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Modelling future land use scenarios based on farmers' intentions and a cellular automata approach

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1 1. Introduction

2 Land use and land cover is the result of a set of complex systems linked by the interaction of
3 environmental, social, and human activities and economic factors (Lambin and Reenberg
4 2007; Robson and Berkes 2011). Land use and land cover changes (LUCC) result from the
5 interaction between these different factors (Geist and Lambin, 2002) in non-linear
6 relationships, and they can take place globally or locally. In peri-urban areas, the main
7 concern about land use/cover is related mostly to the conversion from agricultural land to
8 urban development. The consequences can range from endangered food security (Abrantes
9 et al. 2016; Gomes et al. 2018; Spilková and Vágner 2016) to negative impacts on the
10 economy (Heinet et al. 2008), ecosystems (Seki et al., 2017), and climate variability (Li et al.
11 2009).

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

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

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

32 Cellular automata (CA) are one of the most widely used methods (Macal and North, 2010). It is
33 a powerful method for studying complex systems and exploring principles of system evolution
34 and self-organisation (Mitchell, 1998). CA became more common and popular when, in 1970,

35 John Conway designed the Game of Life (Huang et al. 2009), the most popular 2-D binary CA.
36 Following successive theoretical structure improvements, CA have become a well-established
37 method for modelling LUCC in recent decades, and have been widely used since they were
38 introduced by Tobler (1979). CA have the ability to simulate dynamic development from a
39 bottom-up perspective (Liu et al. 2008) based on complex spatial forms (e.g., Agarwal et al.
40 2002; de Almeida et al. 2003; Wang and Li 2011). CA based on Markov chains are increasingly
41 employed in LUCC (Dezhkamet al. 2017; Sang et al. 2011), incorporating the relationships
42 between land use and driving forces.

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

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

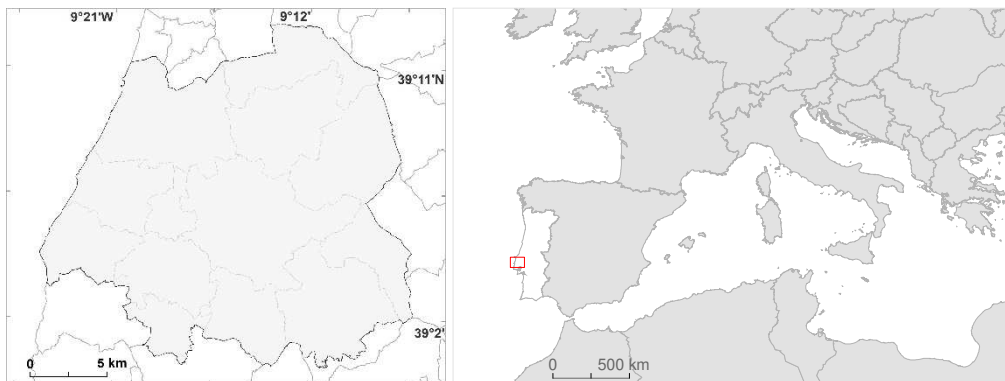
61 The methodology used in this study included interviews with farmers (to capture farmers'
62 LUCC intentions), and then a combination of geographic information systems (GIS), and CA –
63 Markov Chain – developing step-by-step guidelines towards the creation of a simulation
64 model to predict LUCC.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

68

69 **2. Data and methods**

70 **2.1. Study area**

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



73
74 Figure 1 – Location of Torres Vedras municipality (Portugal) in Europe.

75

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

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

89

90 **2.2 Data**

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

94

95 *Land use*

96 Land use maps for the years 1995, 2007, and 2010 were used. The accuracy of the land use
97 maps was validated at the 1:25 000 scale by Direção-Geral do Território (DGT). The land use

98 maps contain over one hundred classes but for the purpose of this study these were
 99 regrouped into the following seven classes: 1 – artificial surfaces; 2 – non-irrigated arable
 100 land; 3 – permanently irrigated land; 4 – permanent crops and heterogeneous agricultural
 101 land; 5 – pastures; 6 – forest and semi-natural areas; and 7 – water bodies and wetlands
 102 (original data source: <http://mapas.dgterritorio.pt/geoportal/catalogo.html>). Artificial
 103 surfaces were grouped in the same land use class due to the urban fabric and service growth,
 104 usually accompanied by population growth (Duranton and Puga 2014; Satterthwaite et al.
 105 2010). However, we divided agricultural land into four land use classes because the focus of
 106 this study is to provide an in-depth analysis of agricultural land use dynamics. Forest and
 107 semi-natural areas were grouped into one land use class, as well as water bodies and
 108 wetlands. Table 1 provides a detailed description of the subclasses included in each land use
 109 class (in %).

