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Eduardo Gomes, Arnaud Banos, Patricia Abrantes, Jorge Rocha, Markus Schläpfer. Future land use changes in a peri-urban context: Local stakeholder views. *Science of the Total Environment*, 2020, 718, pp.137381. 10.1016/j.scitotenv.2020.137381. halshs-02699115

HAL Id: halshs-02699115

<https://shs.hal.science/halshs-02699115v1>

Submitted on 7 Mar 2022

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

Eduardo Gomes^{1,2*}, Arnaud Banos³, Patrícia Abrantes², Jorge Rocha², Markus Schläpfer⁴

¹ Géographie-cités, UMR 8504, Université Paris 1 Panthéon-Sorbonne, France

² Centro de Estudos Geográficos (CEG), Instituto de Geografia e Ordenamento do Território (IGOT), Universidade de Lisboa (UL), Portugal

³ IDEES, UMR 6266, CNRS, Université du Havre, France

⁴ Future Cities Laboratory, Singapore-ETH Centre, ETH Zurich, Singapore

Eduardo Gomes: eduardojonas@campus.ul.pt

Arnaud Banos: arnaud.banos@cnrs.fr

Patrícia Abrantes: patricia.abrantes@campus.ul.pt

Jorge Rocha: jorge.rocha@campus.ul.pt

Markus Schläpfer: schlaepfer@arch.ethz.ch

* corresponding author:

E-mail address: eduardojonas@campus.ul.pt

Full postal address: UMR 8504 Géographie-Cités, Campus Condorcet 5, cours des Humanités, 93322 Aubervilliers cedex, France.

Acknowledgements

The work described in this paper is funded by Fundação para a Ciência e a Tecnologia (Grant n^o. SFRH/BD/103032/2014).

Declaration of interest statement: We have read and understood Science of the Total Environment policy on declaration of interests and declare that we have no competing interests.

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.

Key-words: land use/cover changes; scenarios; peri-urban region; stakeholders; participatory planning.

1 **1. Introduction**

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

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

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

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

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

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

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

54 One of the most critical LUCC conversions in Portugal, particularly in peri-urban
55 regions in the last few decades, has been the transformation from agricultural and
56 natural land to artificial surfaces (e.g., residential, touristic, and industrial uses).
57 Moreover, in the last few years, this phenomenon has been more intensified in the
58 region of Lisbon, with 17% of natural and agricultural land converted to artificial land
59 from 1995 to 2010 (Abrantes et al, 2016). The city of Lisbon has seen major changes in
60 the housing stock. Recent political measures – such as the amendment of the housing
61 rental law (which now facilitates the eviction of tenants), the golden visa (which allows
62 a non-EU citizen to obtain a residence permit by purchasing a real estate property of
63 EUR 500k or more), the tax-free scheme for the retirement income of non-habitual
64 residents, or the growth of tourism in recent years (which has transformed long-term
65 rentals into short-term ones) – have led to an increase in housing prices (Rio Fernandes
66 et al., 2019; Statistics Portugal, 2019). These steeper prices, in turn, have increased the
67 demand for housing outside the city, which made prices soar. This is why the

68 municipality of Torres Vedras, located roughly 50 km north, is one of the potential
69 locations chosen by those who wish to find affordable housing near Lisbon. Accordingly,
70 we selected this municipality as a case study for our analysis. Torres Vedras located in a
71 peri-urban region context has had a population surge in the last few decades that has
72 led to an increase of artificial surfaces with negative consequences, namely the loss of
73 natural and agricultural land (DGT, 2010, 1995). This situation has led to economic and
74 environmental imbalances, and planners need to be prepared, particularly given that
75 agriculture is an important contributor to the local and regional economy (Statistics
76 Portugal, 2011). More efficient policies are urgently needed to preserve natural areas
77 and agricultural land (Abrantes et al., 2016; Gomes et al., 2018).

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

89 Our work aims, precisely, to explore this gap in the existing models by evaluating
90 future LUCC maps through a participatory assessment of representative stakeholders.
91 With this step forward we intend to answer the following research questions: 1) how

92 stakeholder LUCC views may differ from each other and under different scenarios? 2)
93 what are the spatiotemporal divergences in the most plausible land use scenario
94 according to stakeholder views? and; 3) how participatory approach can help planners
95 in the decision-making process since LUCC in peri-urban regions occurs very fast? In this
96 process we:

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

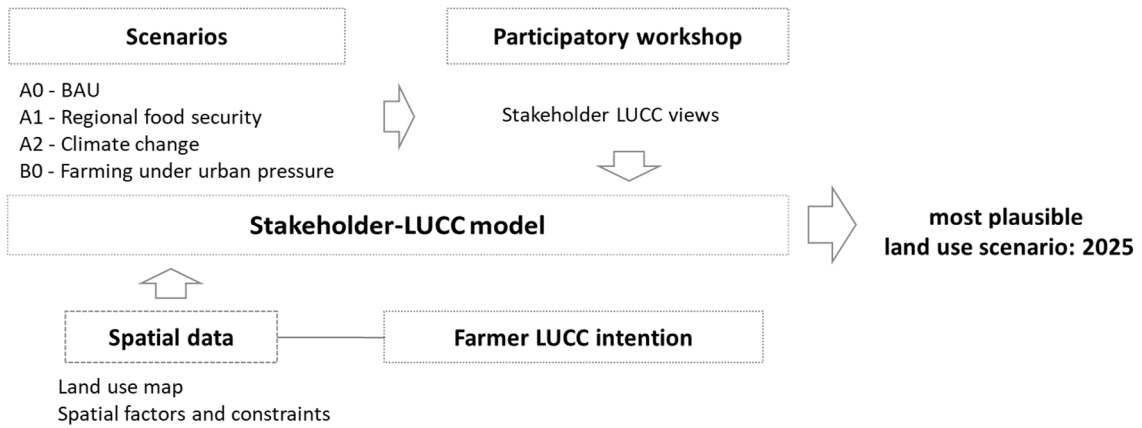
104 The paper is organized as follows: after the introduction, section 2 presents the data
105 and methods used, which include the case study, spatial data, the design of four
106 different scenarios, an analysis of the interviews with the farmers and the participatory
107 workshop, and the construction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

