



On the (ir)relevance of heatwaves in climate change impacts on European agriculture

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Received: 21 April 2022 / Accepted: 15 September 2022 / Published online: 29 September 2022
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Abstract

The Ricardian model is a widely used approach based on cross-sectional regression analysis to estimate climate change impacts on agricultural productivity. Up until now, researchers have focused on the impacts of gradual changes in temperature and precipitation, even though climate change is known to encompass also changes in the severity and frequency of extreme weather events. This research investigates the impact of heatwaves on European agriculture, additional to the impact of average 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. We find that heatwaves have a minor impact on agricultural productivity and that this impact is moderated by average temperature. In colder regions, farm productivity increases with the number of heatwave days. For warmer regions, land values decrease with heatwave frequency. Despite the moderating effect, the marginal effect of heatwave frequency, i.e. the percentage change in agricultural land values caused by one more heatwave day per year, is small in comparison to the effect of average temperature increases. Non-marginal effects are found to be relevant, but only in the case of increased heatwave frequency. According to our results, farms are not expected to suffer more from extreme weather than from mean climate change, as was claimed by several previous studies.

Keywords Ricardian analysis · Climate change · European agriculture · Heatwaves · Extreme weather events

1 Introduction

Besides gradual shifts in land-surface temperatures and rainfall, climate change encompasses changes in the variability of climate and in the severity and frequency of extreme weather events (FAO 2021; Bouwer 2019). An extreme weather or climate event is defined

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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) which have remained relatively stable, the frequency and costs of climate-related extreme events have increased considerably over the years (FAO 2021), although the increase in costs can also be attributed to higher exposure of people and economic resources rather than to climate change itself (Alimonti et al. 2022). The number of yearly climate and weather-related disasters has quadrupled since the 1970s to approximately 150 events per year globally (FAO 2021), although also here this could partly be attributed to increased reporting of weather extremes rather than to increased frequency of the events alone (Masoomi et al. 2018). Regardless, some researchers expect that these events will cause more damage to agriculture than increasing mean temperatures in the future (Wreford & Adger 2010; Easterling et al. 2007). 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 take these extreme events into account, instead of merely looking at the effects of average 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 simulation and panel weather models, is that it captures long-term adaptation to climate change since it assumes that farmers self-adapt to new climatic conditions (Massetti & Mendelsohn 2018; Mendelsohn et al. 1999). Various studies show that not considering adaptation leads to an overestimation of negative climate change effects on agriculture (Butler et al. 2018; Parent et al. 2018). 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 (Van Passel et al. 2017; Vanschoenwinkel et al. 2016), which is also the geographical scope of the present study. Studies adopting this approach have used various variables for representing average climate such as seasonal temperature, degree days or temperature bins (Vaitkeviciute et al. 2019; Massetti & Mendelsohn 2017). Climate variability, which refers to deviations from long-term climate means, is often neglected in climate impact assessments (Ramamasy 2007). This is likely 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 weather variability, which is required 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. Following this reasoning, this study expands upon the Ricardian model by incorporating a measure for a specific type of extreme weather event: 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 thresholds 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.

Since the 1950s, the largest changes in climate extremes have occurred for daily temperature measurements, including heatwaves (Alimonti et al. 2022). This trend is expected to continue in the future. In its AR6, the IPCC states that ‘in Europe, there is very *robust evidence* for a *very likely* increase in... the frequency of heatwaves’ (Seneviratne et al. 2021, p. 1549) and that ‘the number of hot days and hot nights and the length, frequency, and/or intensity of warm spells or heatwaves will increase over most land areas (*virtually certain*)’ (Seneviratne et al. 2021, p. 1518). This emphasises the need for incorporating heatwaves in the Ricardian model, to estimate the long-term effect of these increases. However, the studies on which AR6 is based use current heatwave thresholds for their projections. Also, Alimonti et al. (2022) state that increases in heatwave frequency ‘can easily be explained by increasing global temperatures’. Considering a gradually warming climatic trend, the probability of exceeding these thresholds indeed becomes 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 (Vogel et al. 2020). Additionally, moving heatwave thresholds is in line with the assumption of adaptation. If farmers adapt to a changing climate, temperatures have to exceed this new ‘normal’ to 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). These insights are of importance to this study. The impact of extreme heat on agriculture has been researched previously (Butler et al. 2018; Massetti et al. 2016; Annan & Schlenker 2015; Lobell et al. 2013), but these studies use crop-specific and region-invariant thresholds and do not account for the accumulation of heat over consecutive days. It is important to account for this accumulation because it has been shown that the impact of an abnormally hot day is dependent on the temperature in the preceding days (Miller et al. 2021).