110
 111

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	

112

113 *Driving forces*

114 A set of factors and constraints that represent the attraction and repulsion for land use
 115 conversion were used. The selected driving forces were mapped for each scenario generated
 116 by using common GIS functions, Boolean Logic (1 or 0, True or False), and fuzzy membership
 117 functions (ranging from 1 to 0, representing the attraction or repulsion for land use
 118 conversion). The Euclidean distance of each cell to urban areas, road network, agricultural

119 land, hydrographic network, and coastline was found. These driving forces were selected
 120 following the literature and the interviews with the farmers. Table 2 identifies the list of
 121 driving forces, the hypotheses and references that support each driving force based on
 122 similar studies, and the source of these drivers used to explain LUCC.

123
 124

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

Category	Driving force	Hypotheses and references	Source
<i>Social, economic, and physical elements</i>	Population density	Population density has a positive effect on urban growth (Triantakou et al., 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
<i>Land use regulation</i>	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)		

125

126 *Interviews with farmers*

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

137

138 **2.3 Methods**

139 **2.3.1 Description of scenarios**

140 In our study, four explorative scenarios (plus a BAU – business as usual – scenario) were
 141 developed and were run for the year 2025. The A0, A1, A2, and B0 scenarios intend to assess

142 how farmers define their priorities for future agricultural activity. The four explorative
143 scenarios are as follows:

144

145 *A0 - current social and economic trend*

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

150

151 *A1 - intensified agricultural production*

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

158

159 *A2 - reduced agricultural production*

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

166

167 *B0 - increasing demand for urban development*

168 This scenario assesses an increase of built-up areas and increased expectations of new peri-
169 urban residents. There is a population increase of 50% (in relation to the A0 scenario), as well
170 as increased purchasing power, growing demand for new dwellings and buildings other than
171 dwellings, and improved road access and public transport facilities. Moreover, in this
172 scenario, real estate is viewed as an attractive investment, and urban land prices increase by
173 200% (in relation to the A0 scenario). These issues are recognized by Satterthwaite et al.
174 (2010) and Rauws and de Roo (2011).

175

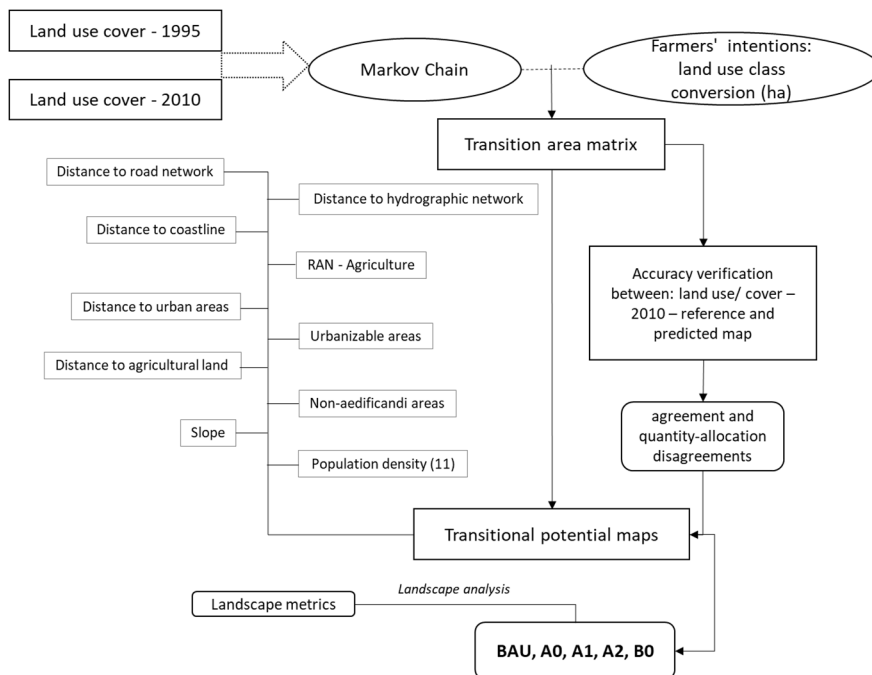
176 **2.3.2 Interviews with farmers**

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

184

185 2.4 Cellular Automata

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



190

191

Figure 2 – Methodological framework.

