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Exploring the Effects of Climate Change on Farming System Choice: A Farm-Level Space-for-Time Approach

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Abstract: Climate change is expected to affect the agricultural sector in ways that are often unclear to predict. If in the short- and medium-terms farmers may adapt to climate change by adjusting their agricultural practices, in the long-term, these adjustments may become insufficient, forcing farmers to change their farming systems. The extent and direction in which these farming system transitions will occur is still a subject that is underexplored in the literature. We propose a new framework to explore the effect of climate change on the choice of farming system while controlling the effect of other drivers that are also known to influence the farming system choice. Using a spatially explicit farming system choice model developed by a previous study in an extensive agricultural region of southern Portugal, we applied a space-for-time approach to simulate the effect of climate change on the future dynamics of the farming systems in the study area. The results suggest that climate change will force many farmers to change the farming system in a foreseeable future. The extent of the projected changes in farming systems is likely to trigger significant social, economic, and environmental impacts, which should require early attention from policy makers.

Keywords: climate change; farming systems; space-for-time; choice modelling; climate scenarios

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1. Introduction

Climate change is expected to bring substantial impacts on the agricultural sector [1,2]. Plenty of research has been published on the subject, mostly focusing on assessing the effects of climate change on crop and livestock productivity [3–5], on the shifting of agroclimatic zones [6,7], or on global food security [4,8,9]. However, the literature focused on anticipating farmers' decisions in their climate change adaptation strategies is surprisingly less abundant.

Farm management decisions are typically made at the whole-farm level, in a comprehensive and internally coherent approach that accounts for the interdependencies between crops, livestock rearing, and other activities, rather than independently for each crop or activity [10]. So, to understand and anticipate farmers' decisions in their adaptation strategies to climate change, an integrated farming systems (FSs) approach should be adopted rather than resorting to a simple crop modelling analysis focused on understanding how climate change will affect a particular crop or activity [11–13]. In this sense, an FS acts as a classification scheme that is useful for identifying groups of farms that carry out roughly the same activities, with similar land use and livestock patterns, employing identical technologies and production methods and which, therefore, can be expected to react in a similar way to external stimuli [10,14]. This is the FS concept adopted in this study. We believe that this FS approach to anticipate farmers' response to climate change is new in the literature, where adaptation studies focused on adjustments to agricultural practices within the same FS have prevailed.

The farming system choice is a farmer's decision that involves the joint consideration of several factors acting alone or in interaction, expanding or narrowing the farmer's set of possible choices, which include both socioeconomic factors (e.g., policy or market context, farm size, water or labour availability, or farmer's idiosyncrasies) and biophysical factors (e.g., soil, slope, or climate) [10,15,16].

The process of modelling the FS choice at the farm level is often faced with data constraints. On the one hand, information is needed to establish the typology that will represent the available FS portfolio for farmers, which may require collecting data on crops, land uses, livestock, and production methods for each farm. On the other hand, it requires characterising farms in terms of the above-mentioned drivers of farming system choice, which can be carried out by resorting to a GIS analysis, if appropriate data are available, or by carrying out expensive and time-consuming surveys. Additional challenges may stem from the fact that some relevant drivers of FS choice are subject to temporal variations, such as prices, or to space–time variations such as climate. In the latter case, the difficulty is further inflated by the fact that in most cases, it is not practicable to collect the required data for a period of time that is long enough to capture the effect of climate change on farmers' choice of FS.

Such difficulties have led researchers who are interested in modelling the effect of climate change on FS choice to resort to proxy approaches, often relaxing the farming system concept to a farm-type approach, such as the typologies built from official statistical databases (e.g., the EU Farm Accountancy Data Network database—FADN, used to classify farms based on production orientation and economic size) [17,18], or the use of farm types derived from farm surveys [5,15]. Such farm-type approaches are not suitable for representing farmers' choices, as they typically include components that are exogenous to that choice, such as the physical or economic size of the farm.

Other works on farming resilience to climate change focus on short- to medium-term adaptation strategies, such as crop diversification, the adoption of more drought-resistant varieties, adjustments in planting and harvest dates, or increasing irrigation [19,20], and do not focus on the long-term impacts where, by hypothesis, the magnitude of climate change may become incompatible with adjustments within the same FS, and may force farmers to undertake deeper changes, eventually leading them to switching into a different FS.

To test this hypothesis, we depart from a recent study that presented an FS choice model developed to explain the spatial distribution of 22 farming systems in the Alentejo region (southern Portugal), based on a diversity of socioeconomic and biophysical drivers, including climate variables [16]. Taking advantage of the considerable extent of the study area used to estimate this model and its internal climate variability, in this study, we used this model to develop a space-for-time approach to simulate climate change scenarios and assess how these will influence the FS choice in the future. The use of a space-for-time substitution procedure is based on the assumption that when the drivers of spatial variation are the same of variation over time, then time can be replaced by space to model future change patterns [21]. Space-for-time has been used before in studies on the effects of climate change on the agricultural sector, for example, to assess how regional crop suitability will shift with climate change [22]. Still, to our knowledge, this coupling of an FS discrete choice model with a space-for-time substitution approach is a pioneer in empirical studies on the effects of climate change applied to the agricultural sector.

The proposed modelling layout allows for the exploration of the effects of climate change in the choice of the FS while ensuring high control over the remaining drivers that are intended to be kept constant, which is a premise that is often assumed in the literature, albeit in an implicit way, and therefore not usually discussed. Thus, the objective of the present study is not to predict which FS farmers will effectively choose in the future, but to understand how climate change alone will influence this decision-making process.

