A Ricardian Analysis of the Impact of Climate Change on European Agriculture

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Abstract

This research estimates the impact of climate on European agriculture using a continental scale Ricardian analysis. Climate, soil, geography and regional socio-economic variables are matched with farm level data from 37,612 farms across Western Europe. We demonstrate that a median quantile regression outperforms OLS given farm level data. The results suggest that European farms are slightly more sensitive to warming than American farms with losses from -8% to -44% by 2100 depending on the climate scenario. Farms in Southern Europe are predicted to be particularly sensitive, suffering losses of -9% to -13% per degree Celsius.

JEL-Code: Q540, Q510, Q150.

Keywords: Ricardian analysis, climate change, European agriculture, climate change economics, quantile regression.

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1 Introduction

Although there have been several economic analyses of the impact of climate change on American agriculture (Mendelsohn, Nordhaus, and Shaw 1994, Mendelsohn and Dinar 2003, Schlenker, Hanemann, and Fisher 2005, Deschênes and Greenstone 2007), there have been few studies in Europe. European Ricardian studies have been limited to single country analyses such as in Germany (Lang 2007, Lippert, Krimly, and Aurbacher 2009) and Great Britain (Maddison 2000). Previous studies of European wide agricultural impacts have relied on crop modelling (e.g. Ciscar *et al.*, 2011). This study addresses this shortcoming in the economic literature by analysing farm level data that has never been analysed before. The data set is collected by the European Union (EU) to administer farm policies. This data set resembles the US Census Public Use sample available for Housing and Population. It contains individual data about farms in small geographic units (similar to US counties) across Europe. The study relies on a sample of over 37,000 farms from all the countries in the EU-15 (Western Europe).

This paper explores a new method to estimate the Ricardian model that is well suited to individual farm level data. A median quantile regression is used to estimate the Ricardian model instead of relying on OLS. The median quantile regression reduces the influence of outliers. For example, there are several high valued farms in Europe that include onsite processing (manufacturing) such as converting grapes to wine, milk to cheese, or olives to olive oil. Similarly, there are high valued farms with agro-tourism businesses that include farm activities but also tourism services. The manufacturing and tourist components may not have the same climate sensitivity and yet they lead to high valued farms. The median quantile regression does not allow such properties to have undue influence on the regression results. In contrast, the OLS regression gives such outlying properties undue influence because OLS minimizes the sum of squared errors.

There is now an extensive literature that has used the Ricardian method to study the climate sensitivity of agriculture (Mendelsohn et al. 1994). There is also a rich literature describing the strengths and weaknesses of the Ricardian technique. The strength of the approach is its ability to measure long run impacts from climate change and its ability to capture the adaptation that farmers have already demonstrated they can do. But there are limitations. The technique does not capture future technical change to either crops or new farming methods. As with all uncontrolled experiments, unmeasured factors correlated with climate can bias the results. It is consequently important that Ricardian analyses measure likely factors that might influence crop productivity such as soils and market access. Especially, as emphasized by Fisher et al. (2012), it is critical that climate is measured carefully. The Ricardian method does not measure either price sensitivity (Cline 1996) or carbon fertilization since both prices and the level of carbon dioxide remain the same across the entire sample. The absence of price effects cause the Ricardian method to overestimate large global damages or global benefits of warming (Mendelsohn and Nordhaus 1996). The beneficial effects from carbon dioxide fertilization (Kimball 2007) must be added to the results of the Ricardian analysis. The Ricardian approach is a comparative static analysis of long run equilibriums. It does not capture the dynamic transition costs of moving from one equilibrium to another (Kelly, Kolstad, and Mitchell 2005). Short run dynamics such as farmer responses to weather changes are much better captured by intertemporal analyses such as Deschênes and Greenstone (2007) and Fisher et al. (2012).

There has also been an extensive debate concerning whether the Ricardian technique properly accounts for irrigation (Schlenker et al. 2005). American Census data cannot address this problem because there is no separate data for rainfed and irrigated farms. However, studies done in other countries have compared the climate sensitivity of irrigated versus rainfed farms. Irrigated farms are less sensitive to warming than rainfed farms in Africa (Kurukulasuriya, Kala, and Mendelsohn 2011, Kala, Kurukulasuriya, and Mendelsohn 2012) and China (Wang et al. 2009). In fact, in China, moderate warming is beneficial to irrigated farms though harmful to rainfed farms. However, in Latin America, the climate sensitivity of both irrigated and rainfed farms are similar (Seo and Mendelsohn 2008). We re-examine this question in this paper by estimating separate Ricardian functions for rainfed and irrigated farms.