110

111 **2. Data and methods**

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

115



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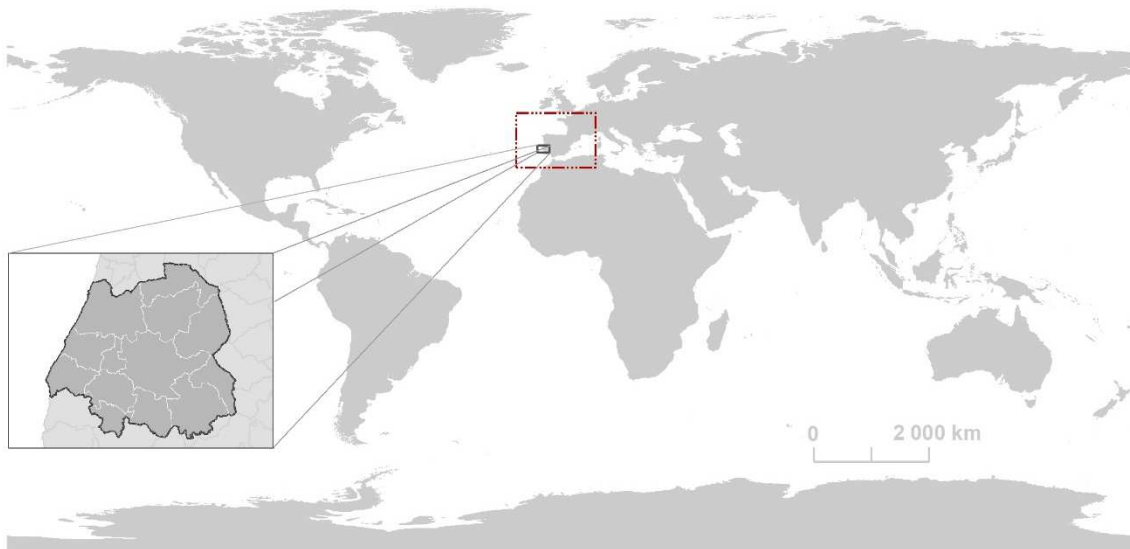
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Figure 1 – Methodological flowchart.

118

119 **2.1 Case study**

120 The Torres Vedras Municipality (Portugal), located on the west coast of Europe, was
 121 selected as the study area (Fig. 2). Torres Vedras is 407 sq. km and it is located roughly
 122 50 km north of Lisbon. Administratively, it is divided into 13 parishes, and the last census
 123 recorded a population of about 80,000 inhabitants (Statistics Portugal, 2011).



124

125

Figure 2 – Location of the Torres Vedras Municipality (Portugal).

126

127 Located in a peri-urban region, the Torres Vedras Municipality was chosen due to an
 128 artificial surface increase of 41% between 1995 and 2010. Moreover, between 1991 and
 129 2011, its population grew by 18%, increasing pressure on natural and agricultural land

130 resources. From the agricultural activity point of view, Torres Vedras is one of the most
131 relevant suppliers of fruits, vegetables, and wine in Portugal (Statistics Portugal, 2009),
132 hence its great importance for the local and regional economy.

133

134 **2.2 Spatial data**

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

139

140 **2.2.1 Land use map**

141 The land use map for the year 2010 was accurate and validated at the 1:25 000 scale
142 by DGT (2010). This land use map represents the most updated available data, and it
143 was aggregated in line with the goals of our study into the land use classes showed in
144 Table 1 and Figure 3.

145

146

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

147

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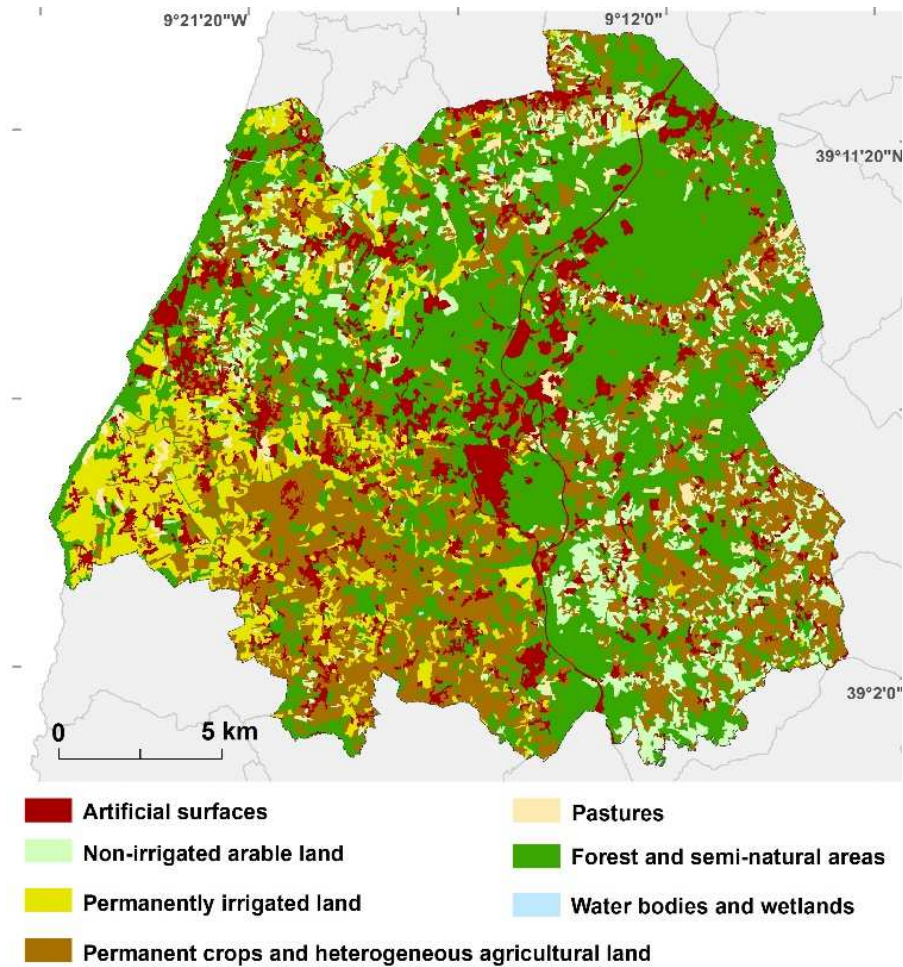


Figure 3 – Land use cover 2010.

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150

151

152 2.2.2 Spatial factors and constraints

153 Table 2 and Figure 4 identify the list of spatial factors and constraints (which
 154 represents the attraction to or repulsion toward LUCC conversion). These data were
 155 selected in line with the most widely cited in the literature (Chen et al., 2018; Nabiollahi
 156 et al., 2018), available data, and the characteristics of our case study (Gomes et al.,
 157 2019a, 2018).

