On the (Ir)relevance of Heatwaves in Climate Change Impacts on European Agriculture

by Charlotte Fabri, Michele Moretti, and Steven Van Passel

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Abstract

This research investigates the impact of heatwaves on European agriculture, additional to the impact of gradual climate change. Using a dataset of more than 60,000 European farms, the study examines whether adding a measure for heatwaves to the Ricardian model influences its results. The study finds that the marginal impact of heatwave frequency, i.e. the percentage change in agricultural land values caused by one more heatwave day per year, is negligible in comparison to the effect of average temperature increases. Non-marginal effects are found to be relevant, but only in the unlikely case of increased heatwave frequency.

Keywords Ricardian analysis, climate change, European agriculture, heatwaves, extreme weather events

JEL classification Q15, Q51, Q54

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1. Introduction

Besides gradual shifts in land-surface temperatures and rainfall, climate change has been said to encompass changes in the variability of climate and in the severity and frequency of extreme weather events (Bouwer, 2019; FAO, 2021). An extreme weather or climate event is defined as the 'occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) ends of the range of observed values of the variable' (IPCC, 2012, p. 116). Examples of extreme weather events are warm and cold spells, wet spells, droughts, and hurricanes. In comparison to geological disasters (e.g., earthquakes and volcanoes) which have remained relatively stable, the frequency and costs of weather-related extreme events have majorly increased over the years. The number of yearly climate- and weather related disasters has quadrupled since the 1970s to approximately 150 events per year globally (FAO, 2021). These events are expected to cause more damage to agriculture than increasing mean temperatures according to some researchers (Easterling et al., 2007; Wreford & Adger, 2010). While farmers anticipate certain degrees of weather variability, extreme events exceed these normal expectations, posing significant challenges to their agricultural output (FAO, 2021). This suggests that studies investigating the impact of climate change on agriculture should therefore take these extreme events into account, instead of merely looking at the effects of gradual temperature and precipitation changes.

One of the most widely used climate impact assessment methods in agriculture is the Ricardian model. This approach is based on cross-sectional regression modelling to estimate the impact of climate change on agricultural productivity indirectly, by measuring differences in land values or farm net revenues (Mendelsohn et al., 1994). The method allows for the estimation of the marginal effect of changes in climate and the prediction of non-marginal changes in land values (or net revenues) for alternative future climate scenarios. The main advantage of this method, as opposed to other climate change impact assessment methods, such as crop modelling, is that it captures long-term adaptation to climate change since it assumes that farmers self-adapt to new climatic conditions (Mendelsohn et al., 1999). The Ricardian approach has been used to estimate the impact of climate change and to value the potential of long-term climate adaptation in European agriculture, which is also the geographical scope of the present study (Moore & Lobell, 2014; Van Passel et al., 2017; Vanschoenwinkel et al., 2016). Studies adopting this approach have used various variables for representing average climate such as seasonal temperature, degree days or temperature bins (Massetti & Mendelsohn, 2017; Vaitkeviciute et al., 2019). Climate variability, which refers to deviations from long-term climate means, is often neglected in climate impact assessments (Ramamasy, 2007). This is because the impact of climate variability on biological systems is more uncertain than the impact of mean climate (Thornton et al., 2014). Also, average climatic trends are easier to predict than day-to-day climate variability, which is necessary to estimate future impacts of extreme weather events. Quantification of the economic impacts of extreme weather events on the agricultural sector is currently lacking, especially in the Ricardian literature. This study attempts to close part of this gap by accounting for one specific type of extreme weather events: heatwaves.

Simply stated, a heatwave is a period of days with temperatures higher than normal. The threshold for defining heatwaves varies geographically since it is dependent on what is 'normal', i.e. the average climate in a region. Therefore, the impact of heatwaves is also location specific. For example, the major heatwave which struck Europe in 2003 caused agricultural yield drops of up to 30% in large parts of Europe, whereas Northern European countries which have lower heatwave threshold benefitted from these higher temperatures (EEA, 2004). Even though heatwaves are mostly associated with agricultural losses, this example shows that also the contrary may be true in some areas.

In its Fourth Assessment Report, the IPCC (2007, p. 750) stated that 'it [is] very likely that heatwaves would be more intense, more frequent, and last longer in a future warmer climate'. Also Fischer and Schär (2010) have predicted an increase in the number of heatwave days per summer by the end of the 21st century. This emphasises the need for incorporating heatwaves in the Ricardian model; to estimate the long-term effect of these increases. However, the IPCC (2007, p. 750) and Fischer and Schär (2010) have based their projections on current heatwave thresholds. Considering a gradually warming climatic trend, the probability of exceeding these thresholds become much higher in the future, regardless of whether this temperature is considered extreme at that time. This might lead to an overestimation of projected heatwaves and consequently, an overestimation of future heatwave impacts on agricultural productivity. Heatwave temperature thresholds should therefore be adjusted to their contemporaneous climate to give a more realistic picture of future heatwave occurrence. Additionally, moving heatwave thresholds are in line with the assumption of adaptation. If farmers adapt to a changing climate, temperatures have to exceed this new 'normal' be considered extreme. This is a valid assumption since studies have shown that damage from extreme weather events in the past has reduced over time due to adaptation (Wreford & Adger, 2010). Increasing heatwave occurrence was part of the rationale for initiating this study but, following the above reasoning, this is rather unlikely.

In the following section, we explain how an appropriate heatwave variable is computed and how it fits into the Ricardian model, along with a description of the data sources used. Section 4 is dedicated to the results, covering regression outputs, marginal effects, and predictions of future land values based on uniform global warming scenarios. This section is followed by multiple robustness checks to test for stability of the results under different model specifications. We end the paper with some concluding remarks.

2. Methodology

2.1 The Ricardian model

The Ricardian approach builds upon the assumption that the land value V (or rent value) is equal to the present value of net revenues NR_t which can be gained from the land in the future (Mendelsohn & Dinar, 2003). If land is expected to generate high revenues in the future, this is reflected in its value. The land value per hectare of farm i can thus be presented as follows:

$$V_i = \int_t^\infty NR_t\, e^{-\varphi t} dt = \int_t^\infty \left[\sum_j P_j Q_{i,j}\left(X_{i,k}, Z_i\right) - \sum_k P_k X_{i,k}\right]_t e^{-\varphi t} dt \qquad (1)$$

Where P_j and P_k are the market prices of outputs j and inputs k respectively, $Q_{i,j}$ is a vector of produced outputs, $X_{i,k}$ is a vector of purchased inputs (other than land), and Z_i are exogenous variables beyond the farmer's control. Farmers are assumed to maximize the net revenues of their farm i by making optimal decisions for the quantities produced $Q_{i,j}$ and the inputs purchased $X_{i,k}$. Since farmers will make choices concerning their inputs and outputs while taking market prices and external factors as given, land values become a function of exogenous factors only:

$$V = f(Z) = f(M, RC, FC, D) \qquad (2)$$

These exogenous factors comprise different categories of variables, of which the meteorological variables M (average climate variables temperature T and precipitation P, and a variable for heatwaves) are the focus of this research. Additionally, there are control variables which can be split into region-specific RC (e.g., socioeconomic variables, market access, welfare conditions, and soil characteristics) and farm-specific control variables FC (e.g., owned land, rented land, subsidies). Farm-specific control variables are those variables for which data is available at the farm level. Lastly, there is a country dummy variable D which captures unobserved country-specific elements which are not represented by the control variables (e.g., country-level support mechanisms, policies, and crop insurances) to reduce the spatial correlation in the model. This dummy variable also accounts for market price differences between countries. The country dummy variable results in intercept differences between countries.

The model estimated in this paper is a cross-sectional model which postulates that agricultural land values and meteorological variables vary together. This implies that the land value change caused by a change in climate can be predicted, if all other variables are kept constant. In other words, if the climate in location 'A' becomes similar to that of location 'B', then the farmers in location 'A' will start behaving like the farmers in location 'B' (Timmins, 2006). Because farmers are assumed to make these optimal choices, adaptation to climate is implicitly accounted for in the Ricardian model. In other words, when the climate changes, farmers are expected to adapt in the best possible way by choosing between different adaptation options.

2.2 A variable for heatwaves

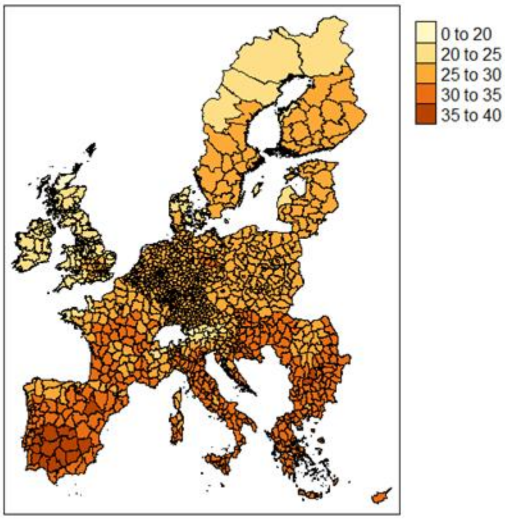
Broadly defined, a heatwave is 'a sequence of days with abnormally hot temperatures. However, there is not one single unambiguous definition of heatwaves and many nations and institutions apply their own criteria for identifying heatwaves (Hooyberghs et al., 2019). All heatwave definitions are characterized by three elements: a minimum number of consecutive days, a temperature threshold, which can be either relative or absolute, and a temperature variable on which to base the calculations. Possible temperature variables are minimum night-time temperature, maximum day-time temperature, or a combination of both.