192

193 *Multicollinearity of driving forces*

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

199

200 *Cell states (fuzzy and Boolean logic)*

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

205

206 *Neighbourhood configuration*

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

210

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

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

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

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

221

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

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

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

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

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

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

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

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

247

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

250

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

Land Use Classes	BAU	A0, A1, A2	B0
Artificial surfaces	BAU	BAU	Farmers' intentions
Non-irrigated arable land		Farmers' intentions	
Permanently irrigated land			
Permanent crops and heterogeneous agricultural land		BAU	BAU
Pastures			
Forest and semi-natural areas			
Water bodies and wetlands			

252

253 *Transition potential maps: logistic regression analysis*

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

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

262

263 Table 4 – Explanatory driving forces used in logistic regression analysis for artificial surfaces,
 264 agricultural land, forest and semi-natural areas, and water bodies and wetlands for each scenario
 265 (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	○					

266

267 *Time step resolution*

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

270

271 *Model assessment*

272 Model assessment implies using techniques to check that the simulations are satisfactorily
 273 estimated (Trucano et al., 2006). There are many techniques to validate the accuracy of
 274 predictions. Kappa index has been widely used to validate LUCC models (Kandziora et al.,
 275 2014; Pan et al., 2010; Yu et al., 2011) measuring the inter-rater agreement between
 276 categorical variables x and y, and evaluating the prediction performance of classifiers (Cohen,
 277 1960). A kappa of 0 indicates that agreement is due to chance, while a kappa of 1 indicates a
 278 perfect agreement (Viera and Garrett, 2005). However, Pontius and Millones (2011) proposed
 279 to quantify disagreement and allocation disagreement. In this study, kappa agreement and
 280 quantity-allocation disagreements have been estimated.

281 Moreover, landscape metrics were used, in the discussion section, to assess the overall
 282 spatial patterns by comparing the variation and the spatial patterns between the reference
 283 map and the predicted scenarios. The mean patch size, the nearest neighbour distance, and
 284 the number of patches were estimated. The mean patch size metric relates the size of each
 285 land use class with the number of patches of each land use class (McGarigal and Marks,
 286 1994). The mean nearest neighbour distance corresponds to the average distance of
 287 developed patches to their nearest developed neighbours, based on edge-to-edge distance
 288 (McGarigal and Marks, 1994). And the number of patches (McGarigal and Marks, 1994)
 289 corresponds to the number of spatial entities.

290

291 **3. Results and discussion**

292 **3.1 Model performance**

293 In this study, different types of kappa coefficients (measuring agreements and quantity-
 294 allocation disagreements) were applied to evaluate the simulation performance of different
 295 scenarios. We compared simulated 2010 land use with the reference map for 2010. Using the
 296 driving forces shown in Table 2 for the BAU scenario, we performed the matrix of Markov
 297 transition areas and the suitability obtained from the logistic regression analysis from 1995 to
 298 2007. Subsequently, we computed the CA-Markov to simulate 2010 land use (Supplementary
 299 material).

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

307

308 Table 5 – Cross tabulation between 2010 - reference map and 2010 - predicted map. Land use classes:
 309 1 (artificial surfaces); 2 (non-irrigated land); 3 (permanently irrigated land); 4 (permanent crops and
 310 heterogeneous agricultural land); 5 (pastures); 6 (forest and semi-natural areas); and 7 (water bodies
 311 and wetlands).

312

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

313

314 From this contingency table analysis we retrieve the observed and expected fraction of
 315 agreement, and the maximum fraction of agreement (van Vliet et al. 2011). To integrate

316 these parameters into the kappa index, Hagen (2002) identifies KHistogram and KLocation,
 317 described as follows:

318

$$319 \quad Kappa = \frac{p_o - p_e}{1 - p_e} \rightarrow \left\{ \begin{array}{l} K_{Histo} = \frac{p_{Max} - p_e}{1 - p_e} \\ K_{Loc} = \frac{p_o - p_e}{p_{Max} - p_e} \end{array} \right\} \rightarrow Kappa = K_{Histo} \times K_{Loc}$$

320

321 where P_o is the correct observed proportion, P_e is the is the expected fraction of agreement,
 322 and P_{Max} is the total number of cells taken in by each class. KHistogram ranges from 1,
 323 indicating a perfect agreement, to 0 indicating no agreement, whereas KLocation ranges from
 324 -1 to 1, in which 1 corresponds to a perfect allocation. Table 6 expresses kappa, klocation,
 325 and khistogram values obtained between 2010 (reference map) and 2010 (predicted map).

326

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

331

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

332

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

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

343

344 **3.2 Logistic regression**

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

352
 353 Table 7 – Regression analysis for each land use class. Land use classes: 1 (artificial surfaces); 2 (non-
 354 irrigated land); 3 (permanently irrigated land); 4 (permanent crops and heterogeneous agricultural
 355 land); 5 (pastures); 6 (forest and semi-natural areas); and 7 (water bodies and wetlands).