The specific objectives of the present study are, therefore, as follows: (1) to simulate the effects of different climate scenarios on FS choice; (2) compare the results achieved with our farm-level FS choice approach with those from crop-modelling approaches; and (3) assess the limits of a space-for-time approach to explore the effects of climate change on farming system choice. Finally, insights on the usefulness of the proposed approach to assess the impacts of farming system dynamics induced by climate change are discussed.

2. Materials and Methods

2.1. Study Area

The Alentejo region (EU NUT II), in the southern part of mainland Portugal, was selected as the study area for this work for 3 main reasons: (1) it is large enough to have significant climate variation, which is a crucial requirement for the space-for-time modelling approach described below; (2) the land use/cover is largely dominated by agriculture; and (3) a recently developed farm-level mapping of farming systems is available for the entire region (see Section 2.2).

The Alentejo region extends ca. 31,550 km^2, covering about 1/3 of Portugal (Figure 1). Its climate is typically Mediterranean, characterised by warm and dry summers that contrast with cool, rainy winters. Average monthly temperatures range from 9.9 °C in January to 23.4 °C in August (annual average 16.3 °C), and total annual precipitation sums 619 mm, mostly concentrated from October to March. Climate gradients across the region are significant, with annual average temperatures increasing from 13.2 °C to 17.8 °C and precipitation decreasing from 1272 mm to 379 mm, while progressing from northwest to southeast.

Figure 1. Location of the Alentejo study area, Portugal.

Agriculture covers about 70% of the territory, with the remaining area corresponding mostly to forest areas (25%), water bodies (3%), and artificial areas (2%). Agriculture is dominated by permanent pastures, annual crops (mostly cereals and forages), and permanent crops (primarily olive groves), in descending order of their weights in farmland. Approximately 40% of the agricultural land is under the canopy of scattered trees, mainly cork and holm oaks (*Quercus suber* and *Q. rotundifolia*, respectively), an agroforestry system locally called "montado".

2.2. Baseline Data

The baseline data for the present research consisted primarily of an FS map for the Alentejo region, a machine learning model predicting these FSs from a set of socioeconomic and biophysical variables, including climate variables, and data on future climate scenarios.

2.2.1. Farming Systems Information

Information on FS was extracted from a recent paper [16] where a typology of 22 FSs was derived from a cluster analysis applied on land use and livestock data for virtually all farms in the Alentejo region in 2017 (Figure 2 and Table S1 in Supplementary Information).

The data were taken from the Integrated Administration and Control System (IACS) and the Land Parcel Identification System (LPIS) provided by the national agency responsible for Common Agricultural Policy (CAP) payments.