A special concern in Europe is whether the EU Common Agricultural Policies may distort climate sensitivities. For example, farm subsidies can hide (exaggerate) climate sensitivity if the subsidies are higher for farms in adverse (favourable) climates. Revisions in EU farm policy have allegedly removed links between production and the level of the subsidy. Further, the analysis relies on country fixed effects to remove the influence of remaining country level policies.

The paper is organized as follows. In section 1, we explain the Ricardian analysis. Section 2 presents the data and the model specifications of the Ricardian model using farm level data. In section 3 the empirical findings are presented as well as projections of future impacts with different General Circulation Climate Models (GCM). The paper concludes with a summary of the results, policy conclusions, and limitations.

2 Methodology

The Ricardian model assumes that farmland value per hectare (*V*) of each farm *i* is equal to the present value of future net revenues from farm activities:

$$\mathrm{V}_i = \int \left[\sum \mathrm{P_j Q_{i,j}}\left(\mathrm{X_{i,k}}, \mathrm{Z_i}\right) - \sum \mathrm{M_k X_{i,k}} \right] \mathrm{e}^{-\varphi \mathrm{t}} \mathrm{dt} \quad (1)$$

where P_j is the market price of each output *j*, $Q_{i,j}$ is the quantity of each output *j* at farm *i*, $X_{i,k}$ is a vector of purchased inputs *k* (other than land), M_k is a vector of input prices, Z_i is a vector of exogenous variables at the farm, and φ is the interest rate.

The farmer chooses the outputs $Q_{i,j}$ and inputs $X_{i,k}$ that maximize net revenues. By solving (1) to maximize net revenues and by folding the vector of prices of outputs and inputs P_j, M_k into the vector of exogenous variables Z_i, V_i can be expressed as a function of only exogenous variables:

$$\mathrm{V}_i = \mathrm{f}(\,Z_i) \quad (2)$$

The cross sectional Ricardian regressions estimates equation (2). It is important that endogenous variables selected by the farmer such as fertilizer or crop choice not be included as independent variables in the regression. Exogenous variables can be grouped into different subgroups: climate variables (temperature, *T*, and rainfall, *R*), and exogenous control variables (*E*) such as geographic, soil variables, and socio-economic variables including market access (which may proxy for price variation).

We rely on a log-linear Ricardian model because land values are log-normally (Massetti and Mendelsohn 2011b, Schlenker, Hanemann, and Fisher 2006)[1]. We use the climatology of each location (the 30 year average seasonal temperature and rainfall) to measure climate. Both agronomic and Ricardian studies reveal that seasonal differences in temperature and precipitation have a significant impact on farmland productivity (see review in Mendelsohn and Dinar (2009)). This literature also suggests that the relationship between climate and land values is hill-shaped. We therefore estimate the following model for each farm *i*:

$$\ln \mathrm{V_i} = \alpha + \beta_\mathrm{T}\mathrm{T_i} + \gamma_\mathrm{T}\mathrm{T_i^2} + \beta_\mathrm{R}\mathrm{R_i} + \gamma_\mathrm{R}\mathrm{R_i^2} + \eta\mathrm{E_i} + \xi\mathrm{D} + \mathrm{u_i} \qquad (3)$$

where *T* and *R* are vectors reflecting seasonal coefficients and seasonal temperatures and precipitations, *E* is a set of control variables; *D* is a set of country fixed effects and u_i is a random error term which is assumed not to be correlated with climate.