In the following section, we elaborate on the Ricardian model, explain how an appropriate heatwave variable is computed and how it fits into the Ricardian model. In Section 3, we describe our data. Section 4 focuses on the results, covering regression outputs, marginal effects and estimations of future land value changes based on uniform global warming scenarios. After this section come 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 agricultural land value V (or rent value) is equal to the present value of all net revenues (NR) which can be gained from that 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:

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

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. The Ricardian literature assumes that farmers maximise 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:

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

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 that 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, we included a country dummy variable (D) to capture unobserved country-specific elements which are not represented by the control variables (e.g., country-level support mechanisms, policies and crop insurances), including market price differences between countries. The country dummy variable results in a different intercept for each country. Our sample includes all countries that were a member of the EU in 2017, except Malta. This represents 27 countries in total.

The model estimated in this paper is a cross-sectional model that 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 approximated if all other variables are kept constant. 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). As we assumed that farmers make optimal choices, adaptation to climate is implicitly accounted for in the Ricardian model. Making adaptation explicit requires the use of structural Ricardian models as has been done in several studies (Chatzopoulos & Lippert 2015; Kurukulasuriya & Mendelsohn 2008; Seo & Mendelsohn 2008b), but is outside the scope of this study.

2.2 A variable for heatwaves

Broadly defined, a heatwave is 'a sequence of days with abnormally hot temperatures'. Warm spells are anomalously warm periods over the entire year, including the winter period (Perkins et al. 2012). In this study, we considered only summer heatwaves, rather than all warm spells. We expect extreme temperatures within the period from June until August to have the largest impact on agricultural productivity, since extreme temperatures in seasons other than summer are not considered extreme by annual standards. Also, winter warm spells occur less frequently than summer heatwaves (Supplementary Information). There is not one single unambiguous definition of heatwaves and many national and international institutions apply their own criteria for identifying heatwaves (Hooyberghs et al. 2019). All heatwave definitions are characterised 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 nighttime temperature, maximum daytime temperature or a combination of both.

In this research, we used the definition of Perkins and Alexander (2013). This is one of the most commonly used meteorological definitions (Breshears et al. 2021). 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. They calculate the percentile threshold over a 30-year reference period of daily maximum temperatures with a 15-day-centred window. Using a percentile threshold, rather than an absolute threshold, is necessary to ensure that an observed temperature is indeed considered ‘extreme’, i.e., located in the right tail of the daily temperature distribution (Perkins-Kirkpatrick & Gibson 2017). The dependent variable for the Ricardian regression, agricultural land value, comes from the European Farm Accountancy Data Network (FADN) database of 2017. The reference period for the heatwave computation is set at the 30 years preceding this land value (1987–2016). We thus constructed the temperature threshold for day d using the following dataset (Russo et al. 2014):

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

In this formula, \cup 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 3-month summer period. Figure A in the Supplementary Information shows the heatwave temperature threshold for d equal to July 1st. This figure shows that in Andalucía (Spain), for example, temperatures at the start of July must exceed 35 °C for three or more consecutive days for it to be considered a heatwave. In parts of Scotland, on the other hand, the heatwave threshold lies below 20 °C. We presented the results of a two-season model, including winter and summer climate and warm spell variables, in the Supplementary Information.

Following the work of Perkins and Alexander (2013), five indices exist for quantifying the characteristics of heatwaves. Firstly, the heatwave number, i.e., the number of yearly events. Secondly, the heatwave frequency, i.e., the total number of days contributing to heatwaves in 1 year. Thirdly, the heatwave duration, i.e., the duration of the longest heatwave in one year. Fourthly, the heatwave amplitude, i.e., the temperature on the hottest day of all heatwave days in 1 year. Lastly, the heatwave magnitude, i.e., the average temperature across all heatwaves in 1 year. Out of these five indices, heatwave frequency is the most suitable variable for inclusion in the Ricardian model. Indeed, both heatwave amplitude and magnitude are highly correlated with the average (summer) temperature. Including either of these metrics in the Ricardian equation would lead to issues with multicollinearity. Also, we consider heatwave frequency 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, we decided to include the variable ‘heatwave frequency’ (HWF) in the model. We calculated this as the average number of days per year contributing to heatwaves over the last 5 years of the reference period (1987–2016). Figure 1a 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