In this research, the definition of Perkins and Alexander (2013) is used. The authors define a heatwave as a period of three or more consecutive days with a daily maximum temperature T^{max} exceeding the 90th percentile. The percentile threshold is calculated over a thirty-year reference period of daily maximum temperatures with a fifteen-day centred window. The dependent variable for the Ricardian regression, i.e., agricultural land value, comes from a farm accountancy dataset of 2017. Thus, the reference period is set at the thirty years preceding this land value (1987-2016). The temperature threshold for day d is thus constructed using the following dataset (Russo et al., 2014):

$$D_d = \bigcup_{y\,=\,1987}^{2016} \bigcup_{i\,=\,d\,-\,7}^{d+7} T_{y,i}^{max} \tag{3}$$

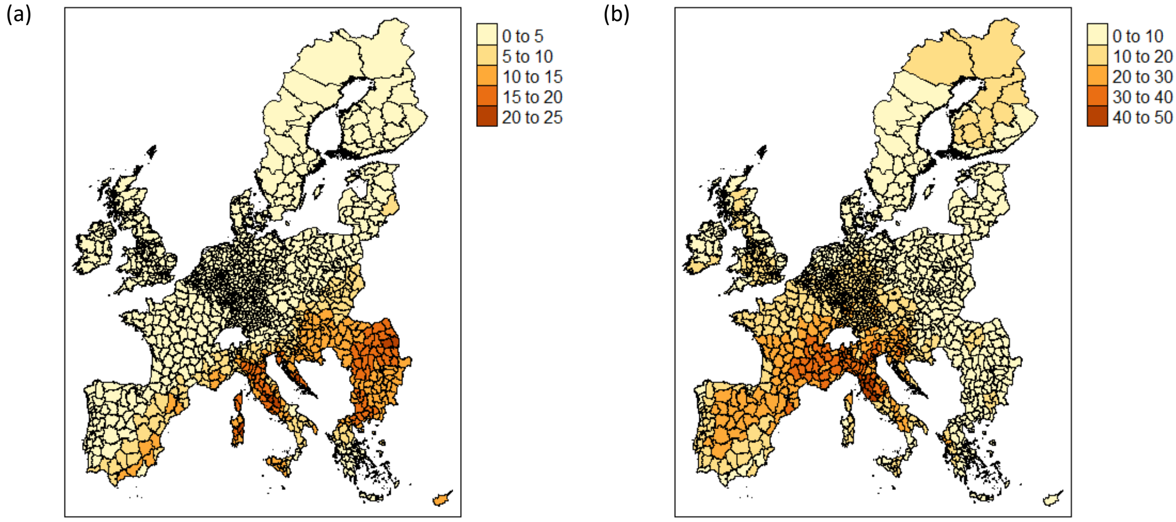
In this formula ∪ denotes the union of sets and $T_{y,i}^{max}$ is the maximum temperature on day i in year y. The 90th percentile threshold for each day of the year is thus based on the maximum temperatures of 450 days. The percentile calculation over the dataset D_d is done for every day d of the considered three-month summer period. Figure 1 shows the heatwave temperature threshold for d equal to July 1st. For example, in Andalucía (Spain), temperatures at the start of July must exceed 35°C for three or more consecutive days for it to be recognised as a heatwave. In parts of Scotland, on the other hand, the heatwave threshold lies below 20°C. In this study we consider only summer heatwaves, rather than all warm spells. Warm spells are anomalously warm periods over the entire year, including winter (Perkins et al., 2012). We expect extreme temperatures within the period from June until August to have the largest impact on agricultural productivity. Winter warm spells are likely to influence farm revenues as well, but not in the same way as summer heatwaves.

Figure 1: 90th percentile temperature threshold (°C) for July 1st



According to Perkins and Alexander (2013), five indices exist for quantifying the characteristics of heatwaves. Firstly, the heatwave number, which is the number of yearly events. Secondly, the heatwave frequency, which is the total number of days contributing to heatwaves in one year. Thirdly, the heatwave duration, which is the duration of the longest heatwave in one year, measured in number of days. Fourthly, the heatwave amplitude, which is the temperature on the hottest day of all heatwave days in one year. Lastly, the heatwave magnitude, which is the average temperature across all heatwaves in one year. Out of these five indices, heatwave frequency is perceived as the most suitable variable for inclusion in the Ricardian model. Both heatwave amplitude and magnitude are assumed to be highly correlated with the average (summer) temperature. A region with a high average temperature is likely to have a high heatwave amplitude or magnitude. In particular, because heatwave thresholds are determined based average temperatures. Including either of these characteristics in the Ricardian equation would lead to issues with multicollinearity. Also, heatwave frequency is considered a more comprehensive variable than both heatwave number, which contains no information on the nature of the events, and duration, which refers to a single event only. Consequently, the variable 'heatwave frequency' (HWF), calculated as the average number of days per year contributing to heatwaves over the last five years of the reference period (2012-2016), is included in the model. Figure 2a shows this average heatwave frequency over Europe. Italy, South-East Spain and Eastern Europe appear to have the highest heatwave frequency. For other regions, the average number of heatwave days per year is limited to five. In the summer of 2003 (Figure 2b), a memorable year in terms of heatwaves, the heatwave frequency in Europe reached over 40 days in some regions.

Figure 2: (a) Average annual heatwave frequency over the years 2012-2016, (b) Heatwave frequency in summer 2003



2.3 Heatwave frequency in the Ricardian model

The regression model used in this study is presented in equation 4. The model integrates heatwave frequency into the standard Ricardian model as follows:

$$\ln V_i = \beta_0 + \left(\sum_{s=1}^{4} \alpha_{s,1} T_{s,i} + \alpha_{s,2} T_{s,i}^2 + \alpha_{s,3} P_{s,i} + \alpha_{s,4} {P_{s,i}}^2 \right) + \beta_1 HWF_i + \beta_2 {HWF_i}^2$$
$$+ \beta_3 T_{3,i} HWF_i + \beta_4 T_{3,i} HWF_i^2 + \beta_5 RC_i + \beta_6 FC_i + \sum_{c \in \text{EU-27}} \beta_c D_{c,i} + \varepsilon_i \qquad (4)$$

In this equation T and P represent average temperature and precipitation, respectively. This average is calculated over 1987-2016, the same as the reference period for the heatwave threshold calculation. Net revenue responds non-linearly to both these variables. Laboratory experiments with crops have shown that the climate response of crops is hill shaped. Consequently, quadratic terms are introduced. Impacts of these variables on land values significantly differ per season, so they are present in the model at a seasonal level s, where seasons go from $s = 1$, winter (the period from December to February) to $s = 4$, autumn (September to November).

As clearly demonstrated by the 2003 heatwave, temperature acts as a moderating variable when estimating the impact of heatwaves on agriculture (EEA, 2004). For this reason, interaction effects should be considered when estimating the impact of heatwaves on agricultural productivity. Heatwave frequency HWF therefore appears in the model as both a main effect and an interaction with summer temperature T_3. With the former, we assume that heatwaves have an impact on agricultural productivity because they form a disruption of regular farm conditions. With the latter, we assume that the impact of heatwaves is dependent on the average summer temperature. In both cases, a linear and quadratic term is introduced because the impact of an extra heatwave day differs depending on how many heatwave days the farm experiences already on average. The dependent variable land value per hectare is log-transformed because land values in the sample appear to be log-normally distributed. Thus, the normality requirements of the linear regression model, which is the technique used to estimate this model, are not fulfilled if the variable is left untransformed.

The derivative of equation (4 with respect to any of the meteorological variables generates the marginal effect of a unit increase in these variables. The marginal effect of temperature or precipitation over the entire year is calculated as the sum of the seasonal marginal effects. Due to the interaction effect, the impact of a unit increase in heatwave frequency does not only depend on the current number of heatwave days, but also on the current average summer temperature as can be derived from equation (5.

$$\frac{d(\ln V_i)}{dHWF_i} = \frac{1}{V_i} \cdot \frac{dV_i}{dHWF_i} = \beta_2 + 2 \cdot \beta_3 \cdot HWF_i + \beta_4 \cdot T_{3,i} + 2 \cdot \beta_5 \cdot T_{3,i} \cdot HWF_i \quad (5)$$

As a result of the logarithmic transformation of the dependent variable, this marginal value is the percentage change in land values as a result of a unit increase in the heatwave frequency.

With this cross-sectional model we are not estimating the drop (or increase) in land values following a single heatwave day, rather, we are comparing regions with different average heatwave frequencies to estimate the impact of a change in the number of heatwave days on land values.

3. Data

The dataset on which this study is based was collected in 2017 by the Farm Accountancy Data Network (FADN). This organisation collects, yearly, accountancy data from agricultural holdings across the European Union (FADN, n.d.). The full dataset comprises a sample of almost 84,000 farms. We remove all farms with less than one hectare of owned land and those with outlier land values. Also, all farms within the category 'specialist horticulture indoor' are discarded since crops in greenhouses are less sensitive to climatic changes. This results in a dataset of 60,976 farms. Each farm in the sample represents a larger number of farms in the population, such that conclusions drawn from the sample can be extended to the population by weighting. From this dataset, land value per hectare is used as the dependent variable and farm altitude, subsidies per hectare, and the ratio of rented as opposed to owned land area are used as independent variables since these are expected to influence land values. These are the farm-specific control variables FC mentioned in the previous section. The altitude of the farm is included as a categorical variable with the following altitude categories: < 300 metres, 300 – 600 metres, and > 600 metres. Missing values are replaced by the average elevation of the region, derived from the World digital elevation model (ETOPO5) (EEA, 2003). Other variables in the dataset, such as the irrigation system used or the type of farming, allow for analysis of subsamples. This is done in section 4 to test for model robustness. For privacy reasons, the NUTS 3 region rather than the exact coordinates of each farm holding is given. NUTS (Nomenclature of territorial units for statistics) is a subdivision of the European Union into economic territories to facilitate the collection of data for EU statistics. To link other explanatory variables coming from different data sources to the individual farms, this data should be aggregated to the same regional level. For this reason, most data were collected in a gridded format. Overlaying this data with a shapefile of the NUTS 3 regions enables the aggregation of the data to a regional level.

All meteorological variables for the present climate are computed based on data from E-OBS (Cornes et al., 2018). This is a dataset of daily weather observations interpolated from weather station values to grid cell values. It is an ensemble dataset, meaning that many different dataset versions were developed and aggregated to reduce uncertainty. The dataset has 100 ensemble members (versions), each developed using different interpolation specifications. For example, different radiuses were used for determining whether a weather station should be included in a certain grid cell or not. The values used for computing the variables are the ensemble medians. The dataset has a 0.25-degree resolution. For computing the heatwave frequency variable, the maximum daily temperatures were used. For the temperature variables, mean daily values were averaged to seasonal mean temperatures. The precipitation variables consist of the mean monthly precipitation per season, also computed using mean daily values.