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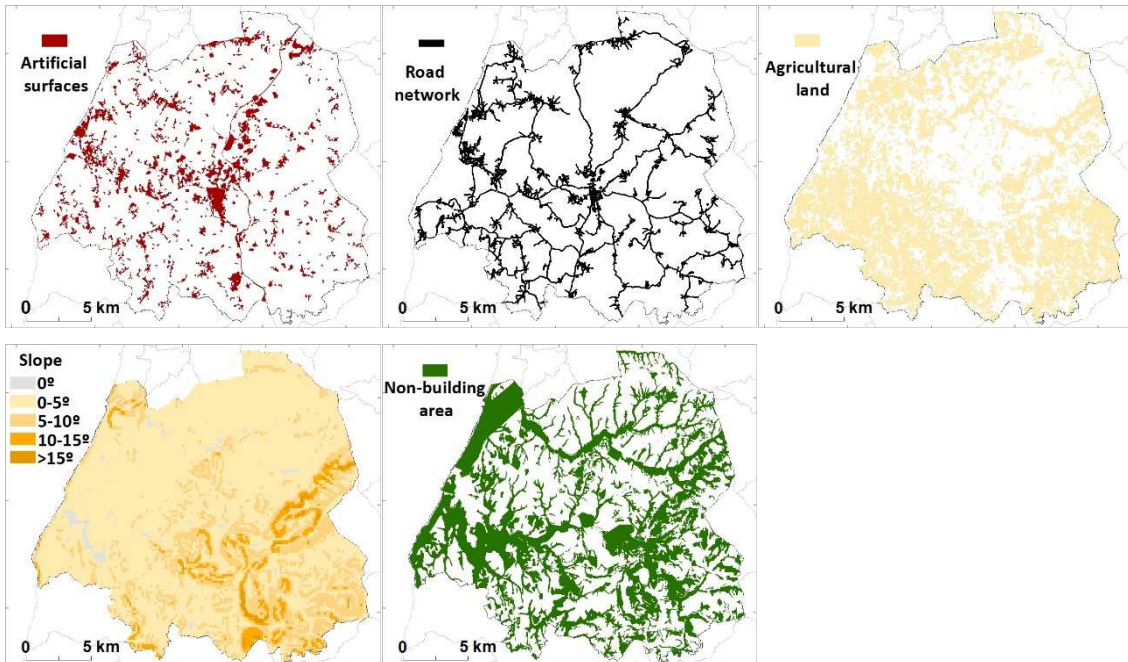
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Table 2 – Factors and constraints.

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

163



164

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168

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

169

2.3 Scenarios

170

Four scenarios were designed for the year 2025 (time reference for the master plan).

171

They were the underlying narratives for stakeholder LUCV views and were described as

172

follows: A0 - business as usual; A1 - regional food security; A2 - climate change; and B0

173

- farming under urban pressure. These scenarios are described in detail in Table 3, and

174 they are in accordance with the policies of the Food and Agriculture Organization of the
 175 United Nations (FAO) and the European Union (EU).

176

177

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).

178

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

181

182 **2.4 Interviews with farmers**

183 We chose to use interviews in our research to support scenario building since it is an
 184 efficient format for description and interpretation. Face-to-face interviews were the
 185 technique used to capture farmer LUCC intentions. The questions focused on the
 186 following three main points addressing the four scenarios: (1) Do farmers intend to

187 expand and/or decrease their farmland; (2) If so, How much? Where? From/to which
 188 land use class? and according to which scenario?; and (3) Do they intend to sell their
 189 farmland for urban development? If so, Partially or totality?

190

191 **2.4.1 Statistical tests**

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

198

199

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

200

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

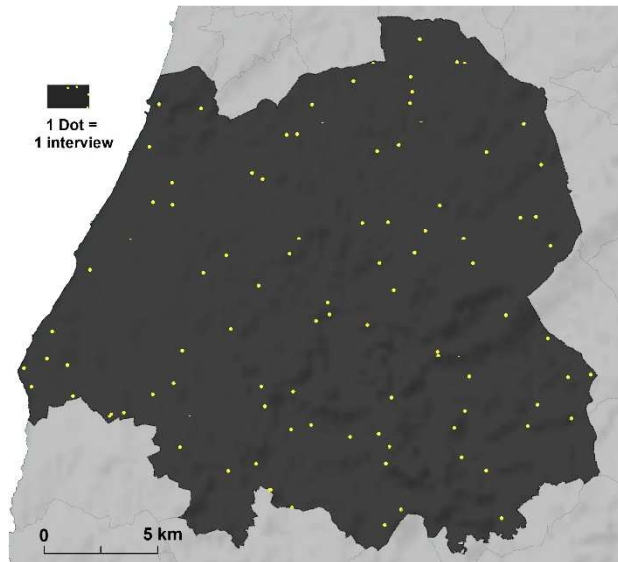


Figure 5 – Farmers interviewed.

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210 **2.5 LUCC models based on farmer LUCC intentions: CA-Markov and ANN-MLP**

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

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

220 The stakeholders evaluated and identified both models, deciding which outcome
 221 would be more plausible according to their own views. CA-Markov chain is a statistical
 222 method that integrates stochasticity in the changes between states (Macal and North,
 223 2010), while ANN-MLP can learn using a training method called backpropagation, in

224 which input data is displayed continually on the network (Morgado et al., 2014; Rocha
225 et al., 2007).

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

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

234

235 **2.6 Participatory workshop**

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

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

248

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.

249

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

254 A questionnaire was answered by each stakeholder that aimed to identify (1) which
 255 LUCC model (CA-Markov or ANN-MLP) was the most plausible for them and in
 256 accordance with the chosen model; (2) whether they consider the LUCC location
 257 plausible; and (3) whether they agree with the percentage of each land use class.