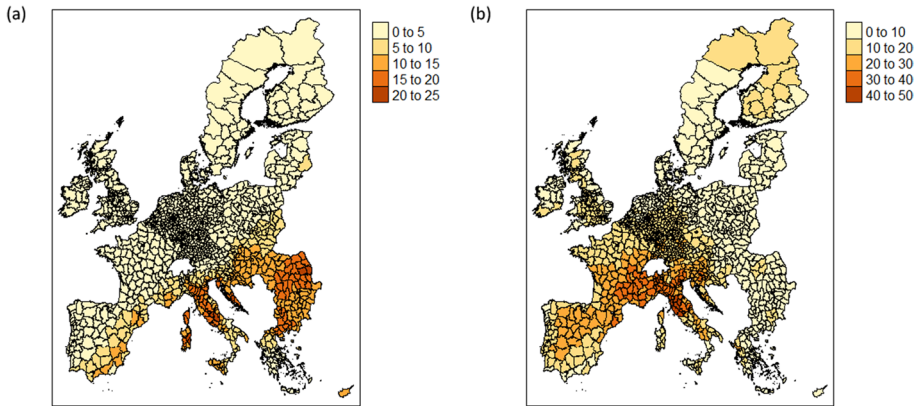


Fig. 1 **a** Average annual heatwave frequency over the years 2012–2016, **b** heatwave frequency in summer 2003.

2003 (Fig. 1b), a memorable year in terms of heatwaves, the heatwave frequency in Europe reached over 40 days in some regions.

2.3 Heatwave frequency in the Ricardian model

The study uses the regression model presented in Eq. 4. The model integrates heatwave frequency into the standard Ricardian model as follows:

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

In this equation, T and P represent average temperature and precipitation, respectively. We calculated the averages over 1987–2016, the same period as the reference period for the heatwave threshold calculation. Laboratory experiments with crops have shown that the climate response of crops is hill-shaped. Consequently, we introduced quadratic terms. The 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 (December to February) to $s = 4$, autumn (September to November). Both the non-linearity and the seasonal differences in climate response were confirmed by previous Ricardian studies using European data (Bozzola et al. 2018; Van Passel et al. 2017).

The 2003 heatwave demonstrated that temperature acts as a moderating variable when estimating the impact of heatwaves on agriculture (EEA 2004). For this reason, we considered interaction effects in our estimations. Heatwave frequency HWF appears in the model as both a main effect and an interaction with summer temperature T_3 . With the former, we assumed that heatwaves have an impact on agricultural productivity because they form a disruption of regular farm conditions. With the latter, we assumed 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 the average number of heatwave days the farm already experiences. We log-transformed

the dependent variable land value per hectare to account for non-normality as suggested by Massetti and Mendelsohn (2011) and Schlenker et al. (2006).

The derivative of Eq. 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 terms, 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 Eq. 5. As a result of the logarithmic transformation of the dependent variable, this marginal value is the percentage change in land value as a result of a unit increase in the heatwave frequency.

$$\frac{d(\ln V_i)}{dHWF_i} = \frac{1}{V_i} \frac{dV_i}{dHWF_i} = \beta_1 + 2\beta_2 HWF_i + \beta_3 T_{3,i} + 2 \cdot \beta_4 T_{3,i} HWF_i \quad (5)$$

Besides the marginal effects, also non-marginal effects can be analysed using the model's results. We used the model to assess land values under alternative climates by inserting new values for the meteorological variables and keeping all other variables constant. Because these forecasts only consider the effect of the meteorological variables, the Ricardian model is a partial equilibrium model. We applied the same approach when comparing model quality through out-of-sample forecasting. We estimated a model based on a random subsample of observations (80%) and then used it to predict the land values for the remaining part of the sample (20%). We then compared these to the actual land values using the RMSE. The model with the lower RMSE—we tested the significance with a Wilcoxon signed rank test—has a higher predictive power. This is also done by Massetti et al. (2016). We treated marginal and non-marginal impacts, as well as out-of-sample forecasts, in Section 4.

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

3 Variables and data

The study used data which was collected in 2017 and provided by the FADN, an organisation affiliated with the European Commission (European Commission, n.d.-b). The FADN liaison agencies collect, annually, accountancy data from agricultural holdings across their country. The full dataset comprises a sample of almost 84,000 farms. We removed all farms with less than one hectare of owned land and those with outlier land values. Also, since crops grown in greenhouses are less sensitive to climatic changes, we discarded all farms within the category 'specialist horticulture indoor'. This resulted 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, we used land value per hectare as the dependent variable. Other variables in the dataset, such as the irrigation system used or the type of farming, allowed for the analysis of subsamples. Section 4 uses these subsamples to test for model robustness. For privacy reasons, the NUTS 3 region rather than the exact coordinates of each farm holding is given in the dataset. To link explanatory variables coming from different data sources to the individual farms, these data are aggregated to the same regional level.