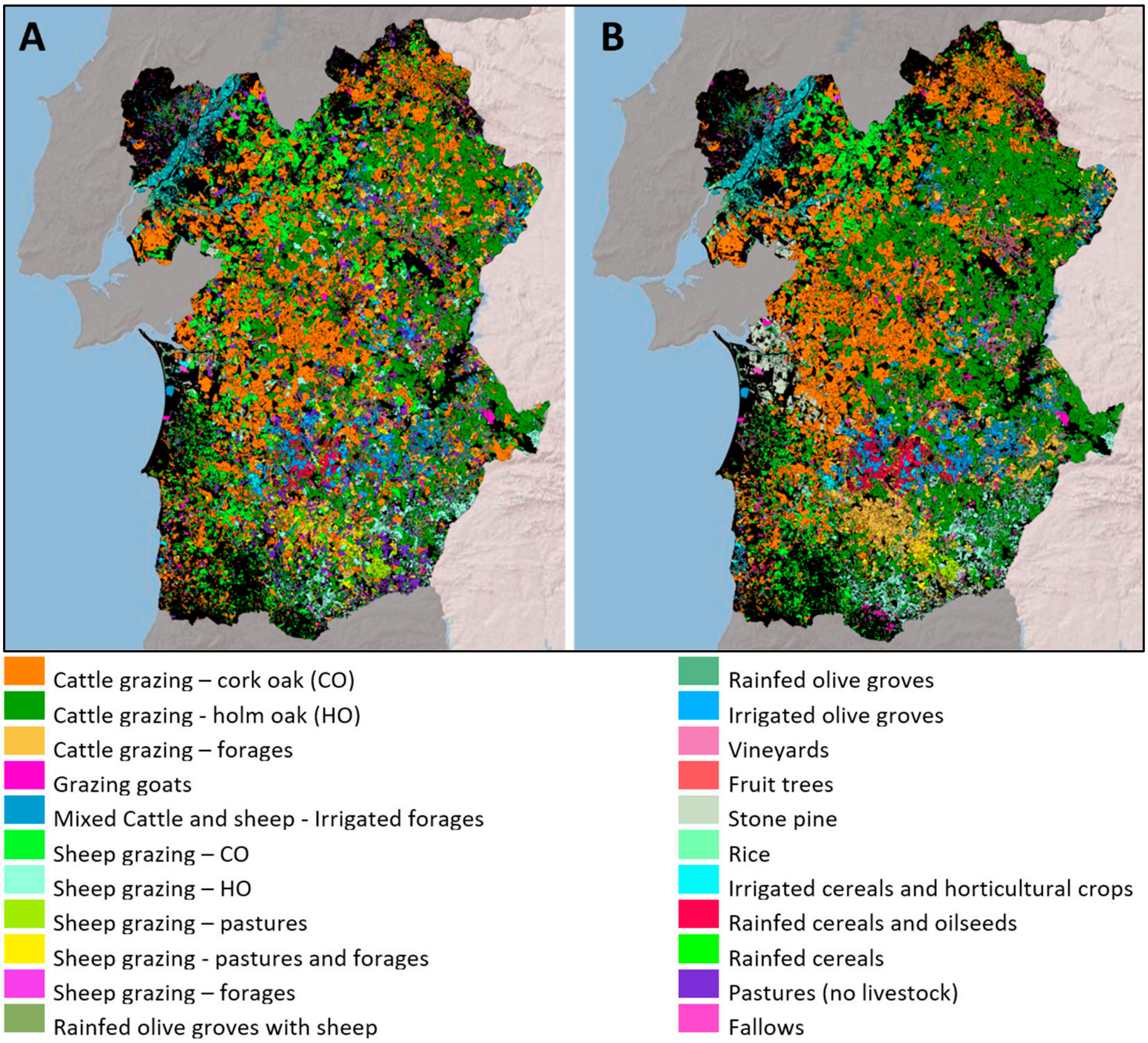


Figure 2. Observed (**A**) and predicted (**B**) spatial distribution of the farming systems of Alentejo, Portugal in 2017. Non-coloured areas (in black) refer to areas that did not apply for CAP payments in 2017, most of which are assumed to be non-agricultural areas, mostly forests (adapted from Ribeiro et al. [16]); see Supplementary Information in the same reference for detailed spatial distribution of each of the 22 farming systems.

All parcels declared by the same CAP beneficiary in the reference year (2017) were aggregated and taken as a single farm. The polygons of these parcels were spatially identified under the LPIS, so farm mapping was made possible (Figure 2). A total of 24,313 farms were thus identified and mapped, roughly covering 2×10^6 ha of utilised agricultural area (about 87% of total utilised agricultural area in Alentejo, according to the most recent 2019 agricultural census in Portugal, and 65% of the total Alentejo territorial area).

2.2.2. Farming Systems Predictive Model

The FS predictive model was also taken from Ribeiro et al. [16], who used a random forest modelling approach to estimate an FS choice model for the Alentejo region. Random forest is a popular machine learning technique that has been extensively used for modelling spatial and spatiotemporal data [23]. Random forest can be applied to both regression and classification problems, depending on the nature of the dependent variable, using bootstrap and aggregation (bagging) to build multiple decision trees based on random subsets of the data and using a random subset of the candidate predictor variables for each node in each decision tree [24]. On a classification problem, each observation is assigned to a class according to the majority of votes from all trees. In this case, the random forest model was used in a classificatory approach to predict the FS (categorical variable) characterising each farm from a broad set of 27 predictors describing farm structure (e.g., farm size, farm spatial fragmentation, and irrigation use), socioeconomic context (e.g., population density, use of hired labour, and main sources of income), and biophysical variables describing soil quality (pH and texture), topography (slope classes), and climate. These climate variables, which are keys for the present study, included the maximum and minimum mean temperatures of the warmest and coldest months, respectively, and annual precipitation, averaged between 1971 and 2000, which were used in model estimation in [16] (at the time, the most recent publicly available 30-year climate averages for mainland Portugal).

All farms were therefore characterised under these variables by overlaying the farm map with raster layers representing the spatial distribution of each variable to extract the average of the pixel values covered by the polygons of each farm, using a GIS zonal statistics tool.

The random forest model showed a good global predictive accuracy (63.7% error rate, which was evaluated positively considering the high number of 22 classes in the dependent variable, for which the random error rate would be about 95.4%).

In this study, the same model was replicated to predict FS choice under climate change scenarios by replacing the values of the climate variables used to estimate the model with new values referring to those climate scenarios, following a space-for-time substitution procedure [21].

2.2.3. Climate Scenarios

Data for climate change scenarios were extracted from the WorldClim database (https://www.worldclim.org, assessed on 19 February 2023), which provides climate projections based on a range of pathways for emission scenarios, known as "Shared Socioeconomic Pathways" (SSPs) [25]. These have been used as inputs for the latest climate models, under the Intergovernmental Panel on Climate Change (IPCC) and the six-assessment report of the Coupled Model Intercomparison Projects (CMIP6) [2,25]. These climate projections consist of monthly values of minimum temperature, maximum temperature, and precipitation, derived from 23 global climate models (GCMs), for four SSPs (1–mm 2.6, 2–4.5, 3–7.0, and 5–8.5) related to increasing levels of anthropogenic greenhouse gas (GHG) emissions, and for four 20-year periods (2021–2040, 2041–2060, 2061–2080, and 2081–2100).

In the present study, long-term climate scenarios for the 2081–2100 period were selected to heighten the effect of climate change on FS choice, since we were interested in capturing the effects on FS change, and not just changes in agricultural practices, like moving to more drought-resistant crop varieties. Three SSP scenarios were used to simulate low (SSP 1–2.6), moderate (SSP 3–7.0), and high GHG emission (SSP 5–8.5) scenarios. For each of these, we extracted the median of the projections provided by 9 of the 23 climate models, which were those with complete information on all climate variables and all SSP scenarios, to extract predictions of maximum and minimum temperatures of the warmest and coldest month, respectively, and annual average precipitation, so they can be comparable to the baseline climate variables used in the estimation of the random forest FS predictive model.