258

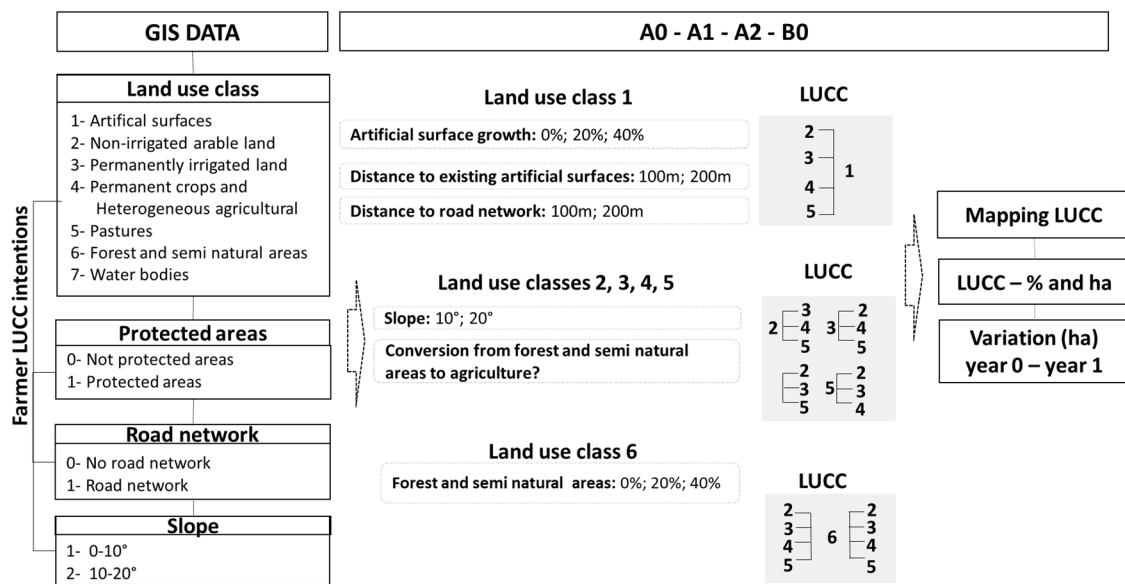
259 **2.7 Stakeholder-LUCC model**

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

266 Taking into consideration the advantages mentioned above, we chose NetLogo
 267 (version 6.0) to integrate the stakeholder LUCC views into a spatial structure. We had
 268 the concern of using open-source software, and we designed it from a user-friendly

269 perspective. The costs of our model’s maintenance and data used are low. We called
 270 this model the stakeholder-LUCC model and it represents a planning decision-making
 271 approach that incorporates a built-in model using spatial data. The stakeholder-LUCC
 272 model allows spatializing future LUCC, showing the outcomes both spatially and
 273 graphically. Figure 6 depicts its flowchart.

274



275

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Figure 6 – Stakeholder-LUCC model flowchart.

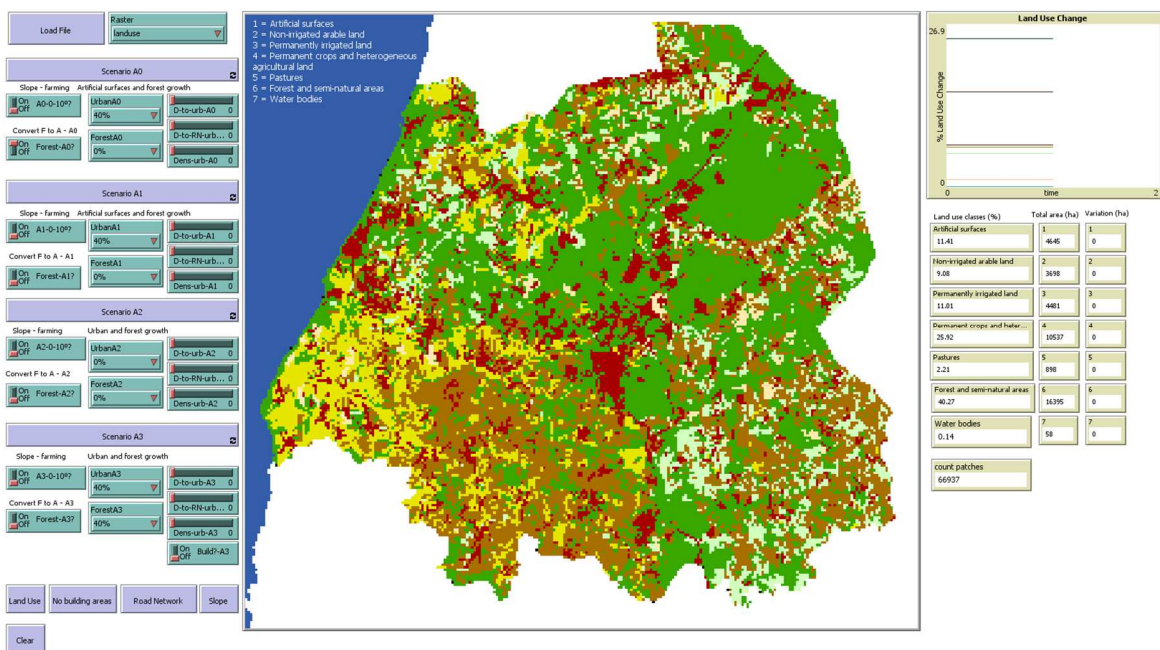
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278 Stakeholder-LUCC model has principles based on spatial proximity (100m or 200m) to
 279 some spatial elements (road network, and artificial surfaces), % of growth defined for
 280 the artificial surfaces and forest and semi natural areas (0%, 20%,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

287 intentions are allocated in each cell of non-irrigated arable land, permanently irrigated
 288 land, permanent crops and heterogeneous agricultural land, pastures, and forest and
 289 semi-natural areas.

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

293



294

295

Figure 7 – The stakeholder-LUCC model interface.

296

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

300

301 3. Results and discussion

302

303

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

304 participatory workshop; the third is related to the integration of stakeholder LUCC views
 305 into the stakeholder-LUCC model; and the fourth depicts a discussion regarding land use
 306 strategies and advances in land use management derived from our paper.

307

308 **3.1 Farmer LUCC intentions**

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

319

320 **Table 6 – Farmer LUCC intentions – probability of change (%) – by scenario and land use class.**
 321 Land use classes: LUC 1 - artificial surfaces; LUC 2 - non-irrigated land; LUC 3 - permanently irrigated land;
 322 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

323

324 According to the achieved results, we highlight the following findings, comparing the
 325 size of each land use class of the farmlands of the interviewed farmers with the expected
 326 growth of each land use class in each scenario: an increase of 47.8% in artificial surfaces
 327 in the B0 scenario; a decrease of 46% in non-irrigated land in the A2 scenario; an increase

328 of 68% in permanently irrigated land in the A1 scenario; an increase of permanent crops
 329 and heterogeneous agricultural land in the A1 scenario; and an increase of 560% in
 330 pastures in the A2 scenario.