We computed all meteorological variables for the present climate 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, using different interpolation specifications, and aggregated to reduce uncertainty. The values we used for computing the variables are the ensemble medians. The dataset has a 0.25-degree resolution. For computing the heatwave frequency variable, we used the maximum daily temperatures. We calculated the climate variables based on the average daily temperatures and precipitations in the 30-year period from 1987 to 2016.

A known weakness of cross-sectional models is omitted variable bias. Omitted variables are those variables which are correlated with both the dependent variable, land value and the variables of interest, the meteorological variables. This causes a bias in the regression coefficients of these variables (Mendelsohn & Massetti 2017). This issue does not hold when all factors that are correlated with both land value and climate are accounted for. However, this approach is not feasible in practice. To address the issue, some researchers adopt a panel model using yearly weather variation as the independent variable of interest and relying on fixed effects to absorb all confounding variation (Blanc & Schlenker 2017; Massetti & Mendelsohn 2011; Deschênes & Greenstone 2007). There is uncertainty as to whether panel models are able to capture adaptation to long-run changes in mean climate (Massetti & Mendelsohn 2018). In this study, to account for omitted variable bias, numerous farm and region-specific independent variables affecting land values have been included in the models. In fact, this is one of the Ricardian studies with the largest number of control variables to reduce omitted variable bias. Oster (2019) has developed a framework for quantifying how important the unobservables would need to be as opposed to the observed control variables to make the variables of interest insignificant. We did this test as a way of verifying whether there is bias occurring from omitted variables.

We included three variables from the FADN dataset as farm-specific independent variables: farm altitude, subsidies per hectare and the ratio of rented as opposed to owned land area. The altitude of the farm is a categorical variable with the following altitude categories: <300 m, 300–600 m and >600 m. We replaced missing values by the average elevation of the region, derived from the World digital elevation model (ETOPO5) (NOAA 1988). We expected elevation to influence land values both because the Common Agricultural Policy (CAP) perceives high altitudes as a natural constraint for effective farming (European Commission, n.d.-a), and because temperatures decline with increasing elevation. The study includes subsidies per hectare because they might encourage investments in land improvement leading to higher land values. Other studies have raised concerns about potential endogeneity resulting from the inclusion of subsidies as a control variable because farmers might make choices to maximise the support they receive (Dall'erna & Domínguez 2016; Massetti & Mendelsohn 2011). Although in 2017, only a minor part of the CAP budget was coupled to farm yields, we need to be aware of potential endogeneity when interpreting the model results. We assumed the fraction of rented land to be relevant since farmers are less incentivised to invest in land improvement when they do not own the land. Thus, we expected land values to be lower, the larger the fraction of rented land.

All additional variables included in the model are region-specific control variables. Soil variables relate to the structure and composition of the topsoil. Several studies have shown that the quantities of gravel, silt and clay influence land productivity. Also, neutral soil is preferred over acidic and alkaline soil types (Van Passel et al. 2017; Vanschoenwinkel et al. 2016). Soil pH thus requires a quadratic term such that land values can be maximised at a pH close to 7. The original data for these variables come from the Harmonized World Soil

Database (Fischer et al. 2008). We used a re-gridded version from ORNL DAAC which has a 0.05-degree resolution (Wieder et al. 2014). Water availability has been shown to be a significant variable in Ricardian analyses (Mendelsohn & Dinar 2009, 2003). Therefore, the model includes the variable ‘Baseline water stress’ from the World Resources Institute, which measures the total annual water withdrawals as a fraction of the total annual available blue water (Gassert et al. 2014). The higher this fraction, the more competition exists between water users. The socioeconomic variables population density, distance from the region centroid to the nearest big city (with > 500,000 inhabitants) and distance to the nearest port are all indicators for the accessibility of markets. Gross domestic product (GDP) per capita controls for regional price levels. The data we used to compute these variables came from various data sources, all listed in the Supplementary Information. We compiled the dataset using the ‘raster’ and ‘rgdal’ packages from the R open statistical software (Bivand et al. 2021; Hijmans 2021; R Core Team 2020). We also used R for all of the following analyses.

4 Results

4.1 Ricardian regression results

Because we assumed that temperature moderates the impact of heatwaves on agricultural productivity, this relationship had to be present inside the model. We estimated two different models: one without interaction effects and one with interaction effects. The model with interaction effects is the model presented in Eq. 4. The model without interaction effects is analogous but excludes the two interaction terms. Consequently, this model is nested into the model with interaction terms. Table 1 presents the regression results. The standard errors are HC_0 White standard errors robust to heteroscedasticity (White 1980).