356

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						

357

358 **3.3 Land use cover changes in the different scenarios**

359 *Evolution: 1995-2010*

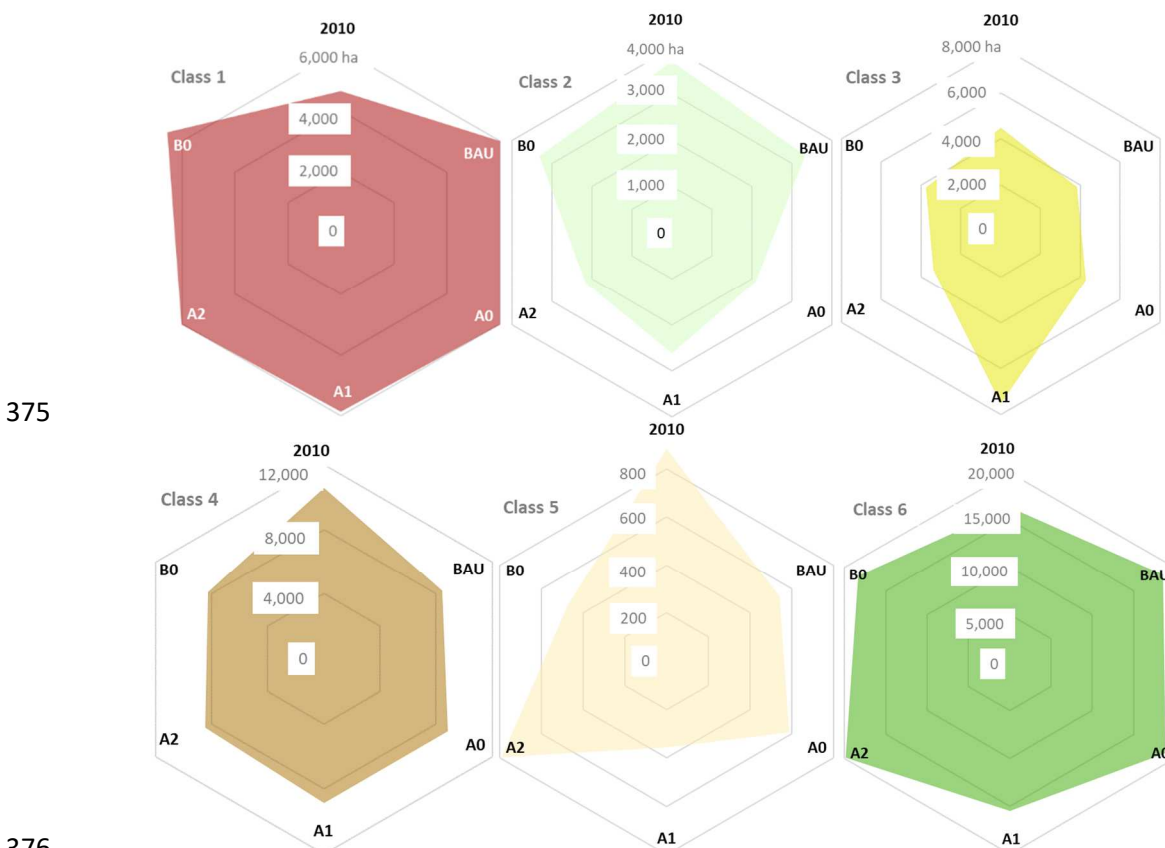
360 Actual land use data from 1995 to 2010 were compared. Artificial surfaces increased by 44%
 361 from 1995 to 2010. Meanwhile, non-irrigated arable land, permanently irrigated land,
 362 permanent crops, and heterogeneous agricultural land decreased overall to 41%. In addition,
 363 according to the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

367

368 *Evolution: 2010-2025*

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

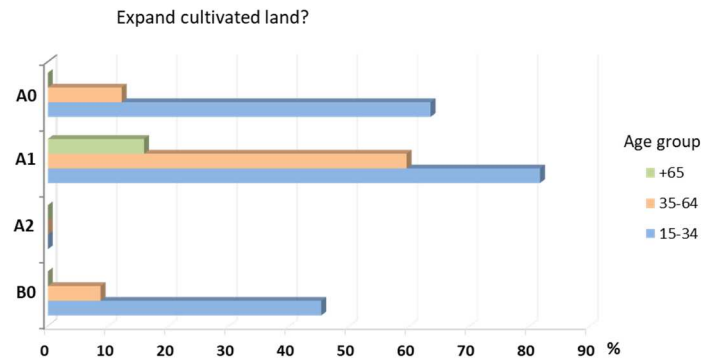
372 In the A1 scenario (intensified agricultural production), a substantial growth of permanently
373 irrigated land (3,043 hectares) was seen, which shows the importance that farmers attribute
374 to water availability in their farms (Fig. 3).



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

380

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



385

386

387

388

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.