331

332 **3.2 Participatory workshop: stakeholder LUCC views**

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

346

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

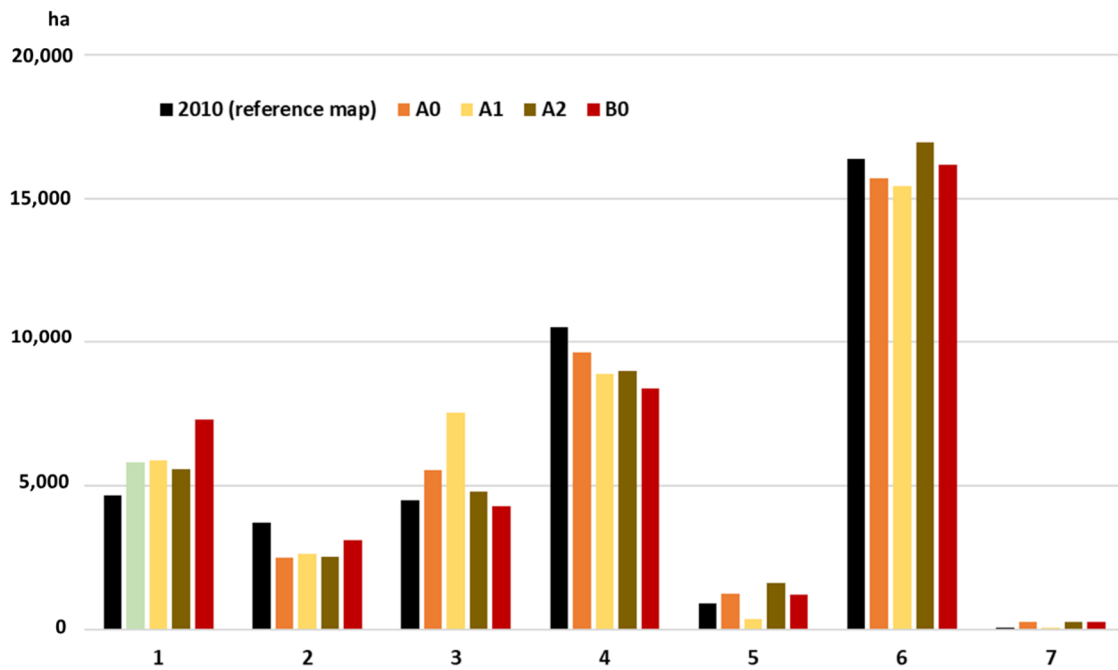
	CA- Markov	ANN- MLP	LUCC % disagreement	LUC 1 (%)	LUC 2 (%)	LUC 3 (%)	LUC 4 (%)	LUC 5 (%)	LUC 6 (%)	LUC 7 (%)
A0	5	1	2	14.3	6.2	13.6	23.6	3.1	38.6	0.6
A1	6	0	0	14.4	6.4	18.5	21.8	0.9	37.9	0.2
A2	4	2	2	13.7	6.2	11.8	22.1	4.0	41.6	0.6
B0	3	3	1	17.9	7.6	10.5	20.6	2.9	39.7	0.6

350

351 As shown, the CA-Markov model was the most elected LUCC model. One of the
352 reasons is related to the neighbourhood principle integrated into this model. This
353 principle defines that each cell is influenced by the nearest cell (Ilachinski, 1987; Schiff,
354 2011). The expansion of land use classes occurs by contiguity and reflects what the
355 stakeholders believe that can happen in terms of land use transformations.
356 Nevertheless, in the B0 scenario, the choice was not consensual. Three stakeholders
357 chose the CA-Markov model and the other three chose the ANN-MLP model as the more
358 adjusted according to their own views. The ANN-MLP model recognizes non-linear
359 patterns (Ebrahimi et al., 2017; Mayoraz et al., 1996; Pijanowski et al., 2002),
360 representing a closer idea of what the stakeholders believe that can happen with the
361 behaviour of the artificial surface growth in the B0 scenario.

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

369



370

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

375

376 3.3 The stakeholder-LUCC model

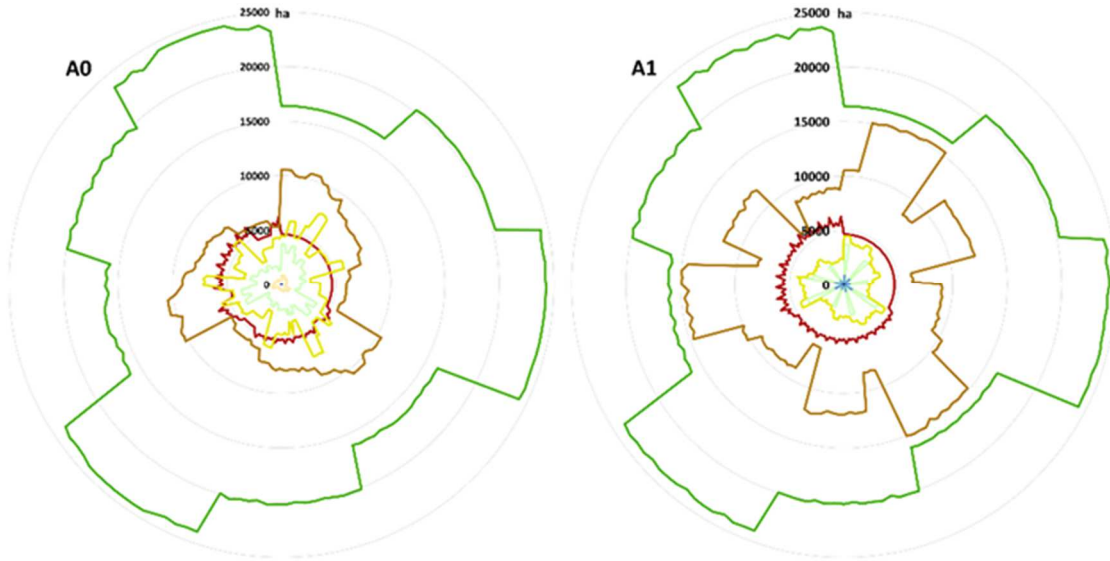
377 3.3.1 Model performance

378 Many researchers have studied the importance of testing the validity of the models (An
 379 et al., 2005; Manson, 2005). Some of these tests represent a functional verification,
 380 which should include efforts to break the model (Parker et al., 2003). They are used to
 381 control if the model is corrupted or produces entirely unreasonable results (An et al.,
 382 2005). The purpose is to identify the robustness of the model and recognise the
 383 inferences of any uncertainty assessment on simulation response (Helton, 2008),
 384 determining if there is a statistically significant change between simulation responses
 385 under different settings.