All additional variables are referred to as region-specific control variables RC in the previous section. Soil variables relate to the structure and composition of the topsoil. The original data for these variables comes from the Harmonized World Soil Database. We use a re-gridded version from the Oak Ridge National Laboratory Distributed Active Archive Center which has a 0.05-degree resolution (Wieder et al., 2014). Water availability has been shown to be a significant variable in the Ricardian analysis (Mendelsohn & Dinar, 2003; Mendelsohn & Dinar, 2009). We include in our model the variable 'Baseline water stress' from the World Resources Institute, which measures the total annual water withdrawals as a fraction of total annual available blue water (Gassert et al., 2014). The higher this fraction, the more competition exists between water users. The socio-economic variables include population density, distance from the region centroid to the nearest big city (with > 500,000 inhabitants) and the nearest port, and Gross Domestic Product (GDP) per capita. The data used to compute these variables were collected from various data sources, all listed in in the Supplementary Information in Appendix A. The dataset was compiled using the 'raster' and 'rgdal' packages from the R open statistical software (Bivand et al., 2020; Hijmans & van Etten, 2012; R Core Team, 2020). The analysis results presented in the following sections were also obtained using this statistical software.

4. Results

4.1 Ricardian regression results

Because we assume that temperature moderates the impact of heatwaves on agricultural productivity, this relationship should be present inside the model. We estimate two different models: one without interaction effects and one with interaction effects. The model with interaction effects is the model presented in equation 4. The model without interaction effects is analogous but excluding the two interaction terms. The regression results are presented in Table 1.

For the model without interaction effects, both heatwave variables are significantly different from zero, and the relationship between log land values and heatwave frequency is concave. In the model with interaction effects both the linear and the quadratic variable are significant, as well as the two interaction terms. This would suggest that the assumptions made in section 2.3 are correct. Heatwaves influence land values by themselves, because they form a disruption of mean climatic conditions, and under the moderating effect of temperature. An ANOVA test confirms that the unrestricted model outperforms the restricted model at a 1% significance level ($F(2, 60{,}914) = 128.54$, $p < 0.001$). In other words, the model with the interaction effects explains the variance in the dependent variable better than the model without the interaction effects. Also, the AIC of the model with interaction effects is significantly lower than the model without interaction effects. This indicates that the former fits the data better than the latter, despite its higher complexity (Burnham & Anderson, 2004). Hence, model comparison suggests that the interaction between temperature and heatwave frequency may not be excluded from the analysis, despite the adjusted R-squareds of the two models being very similar. In what follows, the second model will be used.

Table 1: Regression model without (1) and with (2) the interaction between summer temperature and heatwave frequency

	(1)	(2)		(1)	(2)
Winter temperature	0.015	-0.002	Water stress	0.000^{***}	0.000^{*}
Winter temperature²	0.003^{**}	0.004^{***}	Altitude 300-600m	-0.144^{***}	-0.149^{***}
Spring temperature	-0.052	0.009	Altitude >600m	-0.354^{***}	-0.355^{***}
Spring temperature²	0.015^{***}	0.013^{***}	Belgium (BE)	2.381^{***}	2.324^{***}
Summer temperature	0.304^{***}	0.236^{***}	Bulgaria (BG)	0.581^{***}	0.452^{***}
Summer temperature²	-0.013^{***}	-0.013^{***}	Cyprus (CY)	3.879^{***}	3.690^{***}
Autumn temperature	0.238^{***}	0.261^{***}	Czech Republic (CZ)	1.094^{***}	1.108^{***}
Autumn temperature²	-0.011^{***}	-0.012^{***}	Denmark (DK)	3.299^{***}	3.274^{***}
Winter precipitation	-0.003	0.007	East Germany (EDE)[a]	1.482^{***}	1.498^{***}
Winter precipitation²	-0.008^{***}	-0.009^{***}	Estonia (EE)	0.356^{***}	0.494^{***}
Spring precipitation	-0.131^{***}	-0.146^{***}	Greece (GR)	2.536^{***}	2.571^{***}
Spring precipitation²	0.015^{***}	0.019^{***}	Spain (ES)	1.341^{***}	1.271^{***}
Summer precipitation	0.139^{***}	0.127^{***}	Finland (FI)	2.628^{***}	2.754^{***}

[a] In the regression, East and West Germany are considered separately because when Germany is included as a whole, prediction errors are not distributed randomly over the country. In this case, the model consistently underestimates land values in West Germany and overestimates land values in East Germany.

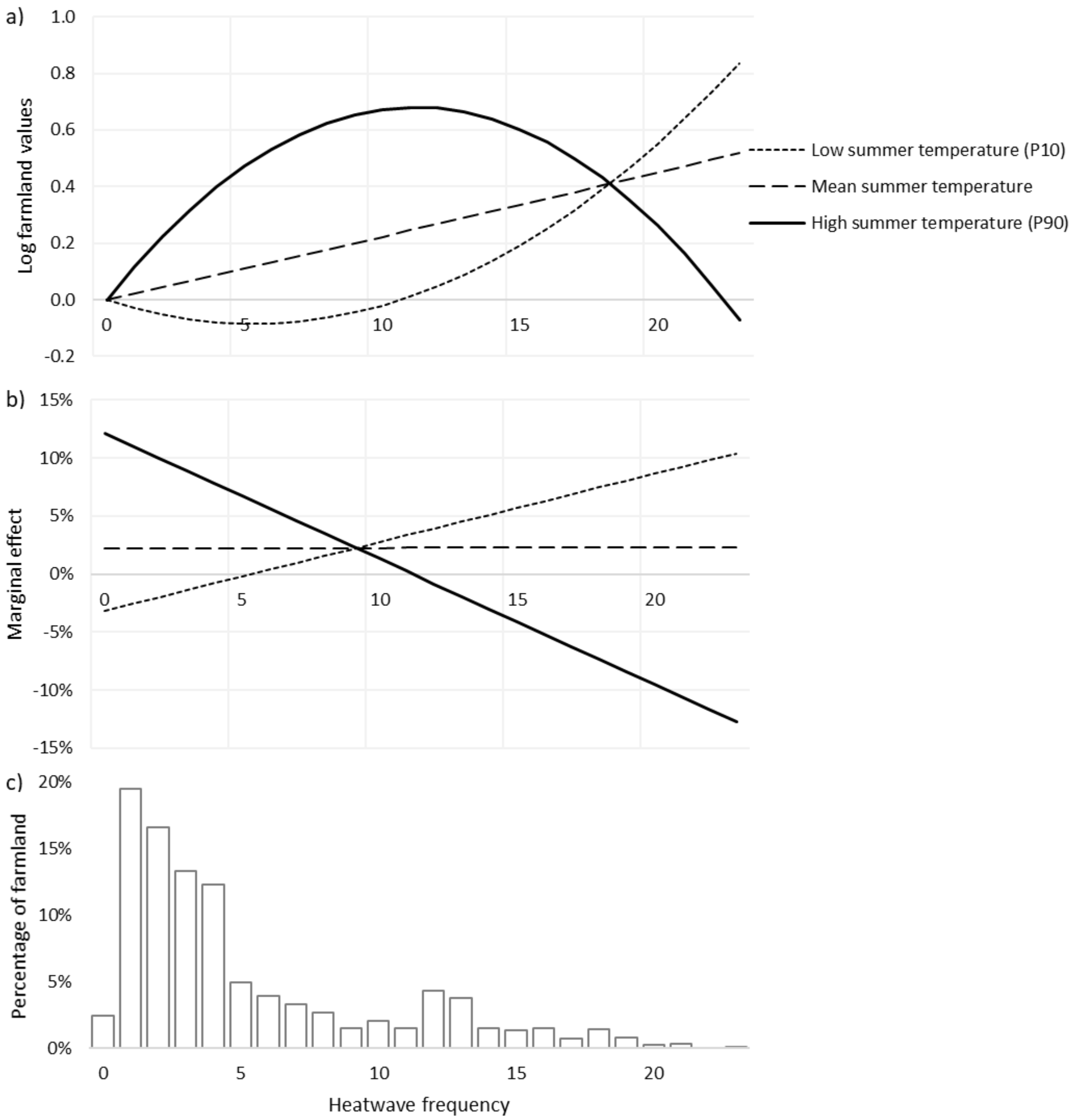
	(1)	(2)		(1)	(2)
Summer precipitation²	-0.007***	-0.008***	France (FR)	0.567***	0.518***
Autumn precipitation	0.073***	0.083***	Croatia (HR)	0.590***	0.478***
Autumn precipitation²	-0.002**	-0.003***	Hungary (HU)	0.524***	0.403***
Heatwave frequency	0.034***	-0.366***	Ireland (IE)	2.554***	2.571***
Heatwave frequency²	-0.001***	0.021***	Italy (IT)	2.611***	2.542***
Summer temp x HWF		0.021***	Lithuania (LT)	0.468***	0.520***
Summer temp x HWF²		-0.001***	Luxembourg (LU)	2.493***	2.413***
GDP	0.002***	0.002***	Latvia (LV)	0.099**	0.194***
Distance to cities	-0.001***	-0.001***	Netherlands (NL)	3.390***	3.311***
Distance to ports	-0.001***	-0.001***	Poland (PO)	1.865***	1.895***
Population density	0.000***	0.000***	Portugal (PT)	0.184***	0.191***
Subsidies	0.006***	0.006***	Romania (RO)	0.535***	0.407***
Fraction rented land	0.004***	0.004***	Sweden (SE)	2.551***	2.546***
Clay in topsoil	0.004***	0.003***	Slovenia (SI)	1.626***	1.602***
Gravel in topsoil	-0.016***	-0.014***	Slovakia (SK)	0.257***	0.194***
Silt in topsoil	0.009***	0.009***	United Kingdom (UK)	2.424***	2.405***
pH H_2O	0.087	0.033	West Germany (WDE)	2.415***	2.387***
pH H_2O^2	0.002	0.007	Constant	2.215***	3.106***
			Observations	60,976	60,976
			Adjusted R^2	0.646	0.648
			AIC	192,915.2	192,662.4

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Because the dependent variable is log-transformed, the beta coefficients of the linear variables can be interpreted as the percentage change in the dependent variable caused by a unit increase in this independent variable. For example, according to these regression results, if the subsidies per hectare were to increase by 100 euros (unit increase), the land values would increase by 0.6%. Analogously, if the fraction of rented as opposed to owned land is increased by 1%, then the land values are increased by 0.4%. The beta coefficients of other control variables also confirm the findings of previous Ricardian studies. The larger the distance from cities or ports, i.e., from markets, the lower the land values. The higher the GDP, the higher the land values. The higher the level of elevation, the lower the land values. This is in agreement with the Common Agricultural Policy, which provides income support to high-altitude farms because it considers it a natural constraint for effective farming (European Commission, n.d.). If competition for water is increased by 1%, meaning that more water is withdrawn as a fraction of supply, land values increase by 0.02%.