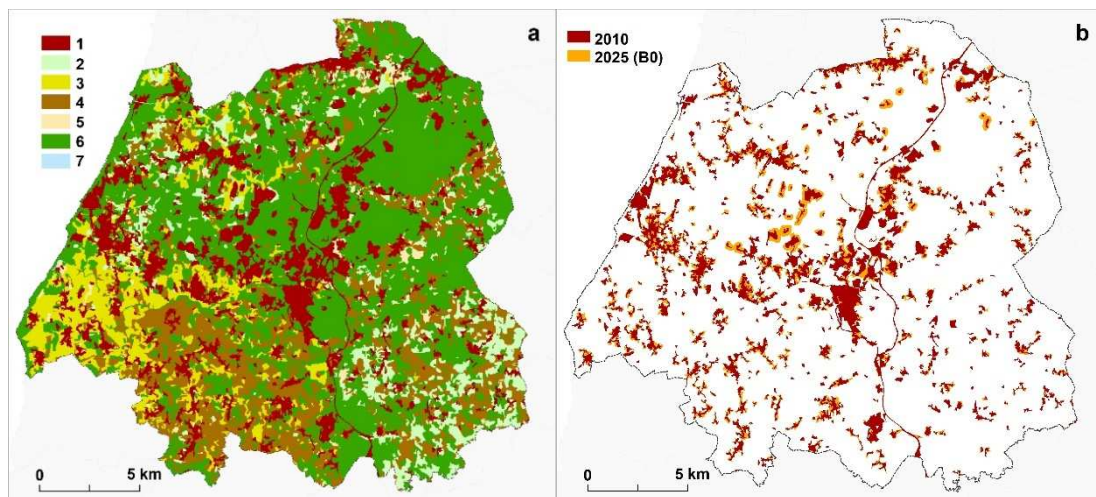
389

390

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392

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.



393

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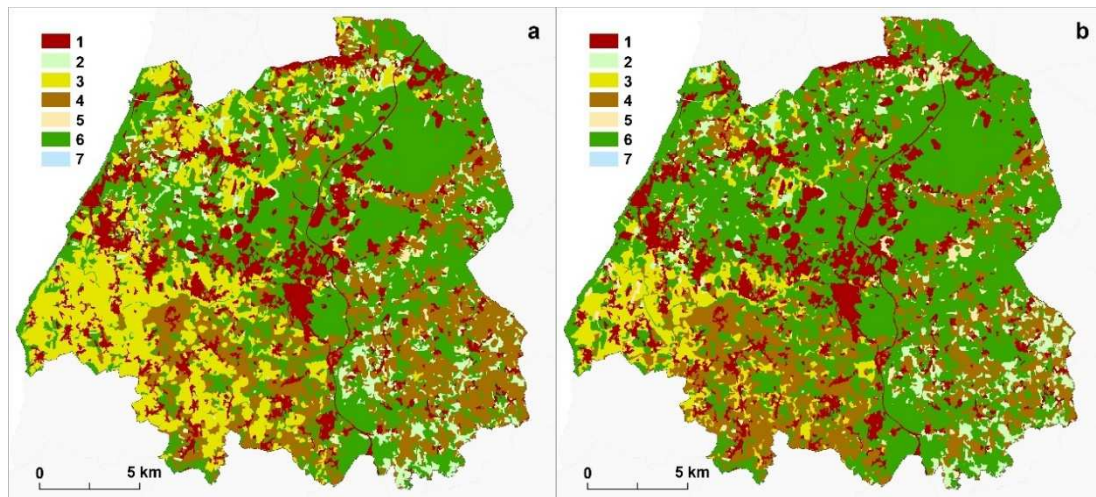
398

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.