386 To identify the disturbance and influence of each parameter on each simulation
 387 response, we used a function in NetLogo called *Behaviour Space* that allowed us to
 388 perform a sweep for all potential simulations. We ran the simulation model with

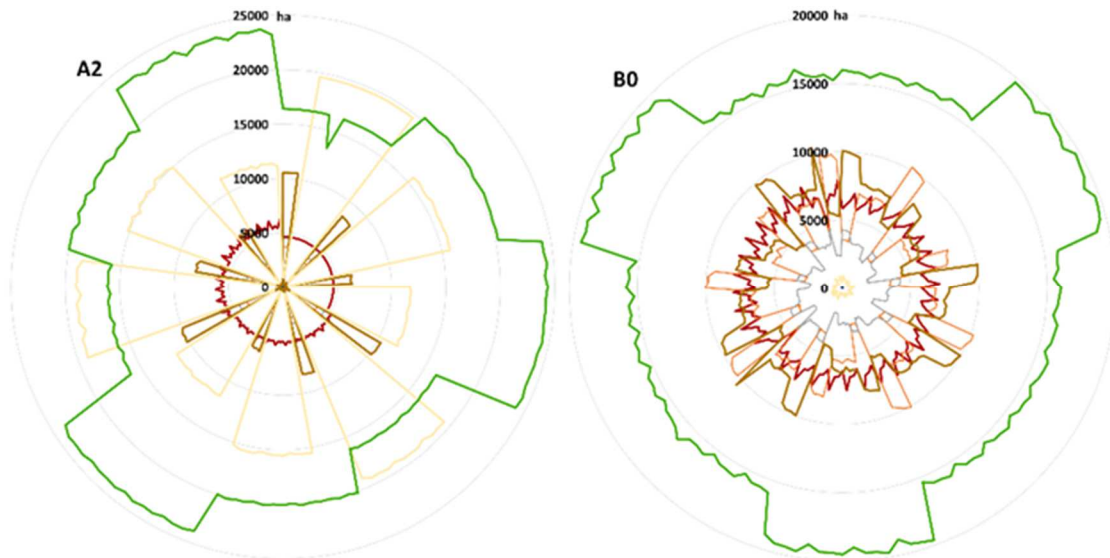
389 different settings, selecting a specific parameter in each of the following groups: artificial
390 surfaces growth: 0%, 20%, or 40% (and according to the distance to existing artificial
391 surfaces: 100m or 200m; and to the distance to road network: 100m or 200m); forest
392 and semi-natural areas growth: 0%, 20%, or 40%; convert forest and semi-natural areas
393 to agricultural land: Yes or No; and farming in areas with the following interval slope
394 degrees: 0-10° or 0-20°. Next, we present a radar charter showing LUCC in all the
395 potential simulations (by scenario) performed in the stakeholder-LUCC model (Fig. 9).

396



397

398



399



400

401

402

Figure 9 – The stakeholder-LUCC model simulations by scenario.

403

404 Figure 9 represents the variation in hectares of the seven land use classes analysed in

405 the A0, A1, A2, and B0 scenario, according to the settings and parameters mentioned

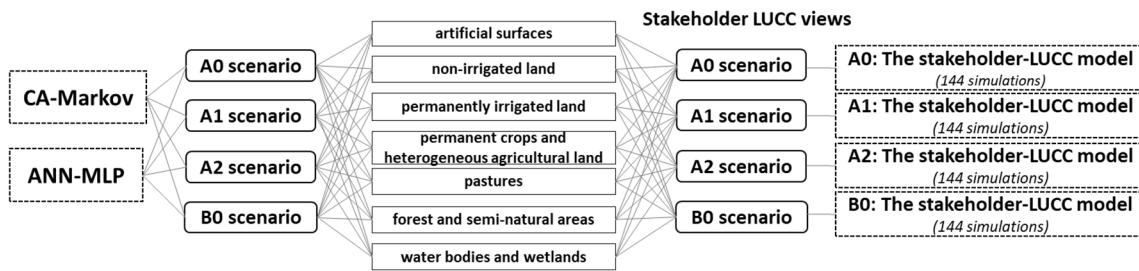
406 above. The outcomes are the result of all possible combinations (144 simulations) for

407 each scenario.

408 **3.3.2 The stakeholder-LUCC model: integrating stakeholder LUCC views**

409 Considering the outcomes of all the simulations, we identified which one, out of the
 410 144 possible simulations (for each scenario), had the lowest deviations compared to the
 411 stakeholder LUCC views. Subsequently, the next step involved identifying in the model
 412 the parameters needed to achieve similar outcomes (in percentage) (Fig. 10).

413



414

415 **Figure 10 – Methodology flowchart representing the integration of stakeholder LUCC views**
 416 **into the stakeholder-LUCC model.**

417

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

423

424 **Table 8 – Selected simulations in the stakeholder-LUCC model by scenario.** Land use classes: LUC
 425 1 – artificial surfaces; LUC 2 – non-irrigated arable land; LUC 3 – permanently irrigated land; LUC 4 –
 426 permanent crops and heterogeneous agricultural land; LUC 5 – pastures; LUC 6 – forest and semi-natural
 427 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
<i>Deviation (stakeholder LUCC views - A0)</i>	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
<i>Deviation (stakeholder LUCC views - A1)</i>	-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
<i>Deviation (stakeholder LUCC views - A2)</i>	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
<i>Deviation (stakeholder LUCC views - B0)</i>	-0.48	-0.66	0.53	-2.62	0.89	1.86	0.49

428

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

432

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

Group		A0	A1	A2	B0	
		<i>Farmer LUCC intentions (%) - static</i>				
a	1 - Artificial surfaces (%)	0	0	0	47.80	
		plus				
		<i>Parameters (%)</i>				
	Distance to artificial surfaces (m)	40	40	40	20	
	Distance to road network (m)	100	200	200	200	
		<i>Farmer LUCC intentions (%) - static</i>				
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			
			<i>Parameters (%)</i>			
	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	
		<i>Farmer LUCC intentions (%) - static</i>				
c	6 - Forest and semi-natural areas	0	0	0	0	
		plus				
		<i>Parameters (%)</i>				
		0	0	0	0	
		<i>Farmer LUCC intentions (%) - static</i>				
d	7 - Water bodies and wetlands	0	0	0	0	