Significance of the heatwave terms in the model with interaction effects suggests that the assumptions made in Section 2.3 are correct. Heatwaves affect land values, because they form a disruption of mean climatic conditions, under the moderating effect of temperature. A Wald test for comparing nested models confirms that the unrestricted model (model 2) outperforms the restricted model at a 1% significance level ($F(2, 60,914) = 125.52, p < 0.001$). 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 and BIC of the model with interaction effects are 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). Lastly, using out-of-sample forecasting the median RMSE of model 2 (0.6962) is significantly lower than the median RMSE of model 1 (0.6984). Hence, model comparison suggests that the analysis should include the interaction between temperature and heatwave frequency, despite the adjusted R -squareds of the two models being very similar. In what follows, we used the unrestricted model. The reader should be aware that, due to omitted variables, there is a bias in the model parameters. Using the approach proposed by Oster (2019), we found that omitted variables can easily cause the meteorological variables—including heatwave frequency—to become insignificant. This means that there is likely at least one confounder which biases the results.

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 these independent variables. For example, according to these

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

	Model 1		Model 2	
	Coef	SE	Coef	SE
Winter temperature	0.157***	0.016	0.131***	0.016
Winter temperature ²	-0.009***	0.001	-0.013***	0.001
Spring temperature	-0.197***	0.036	-0.211***	0.036
Spring temperature ²	0.022***	0.002	0.025***	0.002
Summer temperature	0.658***	0.053	0.555***	0.053
Summer temperature ²	-0.020***	0.001	-0.018***	0.001
Autumn temperature	-0.329***	0.045	-0.262***	0.044
Autumn temperature ²	0.007***	0.002	0.006***	0.002
Winter precipitation	-0.151***	0.012	-0.137***	0.012
Winter precipitation ²	0.005***	0.001	0.005***	0.001
Spring precipitation	-0.016***	0.024	-0.030***	0.024
Spring precipitation ²	0.006***	0.002	0.006***	0.002
Summer precipitation	0.004***	0.013	-0.016***	0.013
Summer precipitation ²	-0.001***	0.001	0.0003***	0.001
Autumn precipitation	0.102***	0.014	0.110***	0.014
Autumn precipitation ²	-0.004***	0.001	-0.004***	0.001
Heatwave frequency	0.019***	0.004	0.126***	0.024
Heatwave frequency ²	-0.001***	0.000	0.002***	0.001
Summer temp × HWF			-0.005***	0.001
Summer temp × HWF ²			-0.0001***	0.000
GDP	-0.001***	0.000	-0.0001***	0.000
Distance to cities	-0.001***	0.000	-0.001***	0.000
Distance to ports	-0.001***	0.000	-0.001***	0.000
Population density	0.037***	0.024	0.037***	0.024
Subsidies	0.003***	0.000	0.003***	0.000
Fraction rented land	0.069***	0.011	0.001***	0.011
Clay in topsoil	0.002***	0.001	0.003***	0.001
Gravel in topsoil	0.015***	0.002	0.009***	0.002
Silt in topsoil	0.002***	0.001	0.001**	0.001
pH H ₂ O	-0.041***	0.069	-0.256***	0.070
pH H ₂ O ²	0.015***	0.006	0.033***	0.006
Water stress	0.001***	0.000	0.001***	0.000
Altitude 300–600 m	-0.186***	0.008	-0.192***	0.008
Altitude > 600 m	-0.440***	0.015	-0.450***	0.015
Constant	3.938***	0.405	5.047***	0.410
Country dummies	Yes		Yes	
Observations	60,976		60,976	
Adjusted R ²	0.638		0.640	
AIC	129,376.2		128,995.0	
BIC	129,926.3		129,563.1	

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. The reported standard errors are White standard errors corrected for heteroscedasticity.

regression results, if the fraction of rented as opposed to owned land is increased by 1%, then the land values increase by 0.1%. This is not in accordance with our hypothesis from Section 3. A possible explanation is that renting land is more flexible than owning land. Farmers thus have the flexibility of selecting the plot of land which gives them higher revenues. Also, in some countries, the majority of land is rented. In this case, the fraction of rented land has little influence on land values. A last potential reason could be that if farmers do not purchase land, they have more resources to spend on land improvement. The beta coefficients of other control variables do 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 level of elevation, the lower the land values. If competition for water is increased by 1%, meaning that more water is withdrawn as a fraction of the supply, land values increase by 0.1%. In contrast to previous studies, the parameters for GDP and subsidies are not significantly different from zero. To check for endogeneity, we compared the results with and without the subsidies variable and found that they do not alter. This implies that subsidies are not a source of endogeneity bias in our model.