For a random variable *Y* with distribution F $(F(y) = P(Y < y))$, the τ-th quantile is defined by $Q_y(\tau) = \inf\{y: F(y) \geq \tau\}$. Most frequently examined quantiles are the median (τ=0.5), the first and last deciles (τ=0.1 and τ=0.9) and the first and last quartiles (τ=0.25 and τ=0.75). Based on equation 3, we can run a quantile regression (Koenker and Bassett 1978) for each different value of τ:

$$Q_{\ln \mathrm{V_i}}(\tau|T,R,E,D) = \alpha(\tau) + \beta_\mathrm{T}(\tau)\mathrm{T_i} + \gamma_\mathrm{T}(\tau)\mathrm{T_i^2} + \beta_\mathrm{R}(\tau)\mathrm{R_i} + \gamma_\mathrm{R}(\tau)\mathrm{R_i^2} + \eta(\tau)\mathrm{E_i} + \xi(\tau)\mathrm{D} \qquad (4)$$

The median quantile regression estimate is more robust against outliers because the effect of the outliers is relegated to the extreme quantiles. In contrast OLS regressions can be strongly influenced by extreme observations because the regression is minimizing squared errors.

Although the entire sample is subject to the rules and regulations of the European Union, these rules are often applied in a different fashion by each country. We control for country specific factors that affect farms by using country fixed effects using cross-sectional data (Koenker 2004). Although one in principle can apply even finer geographic controls to control for unmeasured spatial correlates, an overuse of fixed effects can significantly inflate the variability of the estimates of other covariate coefficients. The risk of ever finer controls is a reduction in the variation within the sample and the increase likelihood that the analysis will be plagued by mismeasurement bias (biasing coefficients towards zero) (Fisher et al. 2012).

The marginal impact of seasonal temperature T_i on land value per hectare at farm *i* is equal to:

$$\left[\frac{\partial Q_{\mathrm{V_i}}(\tau|T,R,E,D)}{\partial \mathrm{T_i}}\right] = \mathrm{V_i}(\tau)(\beta_\mathrm{T}(\tau) + 2\gamma_\mathrm{T}(\tau)\mathrm{T_i}) \qquad (5)$$

Note that the marginal impacts may differ over quantiles (i.e. different values of τ) and that we use a quadratic specification of climate variables. Temperature and precipitation marginals consequently vary depending on both the underlying land value and climate. In order to calculate the marginal impact of warming across all of Europe (or a particular member state), one must sum the effects at every farm:

[1] The log-linear functional form outperforms the linear form. Comparing the ratio of the predicted value (using OLS) to the actual value in each decile, we found that the log-linear model has a more uniform predictive power compared to the linear model.

$$MI_{T_r}(€) \stackrel{\text{def}}{=} \left[\frac{\partial Q_{\mathrm{V_{i,r}}}(\tau|T,R,E,D)}{\partial \mathrm{T_{i,r}}}\right] = \sum_{i=1}^{n} \mathrm{V_i}(\tau)(\beta_\mathrm{T}(\tau) + 2\gamma_\mathrm{T}(\tau)\mathrm{T_i})\omega_\mathrm{i} \tag{6}$$

with *n* the total number of sampled farms in region *r* and where ω_i is a weight that reflects the total amount of farmland that each farm represents. This expression evaluates a small change in T_i at each region *r* and reports the expected response across all regions.

The marginal impact of seasonal temperature on the percentage of land value at farm *i* can be calculated as:

$$MI_{T_r}(\%) \stackrel{\text{def}}{=} \left[\frac{\frac{\partial Q_{\mathrm{V_{i,r}}}(\tau|T,R,E,D)}{\mathrm{V_{i,r}}(\tau)}}{\partial \mathrm{T_{i,r}}}\right] = \sum_{i=1}^{n}(\beta_\mathrm{T}(\tau) + 2\gamma_\mathrm{T}(\tau)\mathrm{T_i})\omega_\mathrm{i} \tag{7}$$

$\mathrm{MI_T}$ (%) is the percentage change in land value associated with a marginal increase in temperature, while $\mathrm{MI_T}$ (€) is the absolute marginal change in land value (in Euro) associated with a marginal increase in temperature. The total impact of a nonmarginal climate change on the value of land in region r is calculated by comparing the estimated value of land under the new temperature and precipitation $(\mathrm{T_1}, \mathrm{R_1})$ to the estimated value of land under the original climate $(\mathrm{T_0}, \mathrm{R_0})$:

$$\Delta \mathrm{W_r} = \sum_{i=1}^{n}\left[Q_{\mathrm{V_i}}(\tau)(\mathrm{T_1}, \mathrm{R_1}) - Q_{\mathrm{V_i}}(\tau)(\mathrm{T_0}, \mathrm{R_0})\right]\omega_\mathrm{i} \tag{8}$$

where

$$Q_{\mathrm{V_i}} = \exp\left(\alpha + \beta_\mathrm{T}\mathrm{T_i} + \gamma_\mathrm{T}\mathrm{T_i^2} + \beta_\mathrm{R}\mathrm{R_i} + \gamma_\mathrm{R}\mathrm{R_i^2} + \eta\mathrm{E_i} + \xi\mathrm{D}\right) \tag{9}$$