2.3. Scenario Assessment

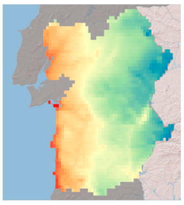
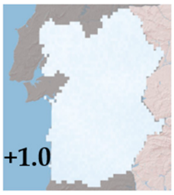
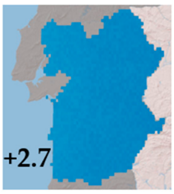
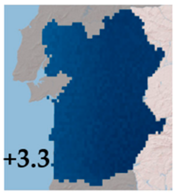
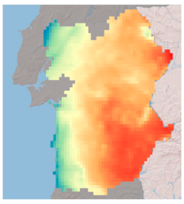
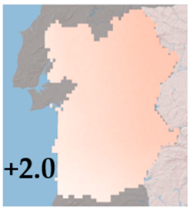
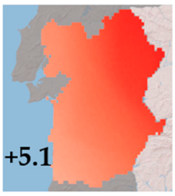
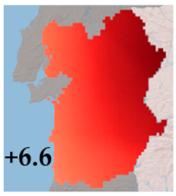
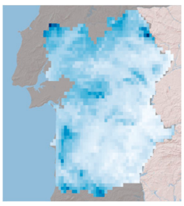
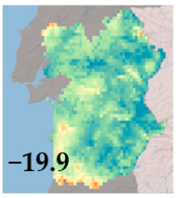
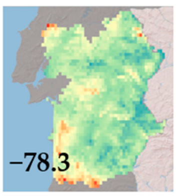
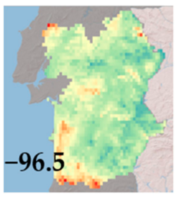
The effects of climate change on FS choice were primarily assessed based on the changes in the land shares of the different FSs in the study area in each scenario. Sankey diagrams [26] were used to graphically visualise the predicted FS areal transitions. Transition matrices with the relative values of the areal transfers between FSs are also shown in Supplementary Information.

3. Results

3.1. Climate Change Predictions

The climate scenarios for the study area in the 2081–2100 period predict significant changes in the climate variables under study, even in the low emission scenario (SSP 1-2.6) (Table 1). The climate anomaly in the average value of the minimum temperature of the coldest month is expected to range from an increase of 1.0 °C in the low emission scenario to 3.3 °C in the high emission scenario. The average maximum temperature in the warmest month is expected to rise by 2.0 °C in the low emission scenario by and 6.6 °C in the high emission scenario. The average annual precipitation is anticipated to decrease by between −19.9 mm in the low emission scenario and −96.5 mm in the high emission scenario, which corresponds to a decrease of about 16% in the total annual precipitation of the baseline period (1971–2000). In the moderate emission scenario (SSP 3-7.0), the forecasts point to anomaly values between the limits of the two extreme scenarios.

Table 1. Distribution of the three climate variables used in the models in the baseline situation (average 1971–2000) in the study area and their predicted anomalies for the long-term scenario of the 2081–2100 period. Figures embedded in the graphics depict the corresponding mean values of the anomaly.

		Anomalies			
	Baseline (1971–2000)	**Low Emission Scenario (SSP 1-2.6)**	**Moderate Emission Scenario (SSSP 3-7.0)**	**High Emission Scenario (SSP 5-8.5)**	**Legends (Baseline | Anomalies)**
Minimum temperature of the coldest month (°C)					4.04 0.90 5.08 1.55 6.12 2.20 7.16 2.85 8.20 3.50
Maximum temperature of the warmest month (°C)					24.9 1.00 27.0 3.00 29.2 5.00 31.4 7.00 33.5 9.00
Annual precipitation (mm)					387.5 -499.0 578.8 -340.5 770.1 -182.0 961.4 -23.5 1152.7 135.0

As expected, these climatic anomalies are not uniform across the study area, showing variations that are particularly evident in the case of the maximum temperature, whose anomalies are about 4 °C higher in the interior, compared to the coastal areas. In the case of precipitation, the effect of relief on climate models is apparent, with more significant decreases expected with an increasing altitude. In the lower areas of the interior, where the current precipitation is quite low (400 mm or less), the forecasts even predict an increase in the average annual precipitation.

3.2. Effects of Climate Change on Farming System Choice

The model predictions show that climate change will substantially impact the FS choice in the study area. Altogether, 23%, 37%, or 40% of the total agricultural area of the study area is expected to change the FS, respectively, in the low, moderate, or high GHG emission scenarios (Figure 3). The impact of climate change, however, is not expected to be the same across all FSs; while some will barely be affected, others will undergo significant changes, either gaining or losing area (Table 2).