The interpretation of the coefficients for climate and heatwave variables is less evident. Figure 2a 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 is 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—average summer temperature around 23 °C (P90)—the relationship between heatwaves and land values is negative. Land values reach a maximum at 4 heatwave days and, from then onwards, the curve declines and every extra heatwave day reduces land values and thus farm productivity. At the weighted mean, land values increase almost linearly with every heatwave day (Fig. 2a), at a rate of about 2.6% (Fig. 2b). For regions with summer temperatures around 16 °C (P10), the curve is steeper, with marginal increases of about 4.7% (Fig. 2b). On both figures, the 95% confidence intervals are shown. From Fig. 1a, we see that the majority of European farmland experiences on average maximum 5 heatwave days. This means that most farms are situated to the left of this point in Figs. 2a and 2b, i.e., farms located in warmer regions experience little impact from higher heatwave occurrence and those in

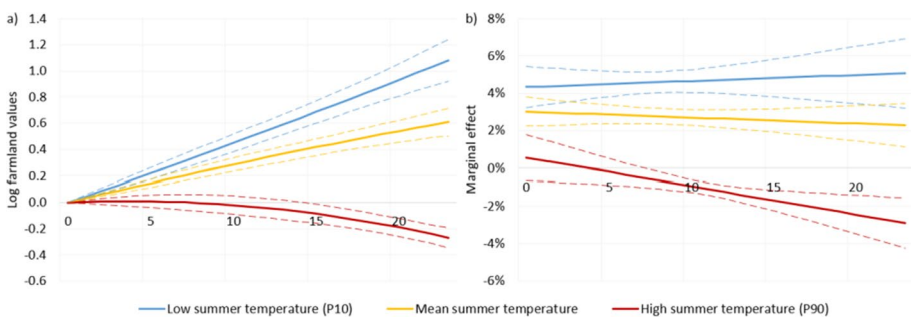


Fig. 2 a Response of farmland values to heatwave days for three different levels of summer temperature, b marginal effect of heatwave frequency in percentage of land values.

colder regions experience gains. One possible explanation could be that extreme temperatures in colder regions are not extreme by European standards. These farmers still have room to adapt using measures previously used by farmers located in warmer regions. This confirms the assumption of the Ricardian model that farmers in a changing climate behave like farmers who have already experienced this climate.

The boxplots in the Supplementary Information compare the average 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 2.9%. This is relatively small in comparison to the effect of a 1 °C increase in the summer temperature which leads to an average decrease in land values of 13.2%. Despite this large detrimental impact, the overall marginal effect of temperature is positive (13.5%) 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, one cannot view these effects separately from each other either. This correlation between variables does not pose a problem when all variables are considered simultaneously, for example when estimating non-marginal impacts.

4.2 Non-marginal impacts

The regression results can be used to estimate welfare impacts caused by future changes in climate. We used uniform warming scenarios rather than the results of climate projections models. For predicting future heatwave frequencies, we would have required accurate temperature projections at a daily level. Although daily projections are available, they are very uncertain. We therefore relied 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. Figure 3 maps the percentage change in land values caused by increases in temperature and heatwave occurrence by NUTS3 region. We let annual temperatures increase with 1.8 °C and 3.7 °C, which are the mean IPCC (2013) forecasts for the period 2081–2100 in comparison to the period 1986–2005 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. This is not necessarily a realistic picture of how climate will evolve but an advantage of these uniform scenarios is that we can attribute the differences in climate impacts to regional differences in climate sensitivity alone (Massetti & Mendelsohn 2011). For heatwave frequency, we proposed three scenarios: a stable heatwave frequency and an increase with 5 days and 10 days, respectively (once and twice the standard deviation of the current HWF distribution).

We see that the majority of Europe experiences welfare growth as a result of both temperature and heatwave increases. This is depicted by the green areas on the maps in Fig. 3. A large part of Southern Europe is negatively impacted by both temperature and heatwave increases. For the most extreme scenario—a 3.7 °C increase and 10 more heatwave days—land value changes go from –74 to +139% over the entire EU sample. For the least extreme scenario, changes range from –25 to +25%. A scenario where heatwave frequency does not change and temperature increases uniformly by 3.7 °C leads to land value changes within the range of –44 to +60%. Other Ricardian studies