435

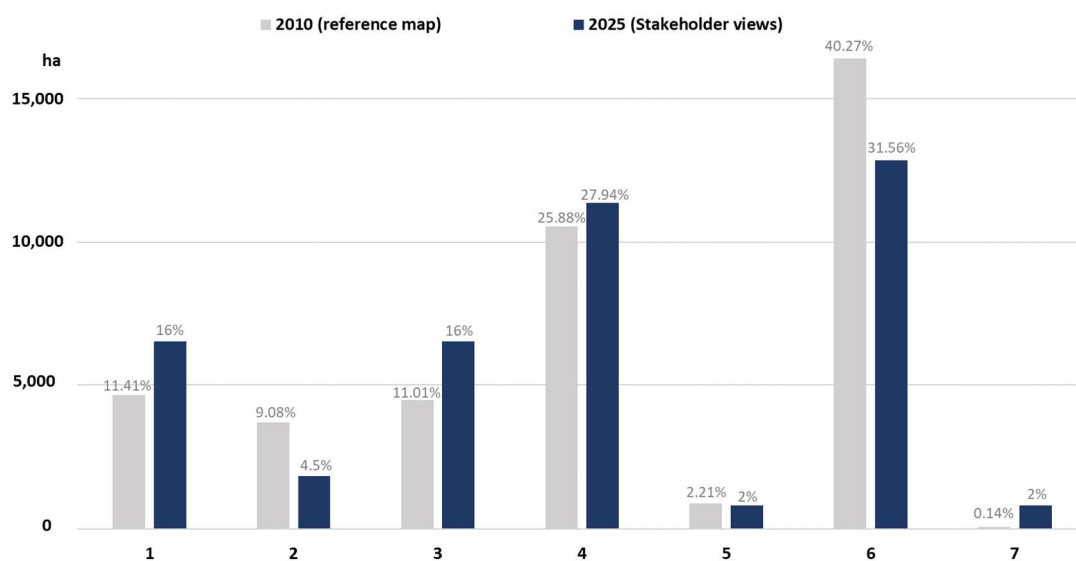
436 As seen in Table 9, farmer LUCI intentions are the most determinant parameter
 437 responsible for the LUCI in the selected simulations, as well as the distance to artificial
 438 surfaces, distance to road network, and slope.

439

440 **3.3.3 Stakeholder views: land use cover 2025**

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

451



452

453 **Figure 11 – Values in ha and percentage of each land use class of the reference land use map**
 454 **and the stakeholder views for 2025.** Land use classes: 1 – artificial surfaces; 2 – non-irrigated arable land; 3

455 – permanently irrigated land; 4 – permanent crops and heterogeneous agricultural land; 5 – pastures; 6 – forest and
456 semi-natural areas; 7 – water bodies and wetlands.

457

458 Comparing these LUCC views with the reference land use map, we can see an increase
459 of 1,869 ha in artificial surfaces (28.7%); a decrease of 1,866 ha in non-irrigated arable
460 land (-101.9%); an increase of 2,033 ha in permanently irrigated land (21.2%); an
461 increase of permanent crops and heterogeneous agricultural land of 838 ha (7.4%); a
462 decrease of 84 ha in pastures (-10.3%); a decrease of forest and semi-natural areas of
463 3,546 ha (-27.6%); and an upsurge of water bodies and wetlands of 756 ha (92.9%).

464 Subsequently, we identified in all the 576 possible simulations for all the scenarios
465 (144*4) which one had fewer deviations in the stakeholder-LUCC model. Therefore, the
466 selected simulation was identified as the A0 scenario (Table 10).

467

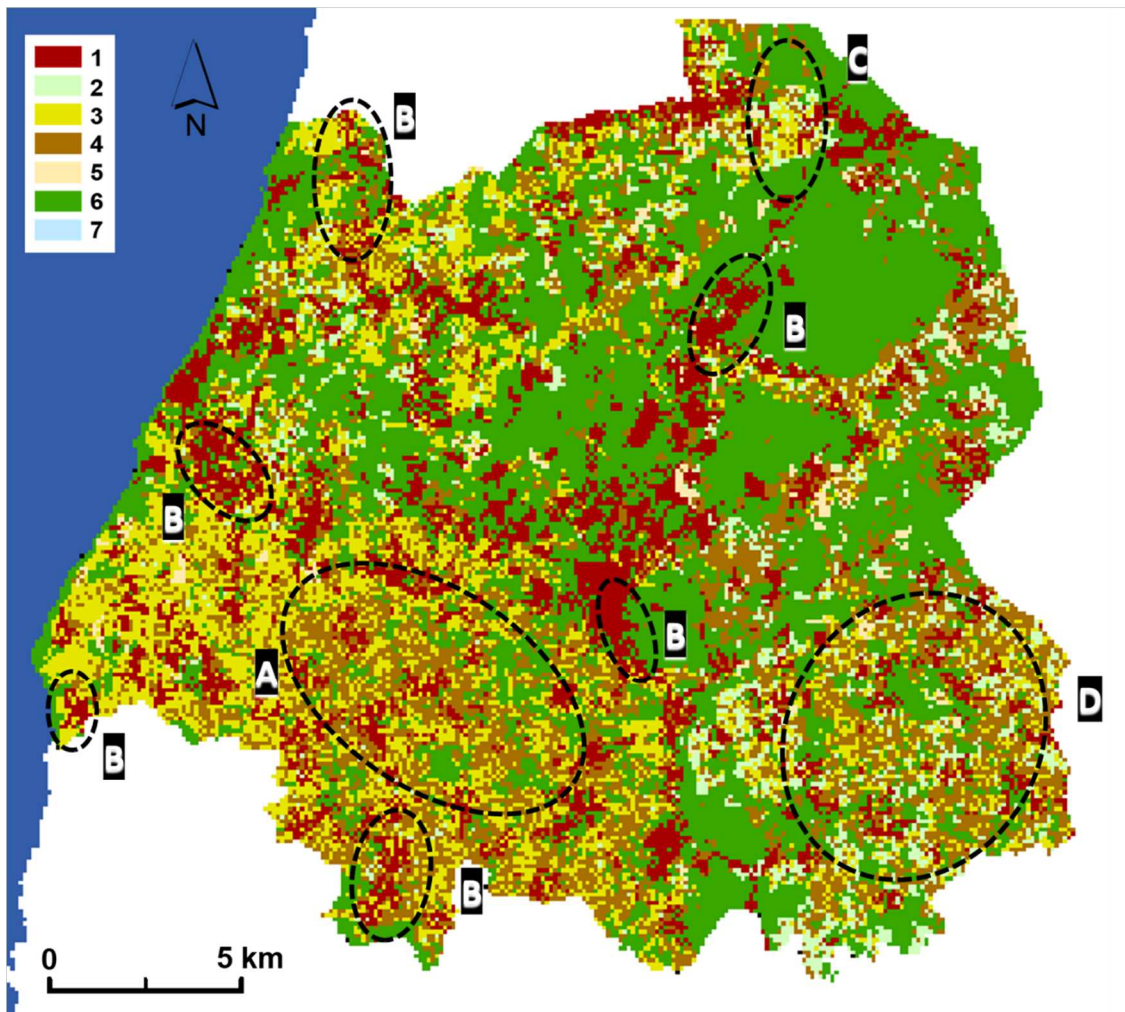
468 **Table 10 – Stakeholder LUCC views (%) for 2025.** Land use classes: LUC 1 – artificial surfaces; LUC 2 – non-
469 irrigated arable land; LUC 3 – permanently irrigated land; LUC 4 – permanent crops and heterogeneous agricultural
470 land; LUC 5 – pastures; LUC 6 – forest and semi-natural areas; 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
<i>A0: selected simulation (%)</i>	<i>15.39</i>	<i>5.63</i>	<i>16.93</i>	<i>21.72</i>	<i>1.35</i>	<i>38.84</i>	<i>0.14</i>