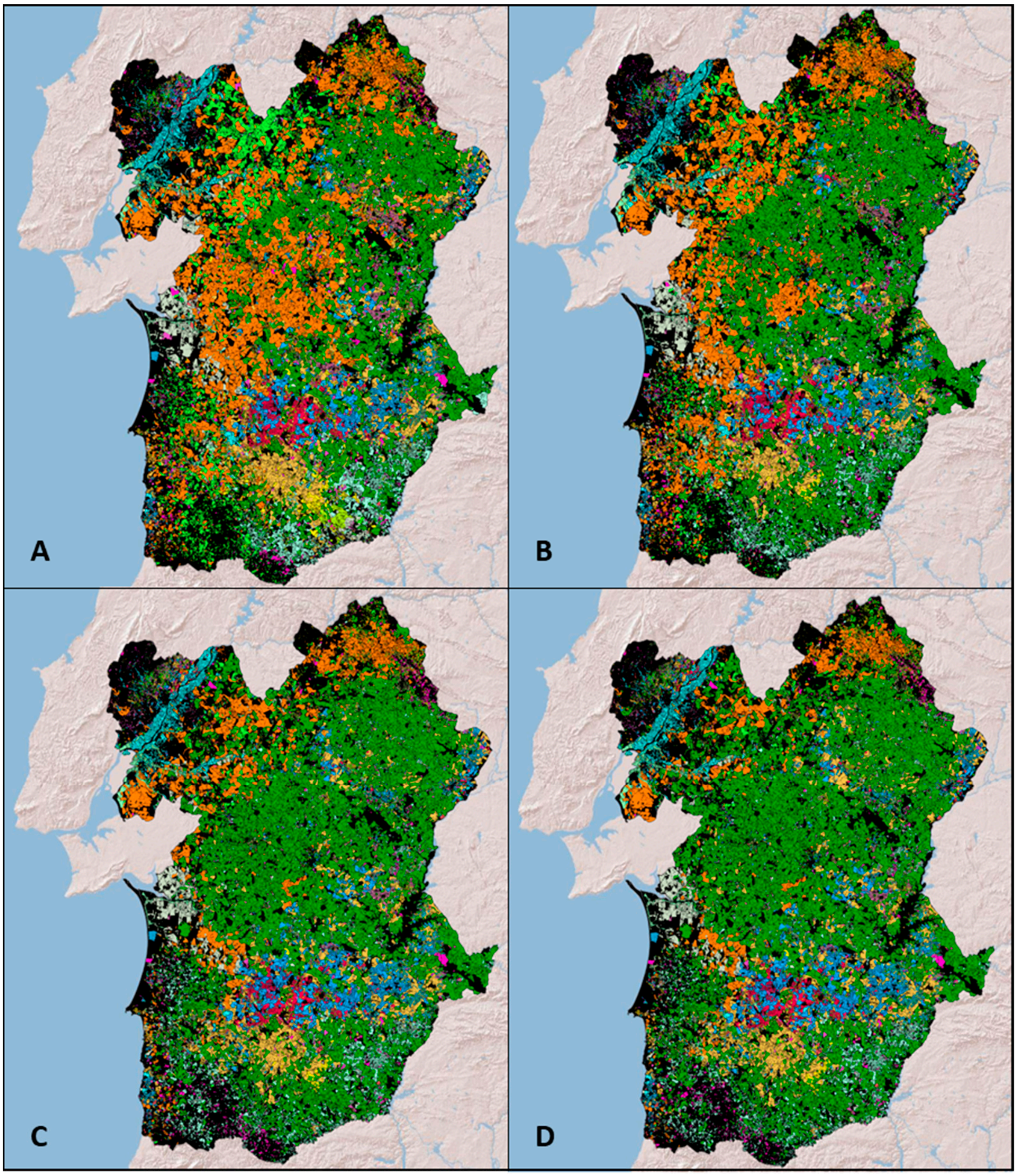


Figure 3. Predicted farming system distribution in the study area in 2017 ((**A**)—baseline scenario) and for the 2081–2100 period in low ((**B**)—SSP 1-2.6), moderate ((**C**)—SSP 3-7.0), and high emission ((**D**)—SSP 5-8.5) climate scenarios (see Figure 2 for colour legend).

Table 2. Expected effects of climate change on current area of farming systems in the long-term (2081–2100) scenarios.

Farming System	Area in 2017 (Predicted)		Expected Relative Changes in Area in Each 2081–2100 Scenario		
	ha	%	Low (SSP 1-2.6)	Moderate (SSP 3-7.0)	High (SSP 5-8.5)
Cattle grazing–CO	495,655	25.2	−22%	−62%	−72%
Cattle grazing–HO	580,656	29.5	44%	80%	89%
Cattle grazing–forages	168,219	8.5	−3%	17%	23%
Grazing goats	21,075	1.1	−12%	8%	6%
Mixed cattle and sheep–irrigated forages	20,090	1.0	−1%	−13%	−18%
Sheep grazing–CO	132,621	6.7	−55%	−89%	−93%
Sheep grazing–HO	100,952	5.1	−11%	4%	5%
Sheep grazing–pastures	32,734	1.7	−48%	−62%	−66%
Sheep grazing–pastures and forages	36,330	1.8	−45%	−61%	−63%
Sheep grazing–forages	18,602	0.9	−23%	−48%	−59%
Rainfed olive groves with sheep	13,396	0.7	3%	−22%	−28%
Rainfed olive groves	15,472	0.8	−15%	−12%	−7%
Irrigated olive groves	89,647	4.6	11%	42%	46%
Vineyards	21,947	1.1	−45%	−58%	−64%
Fruit trees	10,256	0.5	−8%	−33%	−37%
Stone pine	54,665	2.8	−11%	−26%	−29%
Rice	22,220	1.1	7%	−9%	−12%
Irrigated cereals and horticultural crops	50,042	2.5	−9%	−22%	−21%
Rainfed cereals and oilseeds	39,694	2.0	9%	−9%	−12%
Rainfed cereals	19,182	1.0	7%	14%	22%
Pastures without livestock	12,775	0.6	−75%	−84%	−84%
Fallows	12,700	0.6	−13%	−5%	−1%
Total	1,968,929	100.0	–	–	–

The cattle grazing–HO system, which is currently the dominant system covering ca. 30% of the total agricultural area, is expected to be the one experiencing the greatest area increase in any of the three climate scenarios, almost doubling the area in the high emission scenario (89% increase). Most of this growth will come from area currently under the cattle grazing–CO system (Figure 4), which is one of the top area losers, expected to drop between 22% and 72% of its current area, respectively, in the low and high emission scenarios (Table 2). This extensive replacement of cork oak with holm oak agroforestry systems is probably related to the distinct agroecological preferences of both oak species, which currently makes the cork oak dominant to the west and north of Alentejo, where the climate tends to be less hot and dry due to the proximity of the Atlantic Ocean [27], and makes the holm oak more frequent in the warmer and drier southern interior of the Alentejo region [16,28]. Thereby, the widespread decrease in precipitation and increase in summer heat will likely prompt holm oak to expand to areas that are currently dominated by cork oak. However, this expansion of the cattle grazing–HO system towards the more northwestern parts of Alentejo seems to suffer some resistance, only overthrown under the higher GHG emission scenarios, which may be related to the predominance of light texture soils (sandy soils) in this region, which tend to favour cork oak and not holm oak [16].