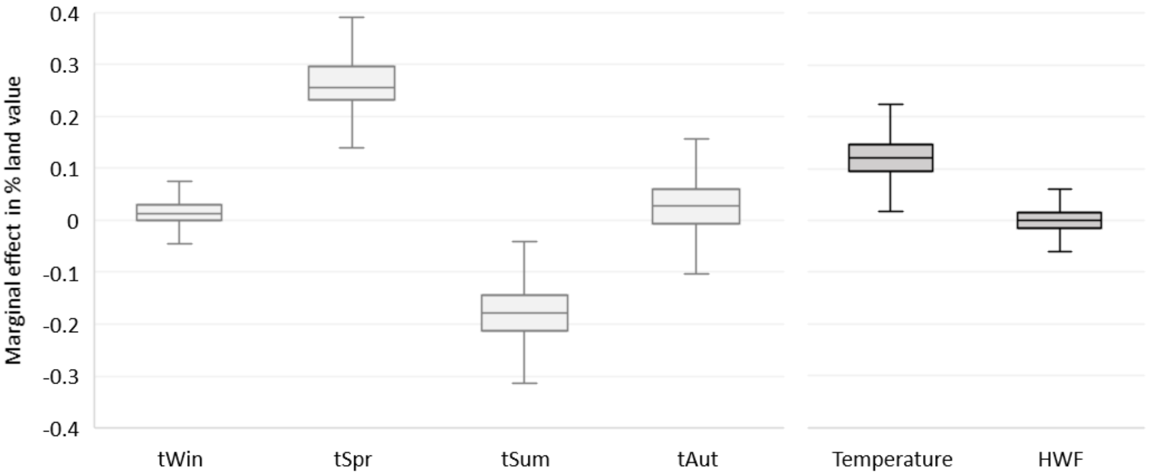
The interpretation of the coefficients for climate and heatwave variables is less evident. Figure 3a shows the correlation between log farmland values and heatwave frequency for the entire range of current heatwave frequencies [0, 23]. None of the other regressors are considered in this plot, so it should be interpreted with caution. Because of the interaction effect, the curve differs for different levels of summer temperature. The 10th and 90th percentile summer temperatures are shown, representing respectively low and high temperatures. Also the weighted mean summer temperature is shown, of which the weight is the amount of land each farm represents in the sample. For high temperatures, the relationship between heatwaves and land values is concave. For regions with an average summer temperature around 23°C (P90), land values reach a maximum at 11 heatwave days. From then onwards, the curve steeply declines and every extra heatwave day reduces land values and thus farm productivity. For regions with summer temperatures around 16°C (P10), the curve is convex. Land values are the lowest at 5 heatwave days and increase with every extra heatwave day beyond this threshold. At the weighted mean, land values increase linearly with every heatwave day (Figure 3), at a rate of about 2% (Figure 3b). From Figure 3c we see that the majority of European farmland (69%) experiences on average maximum 5 heatwave days. This means that most farms are situated to the left of this point on Figure 3a and 3b, i.e. farms located in warmer regions experience gains from higher heatwave occurrence and those in colder regions experience losses. Reasoning for this can be provided by agronomic science. One possible explanation could be that farms in warmer regions produce more heat-tolerant crops or use heat-protection measures for their livestock. These adaptive measures are beneficial, but only up until a certain maximum number of heatwave days.

Figure 3: (a) Response of farmland values to heatwave days for three different levels of summer temperature, (b) Marginal effect of heatwave frequency in percentage of land values, (c) Distribution of current heatwave frequencies in % of farmland



The boxplots in Figure 4 compare the marginal effect of heatwave frequency with the marginal effects of seasonal and annual temperatures. The impact of one more heatwave day on land values is 0.1%, close to zero. This is negligible in comparison with the effect of an increase in the summer temperature by 1°C which leads, on average, to a 18% decrease in land values. Despite this large detrimental impact, the overall marginal effect of temperature is positive (11%) for the current climate. Looking at the marginal effects only, we cannot confirm that heatwaves have a higher impact on agriculture than increased temperature. Due to correlation, these marginal effects may not be interpreted entirely separate from each other. In general, a temperature increase in one season is related to temperature increases in other seasons. And because of the interaction between heatwaves and summer temperatures, these effects cannot be viewed separately from each other either. This correlation between variables does not pose a problem when all variables are considered simultaneously, for example when making predictions.

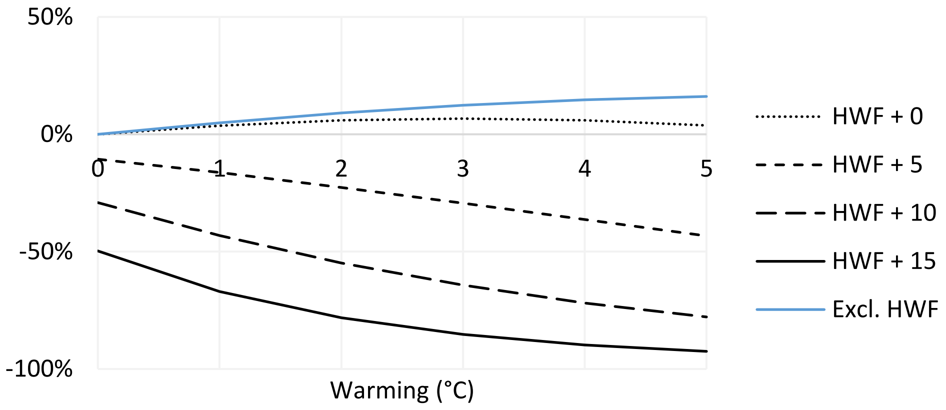
Figure 4: Average marginal effects of seasonal temperatures, annual temperature and heatwave frequency for the EU-27



4.2 Non-marginal impacts

The results of the previous section can be used to estimate welfare impacts caused by future changes in climate. Uniform warming scenarios are used rather than the results of climate projection models. Climate projection models have a significant degree of uncertainty, especially in the case of predicting heatwaves since this requires reliable temperature projections at a daily level. We therefore rely on uniform warming scenarios as previously used by, among others, Mendelsohn et al. (1994) and Massetti et al. (2016). Uniform warming encompasses an analogous temperature increase for every region in every country and for every season. We let annual temperatures increase above current temperatures with 1°C to 5°C. This is not necessarily a realistic picture of how climate will evolve. We would solely like to understand how land values would change if these scenarios were to take place. For heatwave frequency, four scenarios are proposed: a stable heatwave frequency and an increase with 5 days, 10 days, and 15 days, respectively. Considering all annual temperature and heatwave scenarios gives a range of different combinations, which are shown in Figure 5. This graph shows the mean land value change (%) for the entire data sample, where the percentage change in land values of each farm is weighted for the amount of land it represents.

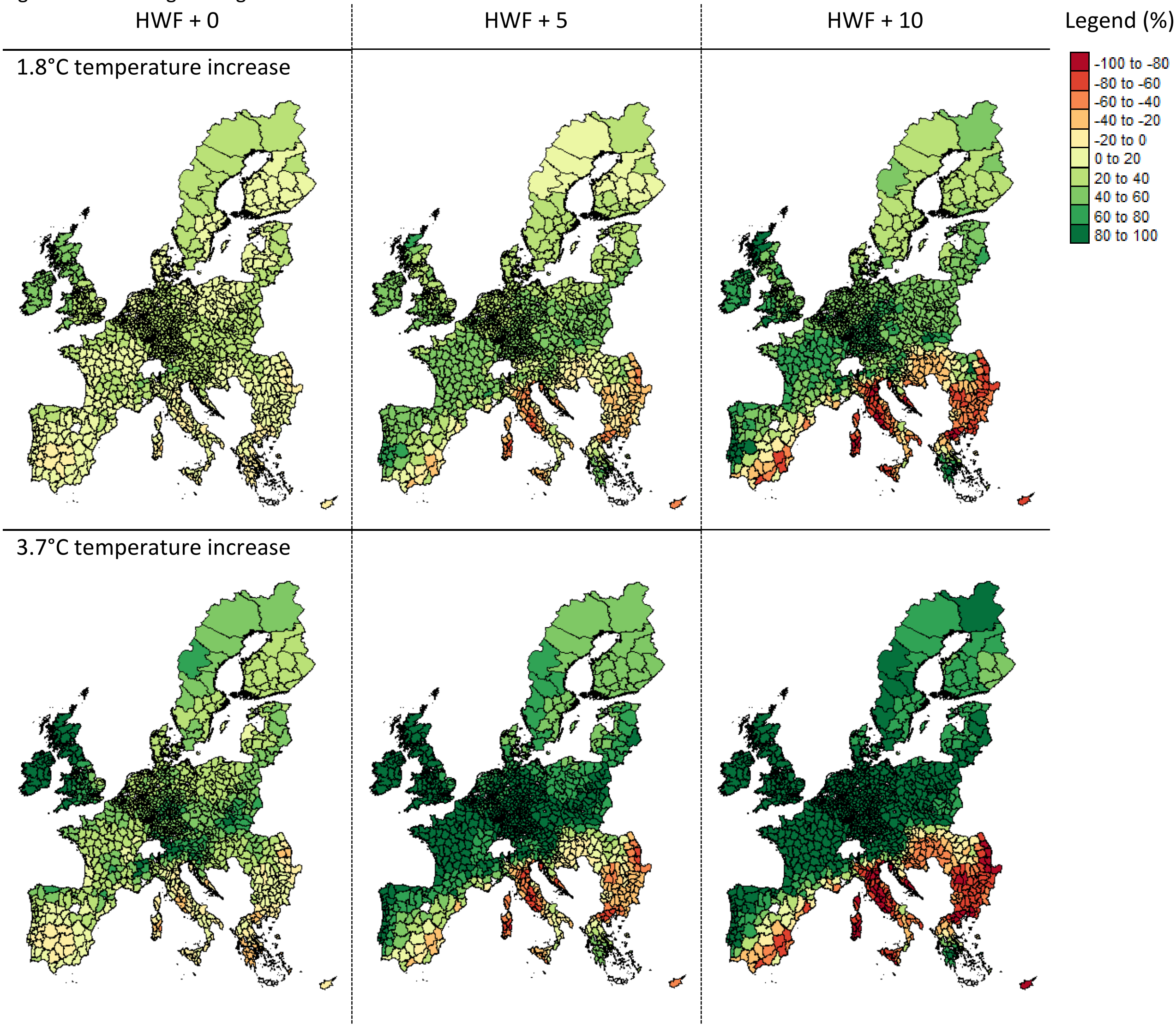
Figure 5: Average land value change as a result of changes in temperature and heatwave frequency for the EU-27