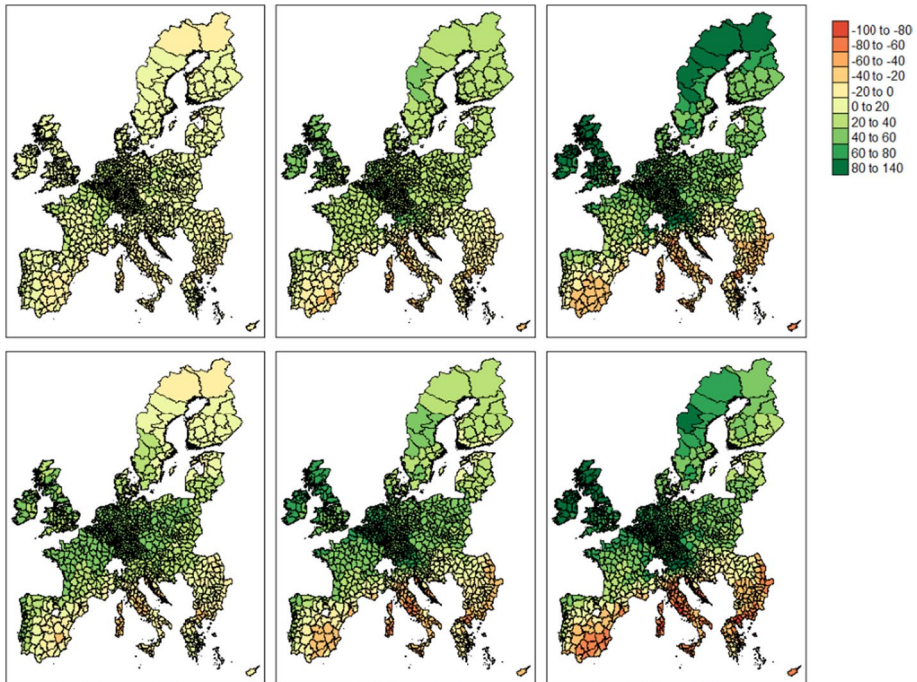


Fig. 3 Percentage change in land values for six different climate scenarios, from left to right: current heatwave frequency, 5 more heatwave days and 10 more heatwave days. First row: current temperature increased by 1.8 °C. Second row: current temperature increased by 3.7 °C

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 under scenarios with temperature increases from 3.1 up to 4.4 °C. 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, a variable which we kept unaltered in this study.

Despite the striking non-marginal impacts, there is doubt on whether 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 that was set in the past becomes higher with increasing mean temperatures. These studies assumed 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. Several studies that 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). Following this reasoning, the most likely scenarios

are those depicted in the left column of Fig. 3. However, this does not mean that the impact of heatwaves will not change in the future. As can be seen from the response curves in Fig. 2, increased temperatures can cause the heatwave impacts to change, regardless of whether the number of heatwave days per year changes, as a result of the interaction with summer temperature.

5 Robustness tests

We have made several assumptions throughout this study, concerning model specifications, variable selection and sample delimitation. In what follows, we tested whether farm response to heatwaves is sensitive to some of these assumptions. Figure 2a from the previous section is reproduced for each of the model specifications and compared to the original plot. The plots are presented in Table C1 in the Supplementary Information.

5.1 Alternative meteorological variables

In their analysis of past heatwaves in Italy, Fontana et al. (2015) use ‘heatwave intensity’ for quantifying heatwaves. The authors calculate the metric as follows: $\sum_i \max(T_{\max,i} - T_{p90,i}, 0)$ 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 we used in this paper. However, interpreting the marginal effect of a unit increase in heatwave intensity is less intuitive. In the figure, we let the heatwave intensity on the X-axis range from 0 to 72 which is the current range of heatwave intensities. Replicating the analysis with heatwave intensity yielded very similar results to the ones presented in Section 4.

Some Ricardian studies use total degree days and precipitation over the growing season rather than seasonal temperatures and precipitation (Vaitkeviciute et al. 2019; Massetti et al. 2016). The degree days variable is obtained by taking the sum of all daily temperatures exceeding 8 °C over the growing season (April to 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, we used uncapped degree days over the growing season and include the interaction between this variable and heatwave frequency. Increasing the average temperature by 1 °C is equivalent to an increase of 183 days over the growing season (i.e. 1 °C for all 183 days of the growing season). From the plot in the Supplementary Information, we found that replacing the seasonal variables by growing season variables does not drastically change our results, i.e. low and medium-temperature farms respond positively to heatwaves, high-temperature farms negatively. The shapes of the curves alter slightly, from concave to convex.

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 similar to the

ones presented in Section 4.2. 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.