In addition to the Cattle grazing–CO system, other systems are expected to suffer significant declines in area. Except for the sheep grazing–HO system, all other sheep-specialised systems (sheep grazing–CO, sheep grazing–forages, sheep grazing–pastures, and sheep grazing–pastures and forages) are predicted to lose area, particularly the sheep grazing–CO system, which will likely lose more than half of its current area (55%) in the low emission scenario, and will almost disappear in the high emission scenario (93% drop). Although the available data do not allow for clarification, this may be related to a preference of the cattle systems for larger farms, which are predominant in the Alentejo region [16], fostering its expansion over sheep systems.

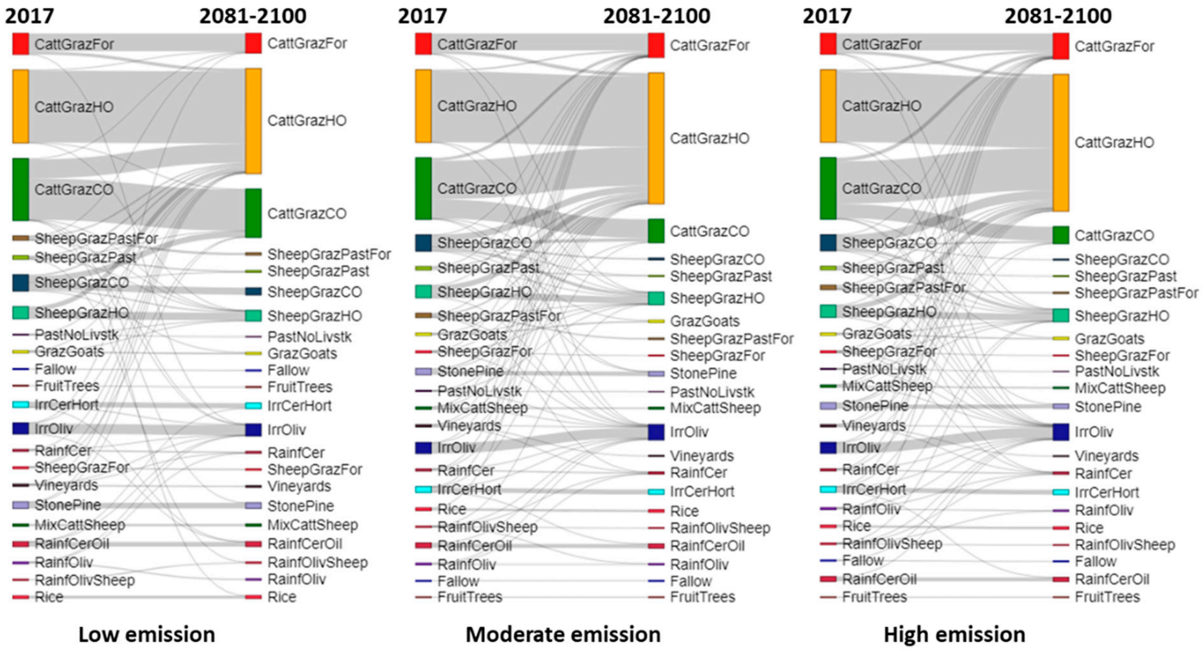


Figure 4. Areal transitions between farming systems from the baseline period (2017) to the 2081–2100 period in each of the three climate scenarios (to avoid over-cluttering the figure, transitions below 1000 ha—ca. 0.05% of the study area—are not shown; farming system names are abbreviated from names in Figure 2).

The grazing goats FS will predictably be one of the livestock-specialised FSs that will be the least affected, probably due to being a low-demanding FS in terms of the socioeconomic and biophysical contexts, only associated with a sloping terrain [16], which will not be altered by climate change.

The vineyards and the stone pine FS are likely to lose considerable area irrespective of the climate scenario. The former will lose area especially to the irrigated olive grove FS, and the latter will lose area especially to the cattle grazing–HO system.

As for FSs that are strongly dependent on irrigation, the irrigated cereal and horticultural crops FS is expected to lose area, while the irrigated olive groves FS is projected to expand significantly in response to climate change, which may expand by up to 46% in the high emission scenario, mainly at the expense of vineyards and rainfed olive groves. The rice FS is expected to remain mostly unchanged, since its choice is strongly influenced by the availability of suitable areas next to water courses, which is a driver of low relevance for most other FSs.

Rainfed cereals are expected to expand in all three scenarios, at the expense of areas from different systems (see transition matrices in Supplementary Information).

Other systems show inconsistent trends across the three scenarios. Cattle grazing–forages and sheep grazing–HO are predicted to lose area in the low emission scenario, but they are expected to expand in the moderate and high emission scenarios. Conversely, the rainfed olive groves with sheep system is anticipated to expand in the low emission scenario, but expected to lose area in the moderate and high emission scenarios.

4. Discussion

4.1. Climate Change and Farming System Choice

The proposed modelling framework proved its suitability to explore the effects of climate change on FS choice. The use of a space-for-time substitution approach proved to be a wise choice to overcome the limitation of having only stationary data on the spatial distribution of FS (relative to a single year), which we believe to be a novelty in the research on the effects of climate change applied to the agricultural sector.

As hypothesised, our findings suggest that the magnitude of climate change expected in the long run scenarios will force many farmers to adjust well beyond agricultural practices, pushing them to undertake an effective FS change. Moreover, such effects are expected in both high and low GHG emission scenarios, although, unsurprisingly, they are clearly more substantial in high emission scenarios. This supports the claims of previous authors on the need for a farming systems approach when investigating farmers' adaptation strategies to climate change, to the detriment of the conventional crop-modelling approaches that populate most of the literature [13].