399

400

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

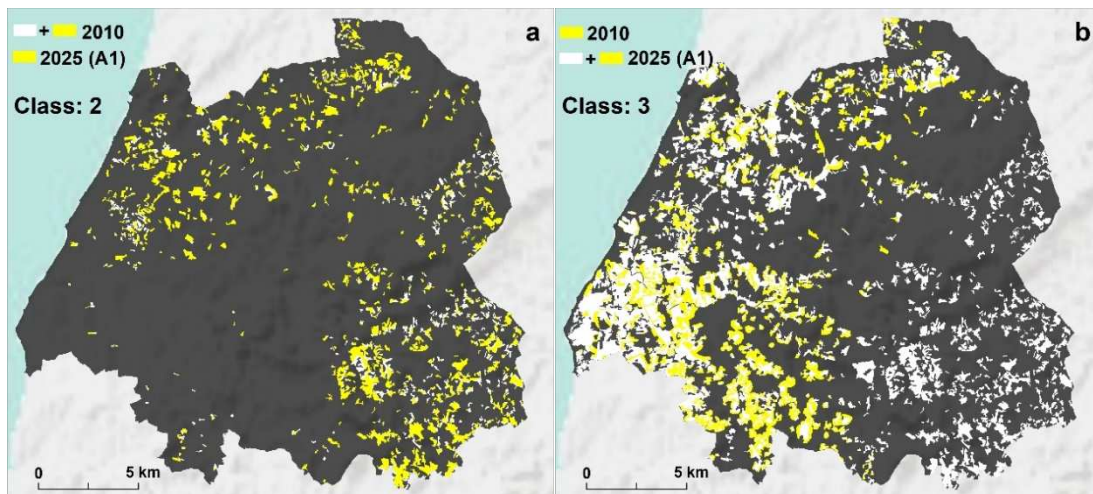


401

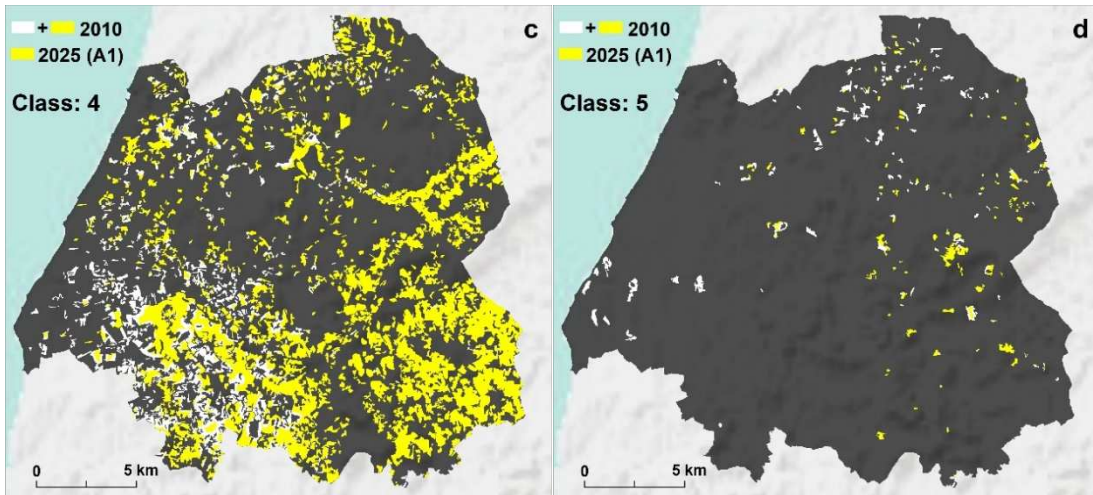
402 Figure 6 – (a) A1 scenario; (b) A2 scenario. Land use classes: 1 (artificial surfaces); 2 (non-irrigated
 403 land); 3 (permanently irrigated land); 4 (permanent crops and heterogeneous agricultural land); 5
 404 (pastures); 6 (forest and semi-natural areas); and 7 (water bodies and wetlands).