Neither the main specification nor the robustness check above deal with spatial correlation in the residuals, potentially biasing the significance levels of the results. Several Ricardian studies have corrected their models' standard errors for spatial correlation using the method proposed by Conley (1999) (Bozzola et al. 2018; Massetti & Mendelsohn 2011). Since we did not have exact farm locations, calculating Conley standard errors based on a spatial weights matrix would not have been appropriate. Rather, we computed cluster-robust standard errors where the clusters are defined as the NUTS 3 regions in which farms are located. We found that none of the four heatwave terms is significant with these standard errors while some of the temperature variables do remain significant. Although this means that the results from Section 4 are not valid when taking into account spatial correlation, it does confirm that heatwaves have a negligible impact on land values in comparison to average temperature.

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), the response curves change: the effect of heatwaves in low-temperature regions is more positive and in high-temperature regions more negative. This is not unreasonable since Eastern Europe, a region with high heatwave frequencies (see Fig. 1), and Scandinavia, a region that benefits from both temperature and heatwave increases (Fig. 3) are excluded from the dataset. Looking at the maps (Supplementary Information), the predicted impacts in the South are even more negative than when predicted by the original model. A comparison between Northern and Southern Europe or Western and Eastern Europe could provide additional interesting insights, but this is beyond the scope of this study.

Other possible sample limitations are the distinction between irrigated and rainfed farms and the distinction between crop and livestock farms (Van Passel et al. 2017; Seo et al. 2009; Seo & Mendelsohn 2008a). Land values of rainfed farms appear to be less sensitive to heatwave frequency increases than land values of irrigated farms. This is in contradiction with previous studies, which found the opposite effect and attributed this to the climate insensitivity of irrigated farms (Van Passel et al. 2017; Mendelsohn & Dinar 2003). In this case, a possible explanation for the lower sensitivity of rainfed farms to heatwaves 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-tolerant crops than farms that have access to irrigation. Looking at the comparison between livestock and crop farms, we saw that for livestock farms there is little distinction between the responses of farms located in high and low-temperature regions. The lack of significance in the interaction between temperature and heatwaves is perhaps because specialised European livestock farms are generally located in cooler and wetter regions (Van Passel et al. 2017). The results from the crops model are very similar to those from the main model in this paper.

6 Conclusion

With this study, we expanded 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 and bearing in mind the study's limitations, several cautious conclusions can be drawn. Based on the results presented in Section 4, we would conclude that heatwaves have a minor 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. In regions with mean temperature farm productivity also increases, but less steeply. For regions with high temperatures, the relationship is negative. However, when taking into account spatial correlation in the residuals—which we have done as a robustness check—the heatwave impacts disappear whereas several of the temperature variables remain significant. Consequently, this research cannot confirm that the agricultural sector will suffer more from extreme weather events than from gradual temperature increases as is generally assumed. This is both because of this insignificance and because there is little evidence that, under moving thresholds, there will be more heatwaves in the future. Also, as shown by the Oster (2019) test, the conclusions related to heatwave impacts are not robust against omitted variable bias. There is likely at least one unobserved confounder which biases these results. Since this also holds for the temperature and precipitation variables, this is likely an issue for most Ricardian studies and not just this one. It would be interesting to apply the Oster (2019) test to previously published Ricardian papers to check whether this is indeed the case.

The study's limitations inhibit us from deriving general policy recommendations at the EU level. Further research is needed to confirm whether policy support is indeed more productively spent on helping farmers adapt to average temperature increases rather than on helping protect farmers against heatwave damage, which the results of this study suggest. Future research could also 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 experiencing different average 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. As mentioned above, a weakness of the Ricardian model is its inability to capture unobserved heterogeneity between farms, even when many control variables are accounted for. In panel models, these omitted variables are captured by the fixed effects. There are however also drawbacks to panel models, such as to what degree adaptation can be accounted for. Also, representative climate projection data would be needed to better 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.

Although this study has not come to any profound conclusions, the study is valuable from a methodological point of view. Over 50 Ricardian studies have been published without ever considering extreme weather events based on location and time-specific thresholds. We highlighted why incorporating extreme weather could be of importance and proposed a method for doing so. Also, more than previous Ricardian studies, this study has acknowledged and addressed the weaknesses of the Ricardian approach.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s10584-022-03438-4>.

Funding This work was supported by the University of Antwerp's University Research Fund in the form of a doctoral project (ID 42475).

Acknowledgements The authors would like to express their gratitude to the European Commission's DG Agriculture and Rural Development for access to the Farm Accountancy Data Network (FADN).

Declarations

Competing interests The authors declare no competing interests.

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