If heatwave frequency remains at the current level (HWF + 0), land values are expected to remain relatively constant with warming annual temperatures. In the scenarios where heatwaves increase with 5, 10, and 15 days, land values are assumed to decrease. Despite this clear negative heatwave impact, there is no reason to believe that heatwaves will occur more or become more severe in the future. Researchers who claim that heatwaves will significantly increase by the end of the century, such as Fischer and Schär (2010) who forecast up to 20-fold increases in certain places, base their calculations on constant heatwave thresholds. The probability of exceeding a temperature threshold which was set in the past, becomes higher with increasing mean temperatures. These studies assume that what is perceived as extreme weather today, will continue to do so in the future. However, this goes against the assumption that humans adapt themselves to the climate in which they reside. Studies which use fully moving thresholds – a more realistic assumption – predict no change in heatwave characteristics (Vogel et al., 2020). These studies depart from the assumption that the probability density function of daily maximum temperatures is shifted with the mean temperature change, and that the variability of daily temperatures (i.e., the shape of the distribution) remains unchanged (Simolo et al., 2010). As can be seen from the response curves in Figure 3, increased temperatures can cause the heatwave impacts to change, even if the heatwave frequency remains constant. This is the result of the interaction with summer temperature. For example, if the average summer temperature in a region were to go from 19°C (weighted mean) to 23°C (P90), the relationship between land values and heatwave frequency goes from positive linear to concave. Therefore, regardless of whether the number of heatwave days per year changes, the impact of heatwaves changes with increasing temperatures. Even when heatwave frequency is expected to remain stable, the model estimated in this paper is slightly more pessimistic than a model which does not account for heatwaves at all. Removing all four heatwave terms from the model and estimating the percentage land value changes for the range of warming scenarios gives a slightly rising curve (blue line in Figure 5).

Apart from the overall effect on land values in Europe, it is also interesting to see how these impacts are distributed across Europe. The following figures map the percentage change in land values caused by increases in temperature and heatwave occurrence by NUTS3 region. Temperature increases are set at 1.8°C and 3.7°C, which are the IPCC (2013) forecasts for 2100 of the RCP 4.5 and the RCP 8.5 climate projection scenarios, respectively. Actual temperature increases by the end of the century are expected to fall within this range.

Figure 6: Percentage change in land values for six different climate scenarios



We see that the majority of Europe experiences welfare growth as a result of both temperature and heatwave increases. Southern Europe is most impacted by temperature, whereas the regions most affected by heatwaves are the ones which experience most heatwave days today (see Figure 2a). Almost all Northern and Central European regions colour dark green for the most extreme scenario, a 3.7°C increase and 10 more heatwave days. This dark green colour refers to a land value increase of 80% or more. This means that all these regions find themselves on the ascending parts of the curves depicted in Figure 3a. Other Ricardian studies using FADN data, which neglect heatwaves, predict much larger losses in Southern Europe. For example, Vanschoenwinkel et al. (2016) and Van Passel et al. (2017) project land value losses of at least 80% in South-west Spain and Portugal. A potential reason for this is that these studies use climate projection models rather than uniform warming scenarios. These climate models predict higher levels of warming in the South as well as precipitation decreases. Again, we should take into consideration that the probability of increased heatwave frequency is rather low if thresholds for heatwaves are updated with increasing temperatures. This suggests that the most likely scenarios are those depicted in the left column (HWF + 0).

5. Robustness tests

Several assumptions were made throughout this study, concerning model specifications, variable selection, and sample delimitation. In what follows, we test whether farm response to heatwaves is sensitive to some of these assumptions. Figures from the previous section are reproduced for each of the model specifications and compared to the original plot. The plots are presented in the Supplementary information (Appendix B).

5.1 Alternative meteorological variables

In their analysis of past heatwaves in Italy, Fontana et al. (2015) use 'heatwave intensity' for quantifying heatwaves. This metric is calculated as follows: $\sum_i \max\left(T_{max,i} - T_{P90,i}, 0\right)$, where $T_{max,i}$ is the maximum temperature on heatwave day i and $T_{P90,i}$ is the temperature threshold for the same day. This variable gives an indication of the number of heatwave days as well as their magnitudes. It is therefore a more comprehensive variable than the heatwave frequency variable used in this paper. However, interpreting the marginal effect of a unit increase in heatwave intensity is much less intuitive. Replicating the analysis with heatwave intensity yields very similar results to the ones presented in section 4. The responses are slightly enlarged because increasing the heatwave intensity does not only affect the event frequency, but also the magnitude of heatwaves (Test 1 in Appendix B).

Some Ricardian studies use total degree days and precipitation over the growing season rather than seasonal temperatures and precipitation (Massetti et al., 2016; Vaitkeviciute et al., 2019). The degree days variable is obtained by taking the sum of all daily temperatures exceeding 8°C over the growing season (April-September). Schlenker et al. (2006) set 32°C as the upper threshold for degree days, whereas Massetti et al. (2016) found that this upper threshold did not influence the results. Therefore uncapped degree days over the growing season are used as climate variables in our model. Additionally, the interaction term from the original model is replaced by an interaction between heatwave frequency and degree days over the growing season. Increasing the average temperature by 1°C is equivalent to an increase of 183 degree days over the growing season (i.e., 1°C for all 183 days of the growing season). From Figure A4 in Appendix B, we find that our model results are not robust to replacement of the climate variables. This is in line with previous study results, which state that using growing season climate variables underestimates the importance of cold temperatures (Vaitkeviciute et al., 2019).

5.2 Alternative regression techniques

Instead of applying ordinary least squares (OLS) to a semilogarithmic regression equation, some researchers use different statistical approaches. For example, Vanschoenwinkel et al. (2016) applied a Linear Mixed Effects model with the fixed effects equivalent to the estimates of an OLS model and random country effects for the intercept. This replaces the country dummy variables used previously. The results of this model appear almost analogous to the ones presented in section 4.1 (Test 3). Our results are thus robust to changing from an OLS model to an LME model. In line with Vanschoenwinkel et al. (2016), this justifies the use of the more simple and intuitive OLS model for the body of this paper.

5.3 Alternative datasets

Because FADN data for Western Europe is supposedly more reliable than Eastern European data, some studies limit their sample to exclusively Western European countries (Van Passel et al., 2017), while some even omit Scandinavia due to data problems (Massetti et al., 2018; Moore & Lobell, 2014). If we reduce the scope to 12 Western European countries (the 15 original countries in the EU, minus Finland, Sweden, and Denmark), we see that the impacts on land values drastically change (Test 4 in Appendix B). This is not unreasonable since Eastern Europe, a region with high heatwave frequencies (see Figure 2), and Scandinavia, a region which benefits from temperature increases (Figure 6) are excluded from the dataset. What we see from the plots for Western Europe is that, regardless of the number of heatwave days, gradual temperature increases lead to welfare losses. For higher heatwave frequencies, this downward slope is steeper meaning that more heatwaves can enhance the damaging effect of increased temperatures. This can be attributed to the fact that, in the reduced geographic sample the large negative impacts from the Mediterranean countries receive more weight than in the EU-27 sample. Also, because these results are more in line with what we would expect from climate change effects on agriculture, this might confirm the data issues which other researchers have experienced. However, we still choose to use the entire dataset because there is insufficient argumentation for excluding almost 40,000 farms from our analysis. A comparison between Northern and Southern Europe or Western and Eastern Europe could provide additional interesting insides, but this is beyond the scope of this study.

Other sample delimitations which have had an impact on results in previous studies are the distinction between irrigated and rainfed farms on the one hand, and the distinction between crop and livestock farms on the other hand (Seo & Mendelsohn, 2008; Seo et al., 2009; Van Passel et al., 2017). Land values of rainfed farms appear to increase with increasing temperatures whereas the land values of irrigated farms are expected to decrease (Figure A11). This is in contradiction with previous studies, which found an opposite effect and attributed this to the climate insensitivity of irrigated farms (Mendelsohn & Dinar, 2003; Van Passel et al., 2017). In this case, a possible explanation for the climate insensitivity of rainfed farms is that these farms cultivate more heat-resistant crops. By not using irrigation, rainfed farms are more vulnerable to weather uncertainties than irrigated farms. They might therefore have a higher incentive to use heat-resistant crops than farms which have access to irrigation. Irrigated farms do seem to be more tolerant to heatwaves. For low levels of warming, land values are higher for regions with higher heatwave frequency. Looking at the comparison between livestock and crop farms, we see that crop farms are more vulnerable to temperature and heatwave increases than livestock farms (Figure A13). This confirms the results obtained by Van Passel et al. (2017).

6. Conclusion

With this study, we expand upon the current Ricardian literature by including the concept of extreme weather. A heatwave metric is incorporated into the Ricardian model such that the model covers extreme weather in addition to average climate. Under the assumptions made, several conclusions can be drawn. Firstly, we found that heatwaves have a significant impact on agricultural productivity and that this impact is moderated by the average (summer) temperature in a region. In regions with lower temperatures, farm productivity increases with the number of heatwave days. For regions with high temperatures, the relationship is convex. Therefore, beyond a certain number of heatwave days, productivity starts to decline. Secondly, adding heatwaves to the Ricardian model causes the predictions of future land values to become more pessimistic. Disregarding heatwaves in forecasts leads to an overestimation of the positive effects of a uniform warming climate on average EU-27 land values. Whereas, if heatwaves are included but kept constant in the predictions, land values are expected to remain stable. Lastly, this research does not confirm that the agricultural sector will suffer more from extreme weather events than from gradual temperature increases as it is generally assumed. On the one hand, because the impact on land values of one extra heatwave day per year is negligible in comparison with the impact of a summer temperature increase. On the other hand, there is no evidence that, under moving thresholds, there will be more heatwaves in the future.