The FS choice model used in the simulations included a variety of drivers of FS choice that were intentionally kept constant except for the climate variables, making it possible to attribute the observed FS dynamics predominantly to the isolated effect of climate change, as was the objective of the present study. This does not mean that the social, economic, technological, policy, or demographic contexts, for example, will remain unchanged in the future, but only that we sought to detach the effects of our variables of interest (climate), to investigate their single contributions in the choice of future FSs, in a ceteris paribus approach. This use of multivariate choice models to study the effect of climate change on FS choice based on a multitude of socioeconomic and biophysical factors is also new in the literature, as far as we know.

The scrutiny of the effects of climate change on FS choice must consider that the simulations were carried out using a predictive model estimated from the data observed on the decisions of more than 23 thousand farmers in their FS choices, based on real farms, and mediated by a very high number of independent variables that included 13 socioeconomic drivers and 14 biophysical drivers, conjointly influencing the decision-making process. Therefore, the effect of simulations on climate variables must be assessed in the context of the joint action of all of these drivers, whose influences on the decision will act differently in each farm, since each one is unique in its characteristics. Also, climate change will not affect all farms equally, since the extent of those changes are differentiated in space, showing an increasing gradient of the average temperatures of the coldest and warmest months from the coast towards the inland, and a drop in precipitation marked by altitude. Under all of these premises, it is not surprising that climate change will not affect all FSs in the same way; while some will be severely affected by the gain or loss of area, others will persist mostly unaffected.

The primary FS shift expected to be induced by climate change until the end of the century refers to the significant westward expansion of the cattle grazing–HO system, towards areas that are currently dominated by the cattle grazing–CO system. These shifts, induced by climate change, are also probably being mediated by other drivers and constraints of FS choice, such as the agroecological preferences of both oak species [16,27,28] expressed by other variables in the model that, although kept constant, are also influencing the FS choice, together with the climate variables. The predicted sharp reduction in the cork oak area is likely to imply significant social and economic impacts at the national level, given the high importance of the cork cluster in Portugal [29]. Other livestock-specialised FSs are also expected to suffer substantial areal shifts, including most sheep grazing systems, which are expected to change to cattle systems, encouraged by the farmland structure of the region, which is marked by large farms [16].

Among the crop-specialised FSs, most will lose area in response to climate change, especially in the moderate and high emission scenarios. In the case of the vineyards and the stone pine FSs, both have strong regional identities in Alentejo agriculture, being pillars of important agro-industrial value chains on regional and national scales, so the prediction of its reduction can lead to important social and economic impacts.

The anticipated increase in the irrigated olive groves FS must be considered with caution, as it is highly dependent on large irrigation systems, whose future sustainability in the study area has been questioned due to the predicted drop in precipitation and its impacts on both the quantity and quality of irrigation water [30,31].

The rainfed cereals FS is also expected to expand in response to climate change, not so much because it is favoured by future climate conditions, but because they are likely to be less affected than most of the competing FSs, as they are typically rainfed extensive systems with a strong dependence on autumn–winter crops (cereals).

4.2. Comparing Farming System and Crop-Modelling Approaches

The proposed FS approach to explore the effects of climate change relies on a discrete-choice modelling framework, where farmers are set to choose the FS—a categorical variable—among a range of possible choices, based on socioeconomic and biophysical drivers. The crop-modelling approaches, or other species-specific approaches often found in the literature, typically assume that farmers operating a given farming system will adapt to climate change by adjusting their farming practices, such as increasing irrigation water or adjusting the sowing/harvesting dates, without shifting to other FSs. In this section, we discuss our results, with reference to those of previous studies focused on key crops or activities in the study area and carried out in comparable agroecological contexts, to explore the similarities and divergences between the results of both approaches.

Despite little current knowledge about the dynamics of Mediterranean oak woodlands in response to multiple drivers [28], previous studies have reported the likelihood of a decline in Mediterranean agroforestry systems resulting from climate change. Research on cork and holm oak canopy cover loss carried out in the same region as the present study (Alentejo) found a likely decline trend for cork oak associated with the increase in the mean temperature, while the decline in holm oak would be mostly associated with increasing cattle numbers [32]. Rising temperatures in recent decades have also been related with increased crown defoliation and tree mortality in both cork and holm oak [32]. Other studies carried out in Spanish Andalusia, a region that borders Alentejo to the west, report that a significant part of the cork oak plantations made in this region in the 1990s of the last century, largely driven by CAP policies encouraging the afforestation of less productive farmland, are probably doomed to succumb due to the deterioration of weather conditions in the future [33]. Our findings are in line with these previous studies, with the novelty of foreseeing an extensive replacement of the cork oak with holm oak.

As for the apparent substitution of sheep with cattle, pushed by the substantial expansion of the cattle grazing–HO system, although research references relating these effects to climate change are scarce, there is evidence mentioning that cattle grazing is prone to reduce grassland heterogeneity in Mediterranean regions, which may decrease the ability to adapt to climate change [34]. Further evidence suggests that climate change will negatively influence perennial grasslands and forage yields in Mediterranean ecosystems [35,36], which may raise doubts about the expansion of cattle grazing systems predicted by our simulations.

The patent increase in the irrigated olive groves FS suggested by our results seems to contrast with the findings of previous studies focused on the impacts of climate change on olive groves, which have questioned the future suitability of this crop in the Mediterranean basin, unless appropriate adaptation measures are implemented [37]. One such possible measure is irrigation [38,39], which is in line with our forecasts of an expansion of the irrigated olive groves FS and a contraction of the rainfed olive groves FS. Warming and drought trends expected for southern Europe in the coming decades, however, are likely to bring major challenges to irrigation expansion due to excessive heat and water stress [30,31]. Additionally, other works have warned of the possible increase in the risk of pest outbreaks in Mediterranean olive groves, as a result of climate change [40]. Therefore, doubts remain about the sustainability of our prediction of an increase in the irrigated olive groves FS, which is particularly important since this crop has been the target of large investments in new plantations in recent years in the study area, cultivated in intensive and super-intensive regimes with irrigation, already being one of the main irrigation crops in the Alentejo region [41].

