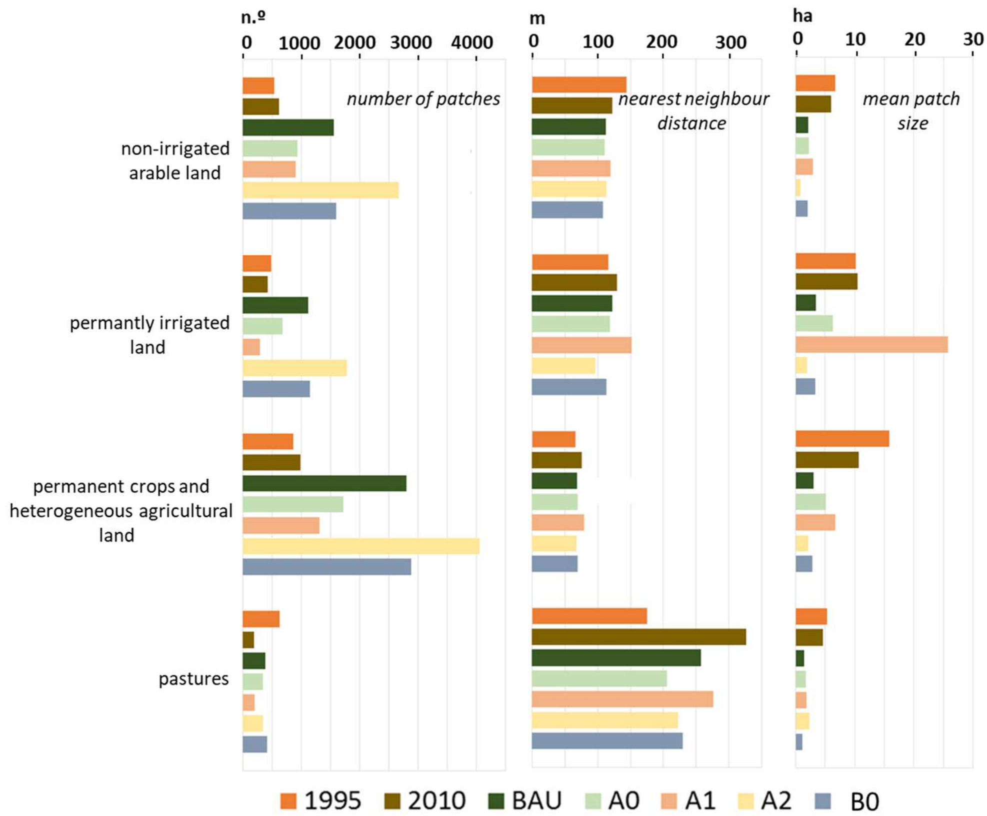


Figure 10 – Evolution of mean patch size, nearest neighbour distance, and number of patches index by reference maps and scenarios.

4. Conclusions

The analysis presented in this study highlights the farmers' LUCC intentions in a business-as-usual scenario, an intensified and a reduced agricultural production scenario, and an increasing demand for urban development scenario, analysing exogenous and endogenous driving forces. We have introduced a methodology to better understand land use dynamics so as to explain and discuss the impact of farmers' decisions on land use transformation. The results show an increase of permanently irrigated land (68%) and a decrease of pastures (-60%) in the A1 scenario; a decrease in non-irrigated arable land (-42%) and permanently irrigated land (-24%) in the A2 scenario, and an increase of artificial surfaces (41%), and a higher decrease of pastures (-47%) in the B0 scenario. The group most prone to continuing the activity is the younger farmers group.

This is a major finding because it suggests that agriculture will persist in the region. Also, a more professional, intensive, and more productive agriculture will be verified, particularly in the A1 scenario.

This study can support local and regional stakeholders in LUCC decision-making processes indicating alternative futures and showing how, where, and which land use conversions may occur. According to the results obtained, we intend to identify suitable land uses to avoid undesirable future consequences (adaptive land use management), anticipating and understanding future land use uncertainties For instance, we can identify how to increase the availability of water – a limited resource – in a scenario of intensified agricultural production, or how to strengthen urban containment policies in a scenario of increasing demand for urban development.

We introduced advances in land use modelling coupling the CA method and farmers' future LUCC intentions, which can lead to a better understanding and management of critical socioeconomic and environmental issues. We have also demonstrated how models can help to solve planning issues, providing solutions to current and future spatial planning problems.

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