3 Data and model specifications

This is the first study that estimates a Ricardian function using all EU-15 countries (Western Europe) of the European Union. The econometric estimates rely on a comprehensive dataset of EU agriculture that we specifically created for this study. Farm-level data is from the FADN (farm accountancy data) survey managed by the EU. The survey provides a large set of harmonized, comparable, farm-level data for all EU countries. FADN data is of high quality because it is used to inform EU farm policy. There are 5,662,480 farms in the EU-15 (census 2007 data), with a total utilized agricultural area of about 120 million hectares. We use a sample of 37,612 commercial farms using 2,253,423 hectares land and covering by stratification 60% of all agricultural areas in the EU-15.

The EU has identified homogenous geographic units across European countries. The units are called NUTS3 (Nomenclature of Territorial Units for Statistics) regions. The exact location of each farm is not released for confidentiality reasons but the NUTS3 region of the farm is known. The median area of the NUTS3 regions in our sample is 3706 square kilometres so they are similar in size to a US county. Our 37,612 farms are situated in 923 NUTS3 regions. The data is very similar to Public Use samples in the United States that reveal the county of each household but not the exact location. Unfortunately, the US Census of Agriculture does not release such a public use sample of farms. The micro data from this EU sample is exceptionally valuable because it measures the property value of each individual farm in a consistent way. It therefore avoids the aggregation problems that plague the county data from the US Census of Agriculture. Specifically, the farm level data allows us to separately analyse irrigated versus rainfed farms and crops versus livestock farms, which is not possible with aggregate data. The farm level data consequently allows us to overcome some of the problems faced in US Ricardian studies, which are based on aggregate data.

The FADN data from 2007 contain many farm specific variables. Each Member State conducts the survey using a harmonized instrument that applies the same bookkeeping principles across the entire sample. The sample is representative of commercial agricultural holdings[2]. It is a stratified sample, based on type of farming, farm size, and region. The weighted sample is representative of all farms in the EU-15. The data set includes the dependent variable (V_i), the agricultural land value per hectare and some farm specific socio-economic variables (e.g., rented land). The agricultural land values are based on observed prices in the region for non-rented land of similar situation and quality sold for agricultural purposes.

The historic climate data for each NUTS3 region was derived from the Climatic Research Unit (CRU) CR 2.0 dataset (New et al. 2002). The climatologies for temperature and precipitation rely on measurements from 1961 to 1990. Soil data are from the harmonized world soil database, a partnership between the Food and Agriculture Organization (FAO) and the European Soil Bureau Network. An overview and detailed description of all model variables and sources can be found in Appendix A. Additional socioeconomic (population density) and geographic variables (e.g., distance from urban areas, distance from ports, latitude, mean elevation) were matched to each NUTS3 region.

Table 1 shows the descriptive statistics of our model variables. The average farm level land value is nearly 16,000 Euro per hectare but there are large differences between farms with very low land values (e.g., marginal land) and high land values (e.g., farms producing high value products).

We explore a number of different analyses to test the robustness of our results. We estimate an OLS regression of the entire sample, and quantile regression models to test the hypothesis that climate sensitivity is different for farms with different land productivity. We also estimate separate regressions for rainfed, irrigated, crop and grazing farms.

In all regressions, we weight each farm using total agricultural land in that farm to control for heteroscedasticity and we add country fixed effects. We control for spatially correlated errors in an OLS regression. As we do not know the location of each farm, we build confidence intervals corrected for spatial correlation by aggregating farm level data at the NUTS3 level.