405

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

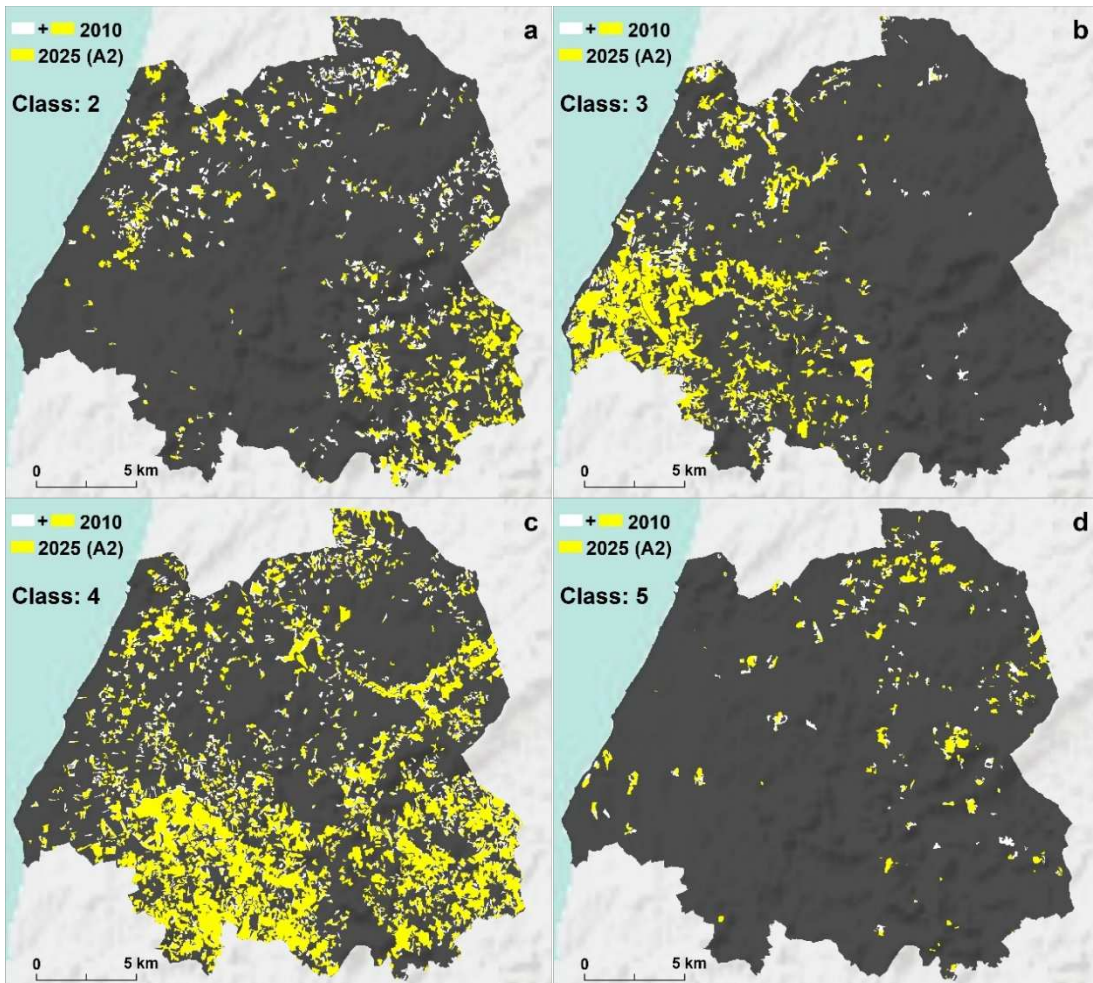


411



412 Figure 7 – Agricultural land use classes in 2010 and 2025 (A1 scenario): (a) non-irrigated land); (b)
 413 permanently irrigated land; (c) permanent crops and heterogeneous agricultural land; and (d) pastures.
 414
 415

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

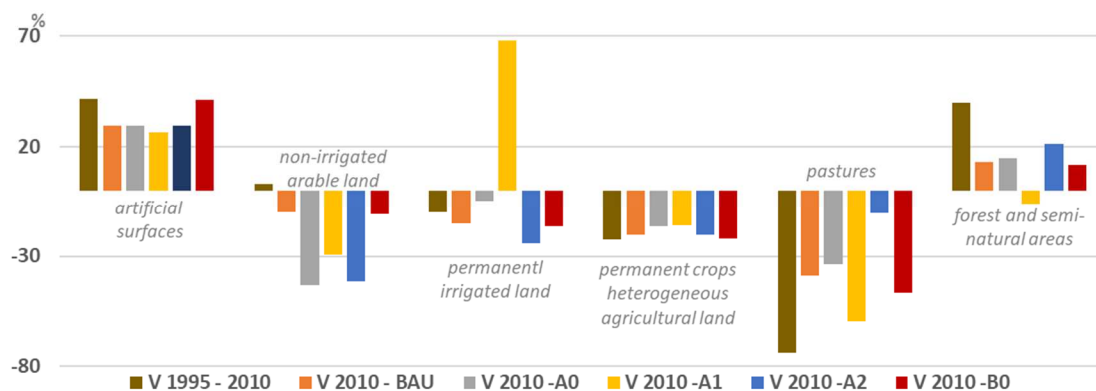


420

421

422 Figure 8 – Agricultural land use classes in 2010 and 2025 (A2 scenario A2): (a) non-irrigated land); (b)
 423 permanently irrigated land; (c) permanent crops and heterogeneous agricultural land; and (d) pastures.
 424

425 Figure 9 shows the variation of land use classes between 2010 and the 2025 scenarios.
 426 Artificial surfaces registered the highest increase in the B0 scenario, the same percentage of
 427 increase that had occurred in the past between 1995 and 2010 (41%). In the A1 scenario,
 428 permanently irrigated land increased by almost 70% when compared to 2010. Pastures
 429 decreased in every scenario — particularly in the A1 scenario — losing 60% of the area.
 430 Forest and semi-natural areas gained land in every scenario except for the A1 scenario.
 431



432
 433 Figure 9 – Land use cover variation by land use class between 2010 (reference map) and the 2025
 434 scenarios.
 435

436 Comparing the results obtained in this study with the literature review on CA LUCC models,
 437 we can state that these results highlight the importance of competition between the various
 438 land use classes at the local level, suggesting a self-organising system. These outcomes also
 439 address complex problems, such as the evolution of LUCC developed by Hasbani et al. (2011)
 440 and Singh et al. (2015).
 441

442 3.3 Competitive interactions between cells

443 When CA are used, cell competition arises when two cells with different characteristics
 444 oppose each other. This is related to the specific characteristics of land use classes, their
 445 capacity and availability to expand to another land use class, and existing factors and
 446 constraints. Therefore, we accordingly compared the percentages of growth that farmers
 447 showed in their LUCC intentions with what happened when we modelled these intentions in
 448 the CA approach. Table 6 shows a comparison between these two evolutions. Regarding the
 449 most similar percentages of growth, permanently irrigated land in the A1 scenario had a

450 similar growth in both farmers' intentions and the percentage of growth between 2010 and
 451 2025 obtained in the CA simulation (68%). The same happened in the case of non-irrigated
 452 arable land in the A2 scenario. Farmers' intentions had a similar percentage of growth for this
 453 land use class (-45.61%) as the results obtained in the CA (-41.57%).