471

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

474



475

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

480

481 Figure 12 shows these transformations spatially. In the location assigned by A, we
 482 identify the site where the probability of conversion from permanent crops and
 483 heterogeneous agricultural land to permanently irrigated land is higher. In the location
 484 assigned by B, which represents artificial surfaces growth, we recognized that artificial
 485 surface expansion occurs along with the road network, and mainly infilling around
 486 existing artificial surfaces. The spatial patterns of the artificial surface growth are
 487 categorized by linear directions, more pronounced in the south and in the west.

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

493

494 **3.4 Land use strategies and advances in land use management**

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

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

511 From the urban growth perspective, according to the economic and social trend in our
512 case study in a medium-long-term period, some indicators can point to a fast LUCC
513 transformation. An increase in housing demand has been verified in the last few years
514 in the metropolitan region of Lisbon (Statistics Portugal, 2019). Therefore, mostly due
515 to the amenities that Torres Vedras can offer and the lower prices of housing compared
516 to Lisbon, this territory may be an attractive target for potential urban development.
517 This attraction can also be driven by the evolution of information technology. In recent
518 years, more people have been able to work from home. They can benefit from the
519 proximity to Lisbon, but they will not need to commute daily. Additionally, we believe
520 electric cars can increase housing demand by new residents. Although the undisputable
521 benefits that these vehicles have in terms of greenhouse effect (zero-emission), due to
522 the low cost of charging, they can indirectly promote the increase of extensive
523 urbanization (Kester et al., 2020). People will be able to commute long distances at a
524 low cost, and the demand for single-family dwellings can increase. Therefore, actions to
525 promote urban containment growth should be implemented (Dawkins and Nelson,
526 2002; Fertner et al., 2016). Moreover, new built-up areas must have environmental
527 concerns, such as high energy efficiency using renewable energies, green roofs, and
528 environmentally friendly construction materials (Hamilton et al., 2013; Li and Yeung,
529 2014).

530 From the agricultural land perspective, policies to protect and monitor it should also
531 be employed (Gomes et al., 2019c). According to our results, the highest increase will
532 be in permanently irrigated land. Therefore, decision-makers should contemplate some
533 measures to improve the irrigation systems and thus make farming more efficient and
534 competitive, e.g. Levidow et al. (2014), and Holzapfel et al. (2009). This was one of the

535 main solutions pointed out by the stakeholders. This is more pressing because the
536 agricultural sector must be aware of climate change. The Intergovernmental Panel on
537 Climate Change (IPCC) projected scenarios for the latitude of our case study that show
538 longer periods of drought and greater scarcity of water (IPCC, 2000), and measures to
539 mitigate this effect must be implemented accordingly. Other transformations that can
540 be seen in the agriculture sector can result from the competition of other markets,
541 demand for new consumption patterns, or the introduction of new technology.
542 Concerning new technology, smart farming is already a reality, and it can increase the
543 quantity and quality of agricultural products, using unmanned tractors controlled via
544 Global Positioning System (GPS), unmanned aerial vehicle (UAV - commonly known as
545 drones) to kill vermin, and precision agriculture (Pivoto et al., 2018; Walter et al., 2017).

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

552 In the context of modelling land use change for spatial planning support, this study
553 aimed at opening up new methodological paths for further research. LUCC simulation
554 experiments have been dealing with different categories of land use and have been
555 conducted by Parker et al. (2003), Lambin et al. (2003), and Valbuena et al. (2010). While
556 LUCC prediction and assessment have been developed, predictions performed in this
557 research are based on new narratives and storylines to understand LUCC dynamics
558 through a new approach. We presented a prospective methodology to better

559 understand spatial and temporal land use dynamics, identifying what is more relevant
560 in the decision process. The results achieved in this research should: (1) inform
561 policymakers and the community, demonstrating future land use alternatives and
562 showing its impacts; (2) show the suitable land use options to avoid undesirable future
563 impacts (adaptive land use management); and (3) simulate LUCC to support planners,
564 creating sustainable development strategies, and anticipating and understanding future
565 land use uncertainties.

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

574

575 **4. Conclusion**

576 The role of human activities in controlling land use has had different effects on land
577 use. Anticipating decisions, indicating alternative futures and their impacts, to support
578 policy-makers is one of the biggest challenges of spatial planning. The mixed-methods
579 (quantitative and qualitative) used in our research by means of the participatory
580 workshop enabled us to strengthen the relations between researchers and
581 stakeholders, and encouraged knowledge sharing and the interchange of different
582 points of view. It allowed us to see how stakeholders can play their part in the decision-

583 making process (local-level actors) and the interactions between spatial factors and
584 constraints. As a result land use recommendations were put forward.

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

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

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

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

617

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