Regarding our prediction of an expansion of the rainfed cereals FS, it contrasts with the results of previous studies that used crop modelling to assess the impact of climate change on wheat production in southern Portugal, foreseeing significant production losses depending on the climate scenario used [42]. As adaptation measures to reverse yield reductions, these authors propose the use of early flowering wheat varieties, or the anticipation of the sowing date. Studies that used the CERES-Wheat crop model to simulate yields under climate change in Mediterranean regions also identified a trend towards reduced yields, recommending the development of adaptation strategies and measures such as the use of adapted genotypes to counteract the negative impact of climate change [43].

We conclude that the two approaches can be complementary, assuming that the short- to medium-term farmers will be able to make this type of adjustment without changing the FS, while our results suggest that in the long term, this may no longer be possible, and many farmers will effectively be forced to change the FS. Whether or not, when the time comes, they will have the means, the knowledge, or the ability to carry out this change remains a critical issue that should concern policymakers, but which is beyond the scope of the present study.

4.3. Strengths and Weaknesses of the Proposed Approach

This work shows that climate change will eventually subject many farmers to an adaptation effort that goes far beyond simple adjustments in agricultural practices, varieties used, or sowing or harvesting dates, forcing them to abandon the current farming system and switch to new farming systems that are potentially very different from those they currently practice. For example, switching from a farming system based on annual crops to a cattle grazing system, which our results show could affect many farmers in this study area, could require large investments in the acquisition of herds, installation of pastures, fencing of grazing plots, and technical training, among others. It is not guaranteed that most farmers are prepared to embark on this process of change, or have the means to do so, whether financial, technological, or know-how. Studies such as the present one can help policy makers to anticipate the support needs that these farmers will require to undergo this change process, while also helping them to foresee its wider impacts on food supply, the environment, or nature and landscape conservation, enabling early action to alleviate the effects of climate change.

An important asset of the proposed framework is that it relies on very detailed and spatially explicit farm-level data, describing livestock and land use/cover at the plot scale, which was made possible by the opportunity to access IACS/LPIS data. Therefore, it is built on observed data from management decisions made by actual farmers, framed by the characteristics of their farms and their biophysical and socioeconomic contexts. This entails a significant advantage when compared to previous studies, mainly based on crop models or on declared data collected in surveys in response to hypothetical scenarios (e.g., [15]). Also, the spatial explicit feature provided by the connection to the LPIS enables areal trade-offs between FSs to be explored and to explicitly map where the changes are expected to take place, which may be valuable to, e.g., inform land planning assessment.

The random forest approach used in model estimation made it possible to work with a high dimensional categorical dependent variable, representing the 22 FS choice-sets available to farmers in adapting to climate change scenarios, which is unprecedented in the literature.

The potential limitation of working with agricultural data for a single year (2017), which, at the outset, would prevent the exploration of temporal dynamics, was overcome by resorting to an approach of substituting time for space, taking advantage of the considerable extent of the study area. Despite being a longstanding approach (see [44] and references therein), space-for-time substitution remains a widely used approach in several fields, especially in ecology, where it emerged (e.g., [21,45]), whenever only stationary data are available.

With minor adjustments, the same basic approach could be used to explore, for example, how public policies could be implemented to encourage farmers to adopt particular FSs, aimed at ensuring desired levels of food security or the sufficient provision of socially valued public goods, provided that the random forest choice model includes some comparative profitability variable discriminating the FS. Such possibilities stand as proposals for future research.

Regarding the shortcomings of the framework, it should be noted that it deals solely with changes in the averages of climate variables, and not with changes in their variability. Indeed, climate change pressures on farmers' decisions will likely be felt earlier—if not already felt—due to the increasing frequency of extreme events, such as droughts, heat waves, or floods, which may significantly anticipate the need for farmers to adapt to climate change. This drawback, however, is hardly avoidable because current climate models do not provide scenarios of climate variability change, but only changes in their average values.

The framework's implementation is also quite demanding in baseline data, both to derive the FS typology and to estimate the choice model. In fact, the approach is only feasible when data comparable to that in the IACS/LPIS are available, which is often not the case, particularly in developing regions where such research could be of particular interest, e.g., in the context of food security issues.

The fact that the framework deals only with existing FSs, observed in the reference year (2017), may also entail some weakness, as it hinders the emergence of new FSs that are potentially better suited to cope with climate change [10]. Nevertheless, the high number of categories in the FS typology must have contributed to minimise this possible problem.

Finally, it must be recognised that some of the results achieved are hard to explain based on the available information, such as the fact that the cattle grazing–forages FS loses area in the low emission scenario and increases area in the higher emission scenario.

5. Conclusions

Not underestimating that the relationship between climate and agriculture goes both ways, since agriculture is also a driver of climate change, the present study focused on investigating the effect of climate change on the choice of FS. The results indicate that climate change alone is prone to lead many farmers to change their FSs as an adaptation strategy. Such changes are likely to modify the pattern of ecosystem services that is currently provided by agriculture, including at the provisioning, regulating, supporting, or cultural levels. This calls for further research on the exploration of these effects, opening the way for climate change impact assessments and the consideration of policy options. Indeed, previous work has suggested that changes in policy, as well as technology or prices, may have stronger impacts on farmers' decisions than climate change [13,46], meaning that there will be room for policy to help ease the adaptation effort that farmers will have to endure.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/land12122113/s1, Transition matrices for areal changes of farming systems from 2017 to 2081–2100 in three climate change scenarios in the Alentejo region, Portugal.

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