454 Nevertheless, for one land use to gain land another one must lose it. In the A0 scenario,
 455 farmers intended to increase permanent crops and heterogeneous agricultural land by 10%;
 456 however, in the CA simulation, there was a decrease by -16% (for this land use class) (Table
 457 8).

458

459 Table 8 – Comparison between the evolution of each agricultural land use class according to farmers'
 460 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

461

462 3.4 Land use strategies

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

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

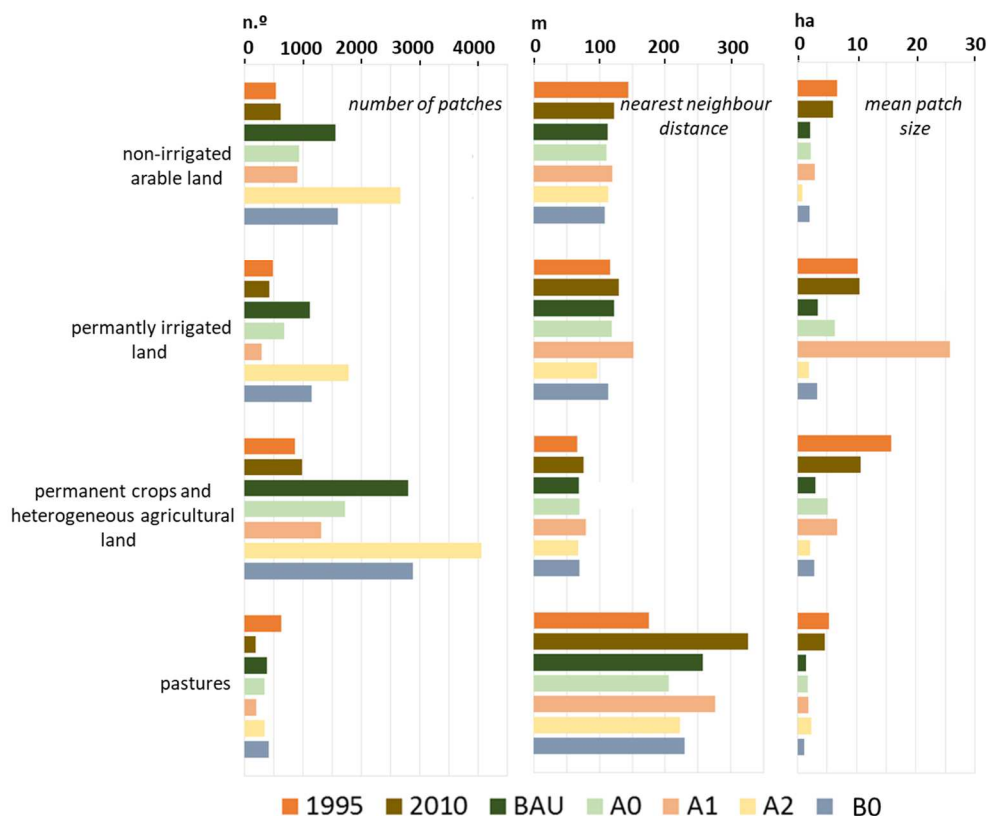
480 a) In the A1 scenario, the number of patches in permanently irrigated land dropped from
 481 426 (in 2010) to 292 (Fig. 10). This reveals the compactness of this land use class and its

482 expansion concentrated on the same land use class. Moreover, this land use class had a
483 high increase; hence, measures to improve irrigation systems to make the farmers more
484 efficient and competitive should be considered – e.g., Levidow et al. (2014), and Holzapfel
485 et al. (2009);

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

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

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



501

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

504

505 **4. Conclusions**

506 The analysis presented in this study highlights the farmers’ LUC intentions in a business-as-
 507 usual scenario, an intensified and a reduced agricultural production scenario, and an
 508 increasing demand for urban development scenario, analysing exogenous and endogenous
 509 driving forces. We have introduced a methodology to better understand land use dynamics
 510 so as to explain and discuss the impact of farmers’ decisions on land use transformation. The
 511 results show an increase of permanently irrigated land (68%) and a decrease of pastures (-
 512 60%) in the A1 scenario; a decrease in non-irrigated arable land (-42%) and permanently
 513 irrigated land (-24%) in the A2 scenario, and an increase of artificial surfaces (41%), and a
 514 higher decrease of pastures (-47%) in the B0 scenario. The group most prone to continuing
 515 the activity is the younger farmers group.

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

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

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

531

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