Future research could help overcome some of the limits of this paper. The conclusions presented here are the result of a cross-sectional analysis. This means that they are drawn based on a comparison of farms with different heatwave frequencies. A panel model would enable estimation of the immediate effect on net revenues after a year with many or severe heatwaves. Net revenue is likely to respond more strongly to heatwaves than land values. A weakness of the Ricardian model is its inability to uncover causal relationships because of the unavoidable omitted variable bias. In panel models, these omitted variables are captured by the fixed effects. Also, the conclusions drawn are only applicable to heatwaves. Additional research would be needed to make any statements about phenomena like droughts and storms. At the time of writing, the CMCC and Leithà were working on the development of a general extreme weather index E^3CI, covering multiple extreme weather events (IFAB, 2021). The combination of this variable with the Ricardian approach could potentially offer some interesting insights. Lastly, representative climate projection data would be needed to assess the impact of future climate on land values. The uniform warming scenarios used for this paper are not representative of actual warming. Not every region will experience the same levels of warming. The alternative is to make predictions based on climate models, but in order for these models to be used for the analysis of extreme weather they require a higher degree of certainty and unbiasedness.

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Appendix A: Variable definitions and sources

Variable	Description	Source
Meteorological variables		
Season temperatures	Average temperature per season over the period 1987-2016 (°C)	E-OBS
Season precipitation	Average monthly precipitation per season over the period 1987-2016 (cm/month)	E-OBS
Heatwave frequency	Average number of days per year contributing to heatwaves (period 2012-2016) (days/year)	E-OBS
Farm-specific variables		
Agricultural land value	The value of agricultural land (EUR/ha)	FADN
Rented land	The fraction of the utilized agricultural land area which is rented (ha/ha)	FADN
Subsidies	Subsidies linked to production, in euros per hectare of utilized agricultural land (100 EUR/ha)	FADN
Altitude	Codes indicating the location of the majority of the UAA of the holding: 1 = below 300 metres; 2 = from 300 to 600 m; 3 = above 600 m;	FADN, Missing values replaced using data from the World digital elevation model (ETOPO5)
Regional-specific variables		
Population density	Number of persons per square kilometre in 2015 (persons/km²)	Center for International Earth Science Information Network
Road density	Meters of highway per squared kilometre in 2018 (m/km²)	Global Roads Inventory Project
GDP	GDP per capita in 2015 (PPP) (thousands 2011$/capita)	Dryad (Kummu et al., 2020)
Distance to cities	Distance between the region centroid and the nearest city with a population of more than 500,000 inhabitangts (km)	Natural Earth
Distance to ports	Distance between the region centroid and the nearest medium or large port (km)	World Port Index
Silt in topsoil	Fraction of silt in the topsoil (% weight)	HWSD (regridded ORNL DAAC)
Sand in topsoil	Fraction of sand in the topsoil (% weight)	HWSD (regridded ORNL DAAC)
Gravel	Fraction of gravel in the topsoil (% volume)	HWSD (regridded ORNL DAAC)
Clay	Fraction of clay in the topsoil (% weight)	HWSD (regridded ORNL DAAC)
pH of topsoil	pH of the water in the topsoil (-log(H+))	HWSD (regridded ORNL DAAC)
Baseline water stress	Ratio of total annual freshwater withdrawals relative to annual renewable freshwater supply (%)	World Resources Institute
Country dummy variable		
Country	Austria, Belgium, Bulgaria, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, Greece, Ireland, Italy, Lithuania, Luxembourg, Latvia, Netherlands, Poland, Portugal, Romania, Sweden, Slovenia, Slovakia, United Kingdom	

Appendix B: Robustness tests

Test 1: Heatwave variable choice

Figure A1: Response of log farmland values to heatwave frequency (a) and heatwave intensity (b) for different levels of average summer temperature

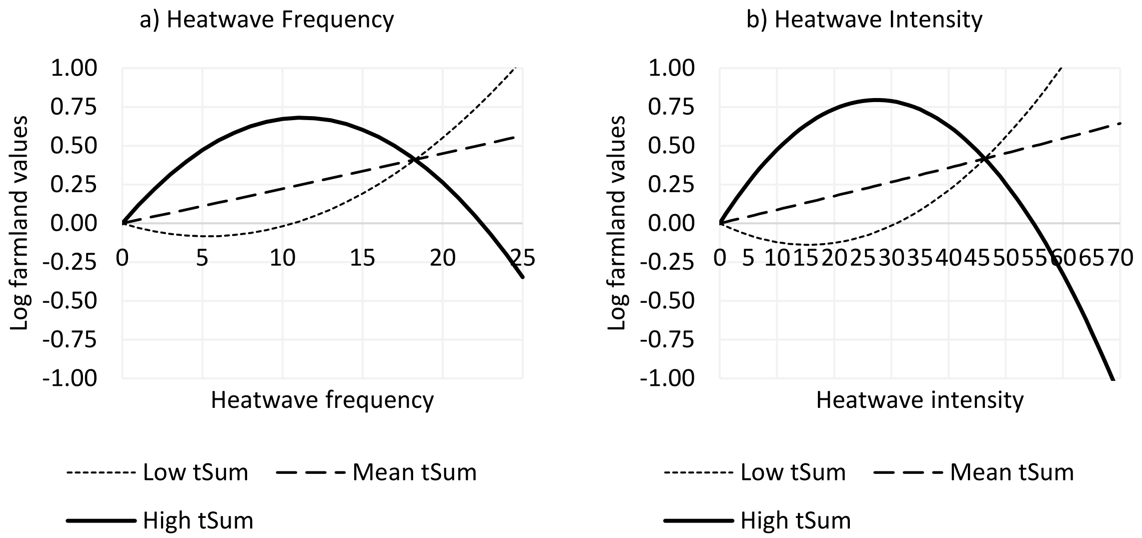
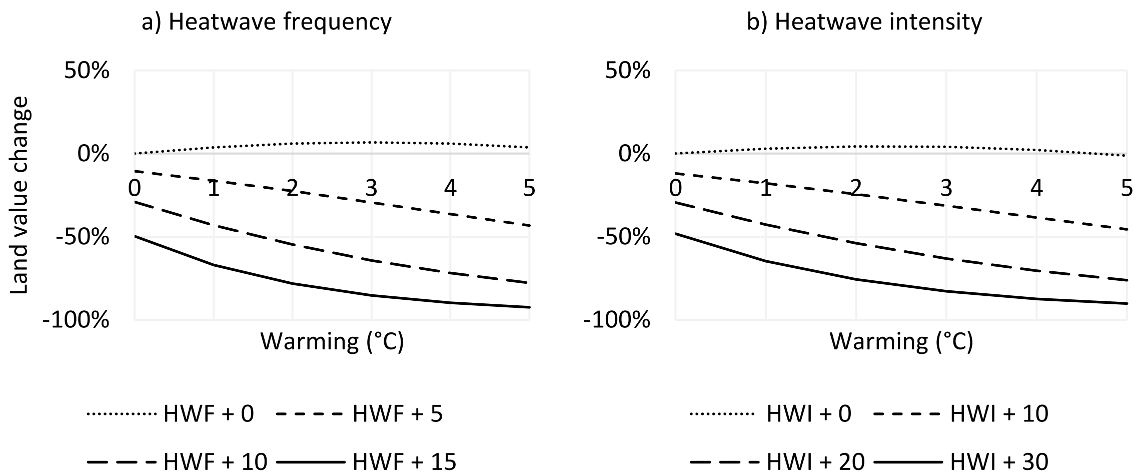


Figure A2: Average EU-27 land value change predicted by a model with heatwave frequency (a) and a model with heatwave intensity (b) for four different heatwave scenarios and under uniform warming



Test 2: Climate variable choice

Figure A3: Response of log farmland values to heatwave frequency for a model with seasonal temperature and precipitation variables (a) and a model with growing season degree days and precipitation (b) for different levels of average summer temperature

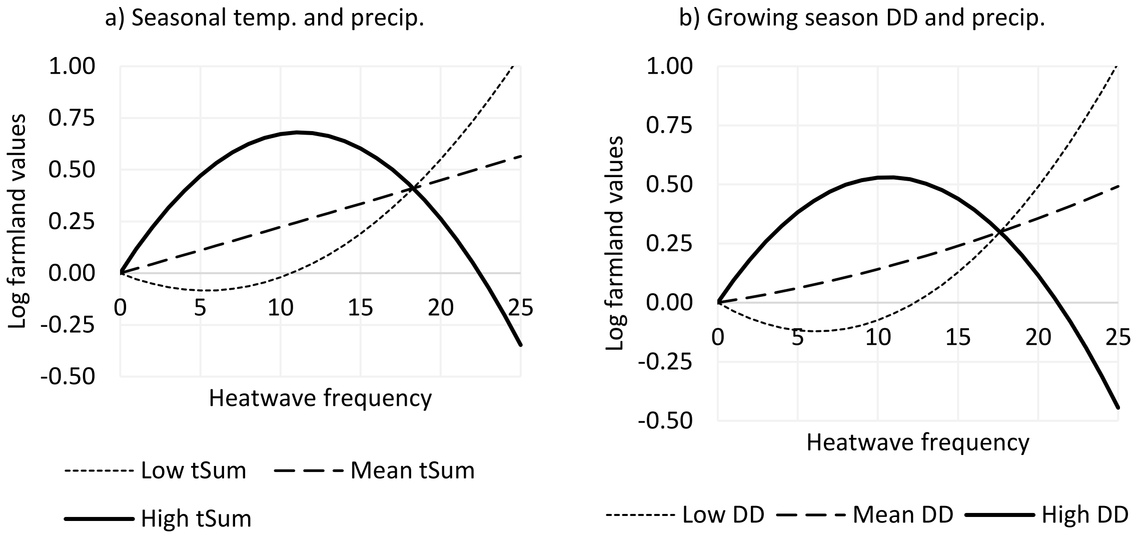
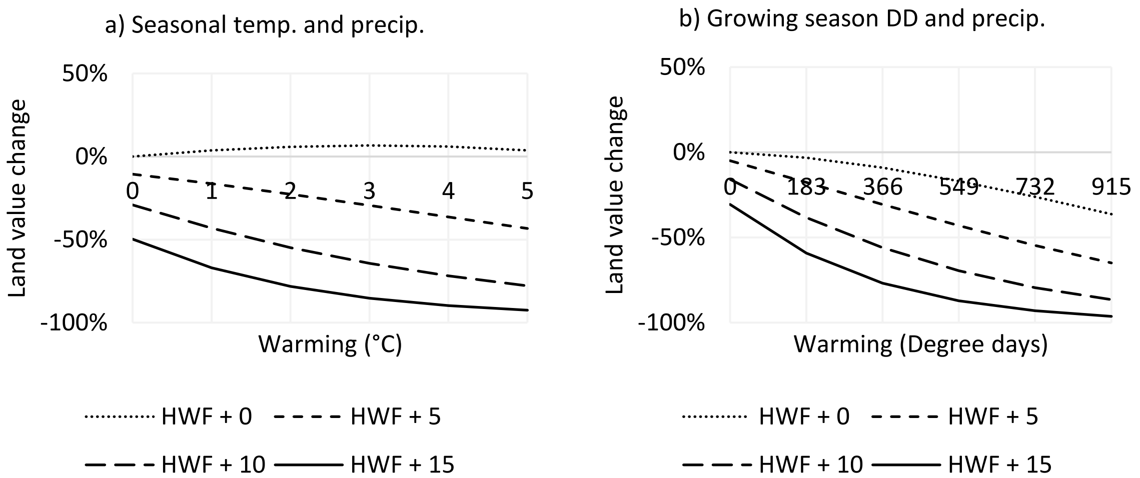


Figure A4: Average EU-27 land value change predicted by a model with seasonal temperature and precipitation variables (a) and a model with growing season degree days and precipitation (b) for four different heatwave scenarios and under uniform warming



Test 3: Regression technique

Figure A5: Response of log farmland values to heatwave frequency modeled with OLS (a) and LME (b) and for different levels of average summer temperature

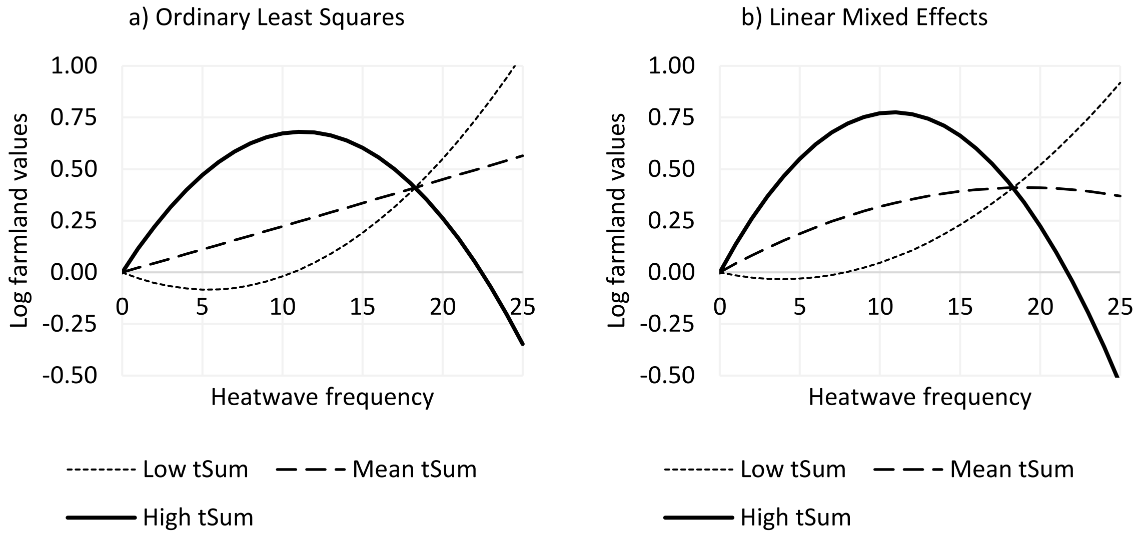
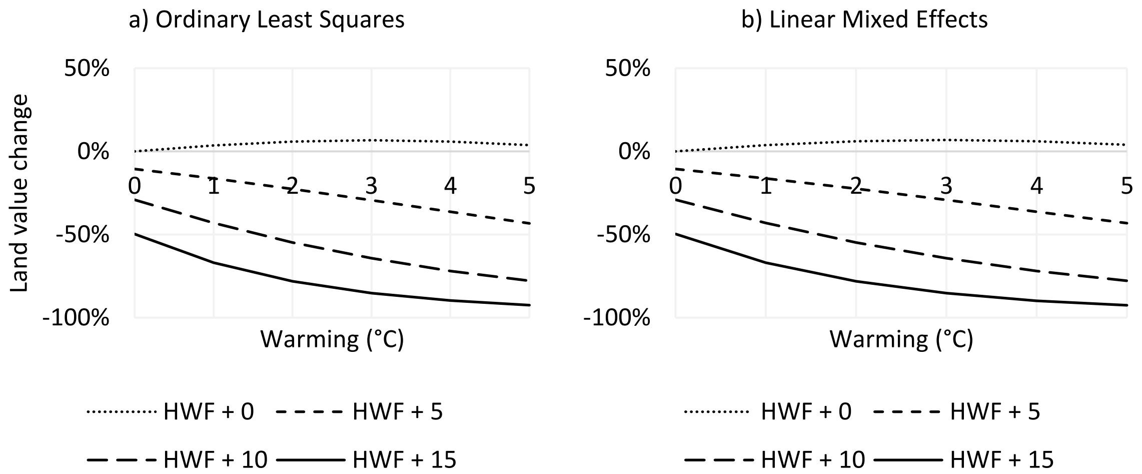


Figure A6: Average EU-27 land value change predicted by an OLS model (a) and by an LME model (b) for four different heatwave scenarios and under uniform warming



Test 4: Geographical sample

Figure A7: Response of log farmland values to heatwave frequency for the full data sample (EU-27) (a) and for Western Europe only (b) for different levels of average summer temperature

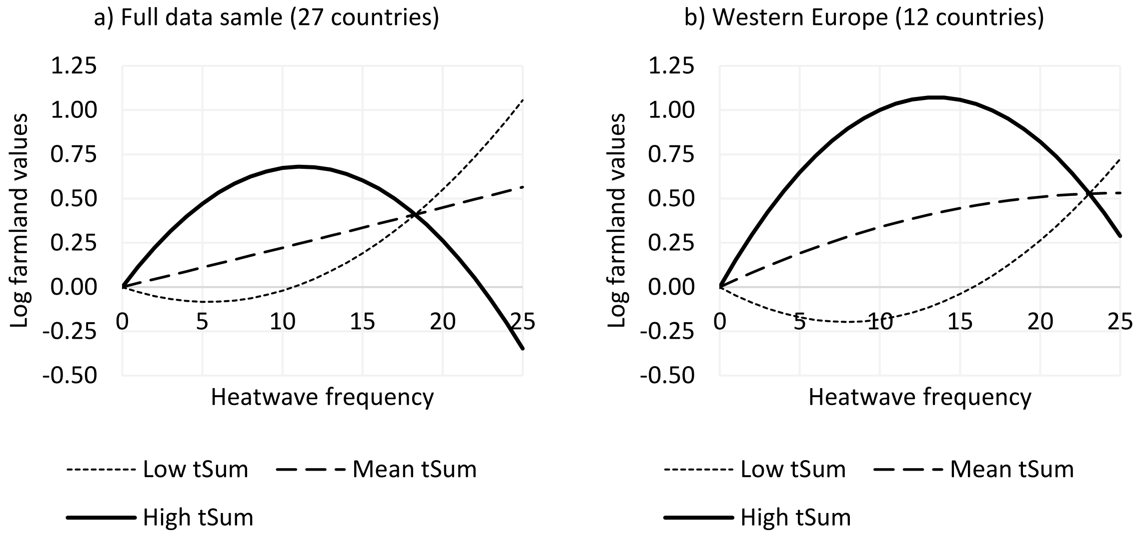


Figure A8: Average climate change-induced land value changes for the full data sample (EU-27) (a) and for Western Europe only (b) for four different heatwave scenarios and under uniform warming

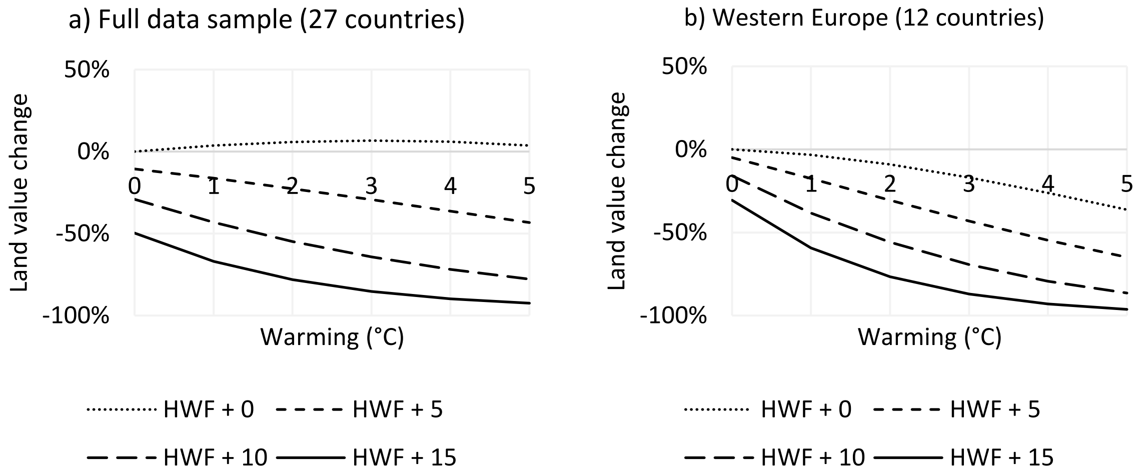
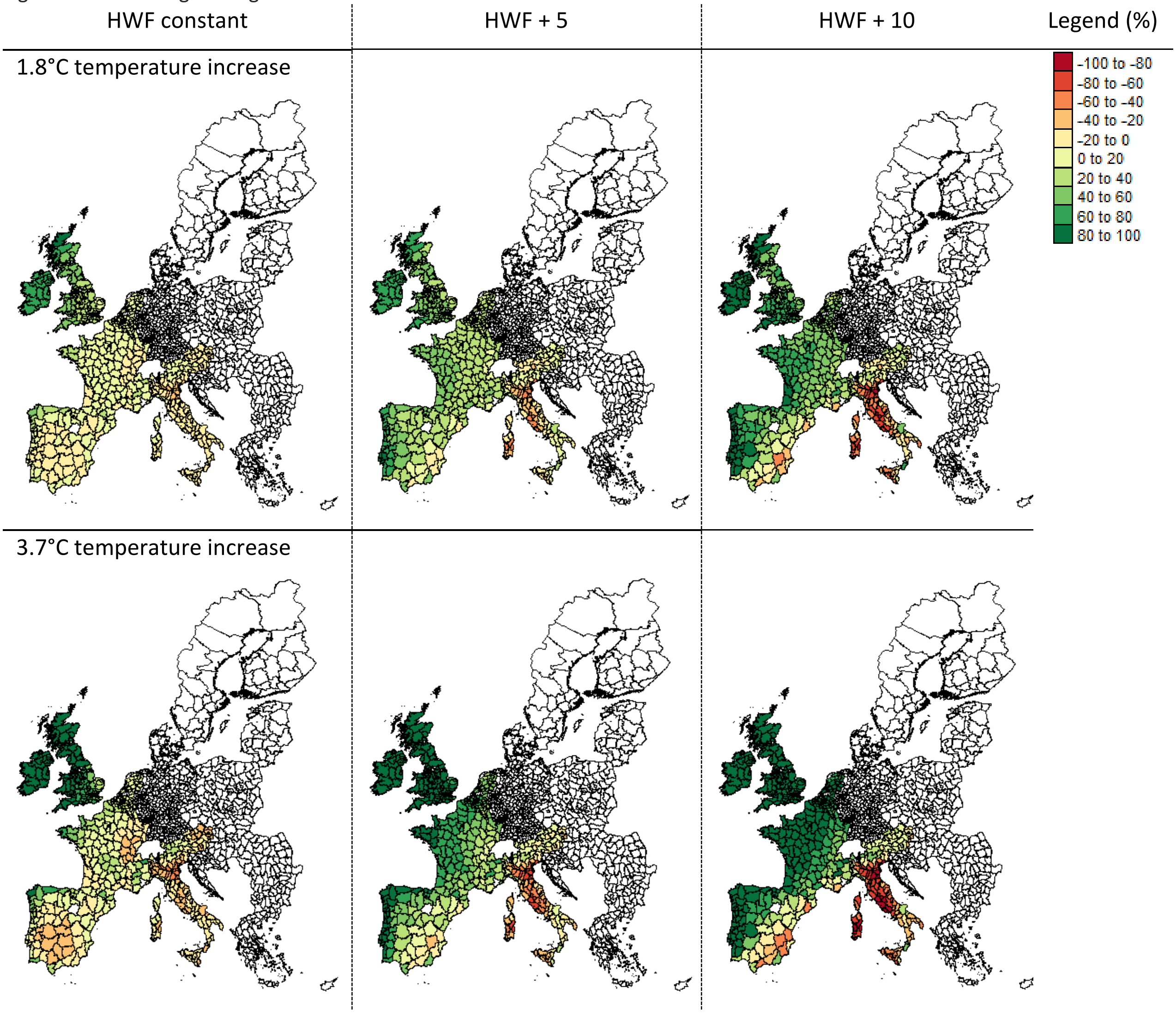


Figure A9: Percentage change in land values for six different climate scenarios



Test 5: Farm irrigation

Figure A10: Response of log farmland values to heatwave frequency for irrigated farms only (a) and for rainfed farms only (b) for different levels of average summer temperature

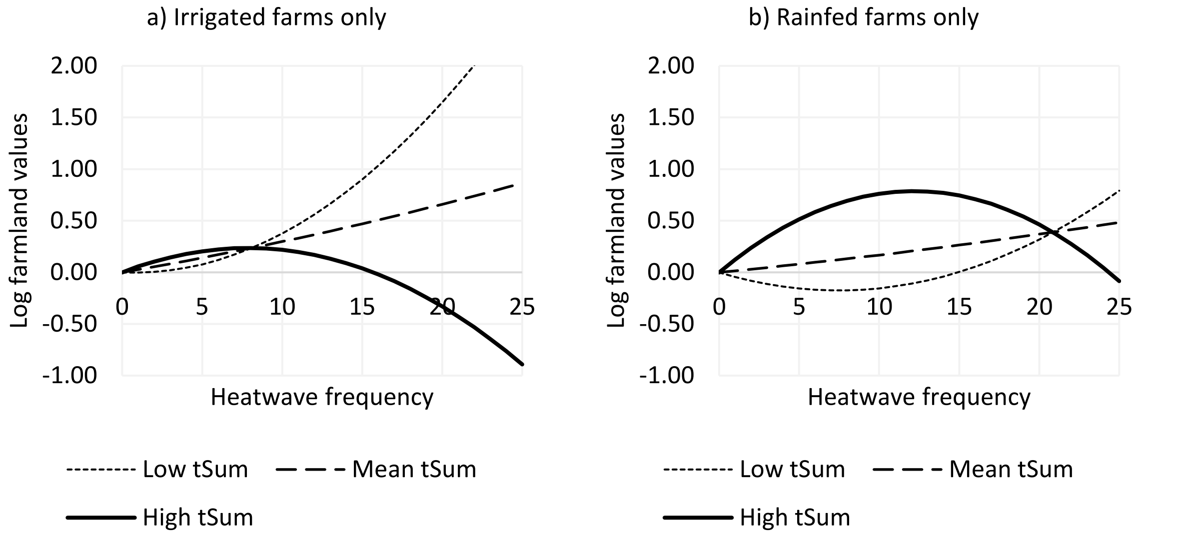
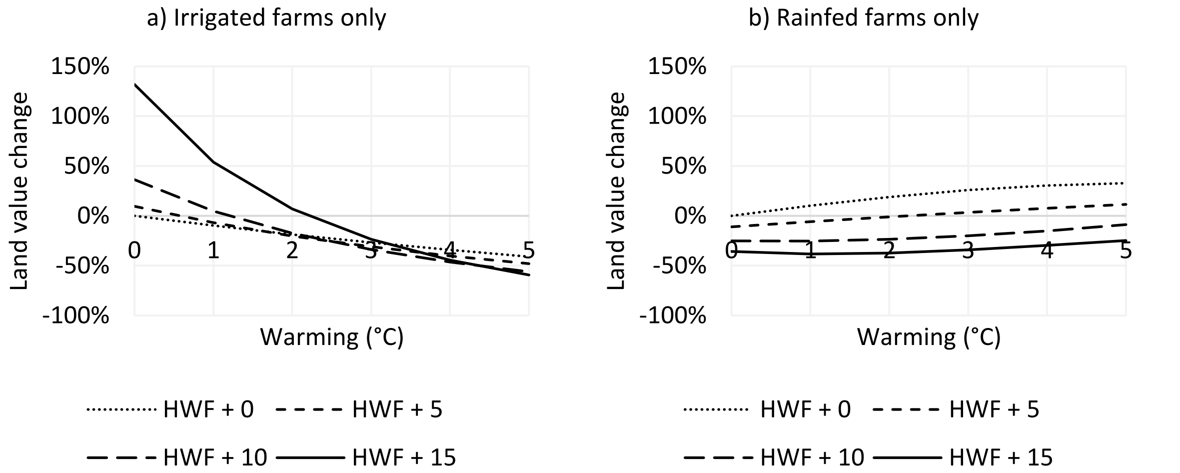


Figure A11: Average EU-27 land value change predicted by a model based on irrigated farms only (a) and a model based on rainfed farms only (b) for four different heatwave scenarios and under uniform warming



Test 6: Types of farming

Figure A12: Response of log farmland values to heatwave frequency for livestock farms only (a) and for crop farms only (b) for different levels of average summer temperature

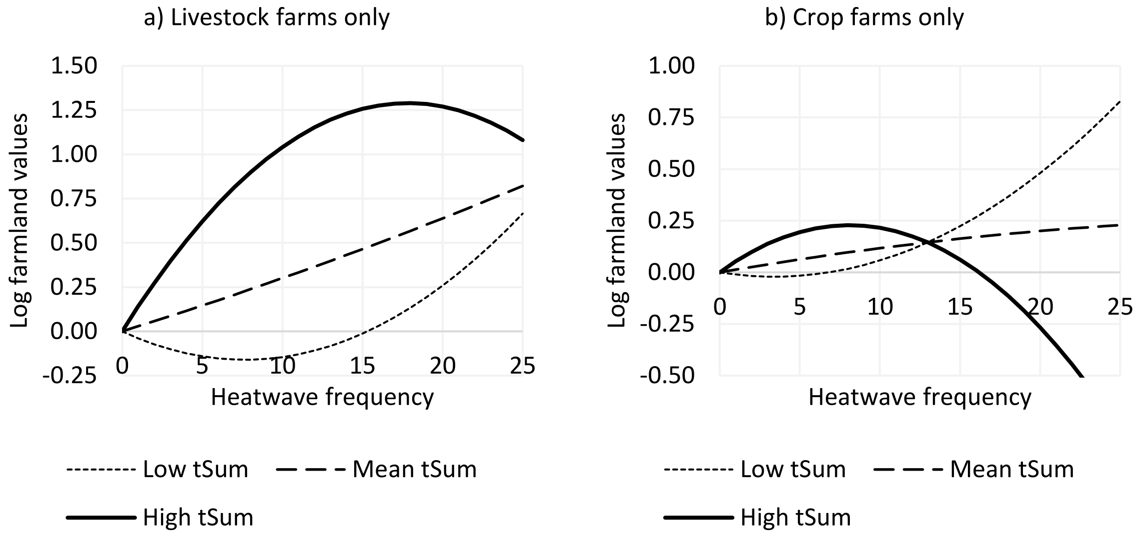


Figure A13: Average EU-27 land value change predicted by a model based on livestock farms only (a) and a model based on crop farms only (b) for four different heatwave scenarios and under uniform warming