We use the results of the regressions to estimate the marginal and nonmarginal impacts of climate change. In order to provide realistic estimates of nonmarginal climate change impacts, we use climate change scenarios for 2100 generated by three General Circulation Models (GCMs) that use the A2 SRES (Special Report on Emissions Scenarios) emissions scenario (Nakićenović et al. 2000). In the SRES A2 emission scenario the concentration of CO_2 reaches the level of 870 ppm in 2100 (compared to about 398.0 ppm in February 2014)[3]. We rely on the results of 3 climate models to predict the future climate outcome (i) Hadley CM3 (Gordon et al. 2000), (ii) ECHO-G (Legutke and

[2] A commercial farm is defined as a farm, which is large enough to provide a main activity for the farmer and a level of income sufficient to support his or her family. The land use and value of non-commercial farming in the EU-15 is negligible.
[3] Data from Mauna Loa Observatory, Hawaii, USA.

Voss 1999), and (iii) NCAR PCM (Washington et al. 2000). These climate models were selected to reflect a wide range of plausible outcomes for the SRES A2 emission scenario[4].

Table 1: Descriptive statistics

variable		mean	min	max	sd
	Farm specific socio-economic variables				
Agricultural land value	Euro/ha	15970.40	4.74	2060296.00	29615.89
Land owned	ha	33.91	1.00	2695.53	67.19
Utilized agricultural area	ha	59.91	1.00	7845.25	109.35
Farms represented	number	59.25	1.00	10550.00	212.25
Share rented land	ha/ha	0.31	0.00	0.99	0.33
	Regional socio-economic variables				
Pdnsty	Cap/km²	155.94	2.00	3048.00	211.38
	Regional specific climatic variables				
Temp. winter	°C	3.68	-14.94	12.01	4.04
Temp. spring	°C	9.67	-2.77	15.96	2.96
Temp. summer	°C	18.64	6.83	26.15	3.32
Temp. autumn	°C	11.97	-1.81	19.67	3.49
Prec. winter	10mm	7.18	1.89	25.54	2.83
Prec. spring	10mm	6.30	2.08	17.06	2.29
Prec. summer	10mm	5.66	0.15	20.98	3.46
Prec. autumn	10mm	7.49	3.56	28.71	2.49
	Regional specific soil characteristics				
t_gravel	(%vol)	9.35	2.44	18.35	2.71
t_silt	(%wt)	31.66	10.83	45.99	5.78
t_sand	(%wt)	45.93	28.25	83.02	9.34
t_clay	(%wt)	21.49	5.79	40.22	4.69
pH		6.31	4.18	7.88	0.70
	Regional specific geographic variables				
Cities500k	km	116.67	0.97	842.84	81.64
PortsML	km	160.96	0.91	536.51	108.00
Elevation mean	m	393.79	0.01	2091.87	330.79
Elevation range	m	1201.17	1.00	4255.00	904.21
Latitude	°	45.81	35.14	67.71	6.05
Longitude	°	7.48	-9.19	29.97	9.04

A detailed description of all model variables can be found in appendix A

We attribute the climate generated by GCMs to each NUTS3 region centroid by interpolating the four closest grid points of the GCM scenario using inverse distance weights. Estimates of the change of temperature (level) and precipitations (percentage) at NUTS3 level are obtained comparing climate in 2071-2100 predicted by the model with the A2 scenario and climate in 1961-1990 reconstructed by the same model. We then modify CRU 1961-1990 climate data for each NUTS3 region using the estimated temperature and precipitation changes.

The Hadley model predicts an average warming of 4.4°C with a 34% loss of annual precipitation, the ECHO-G model predicts a warming of 4.3°C with a 21% loss of precipitation, and the PCM model

[4] It is important to note that the models used for this study are representative of the whole set of GCM scenarios available (about 20) but they do not necessarily forecast the most likely climate scenarios, nor the average of the three estimates should be interpreted as being the expected future impact of climate change. Due to structural uncertainty, it is questionable to attribute probabilities to GCM scenarios and to interpret the average outcome as the scenario with the highest probability of being true.

predicts a warming of 2.8°C with a 5% loss of precipitation across Western Europe. The three climate scenarios effectively represent a severe, moderate, and mild possible outcome, respectively. The mean temperature and precipitation in each member state of each scenario can be found in Appendix B.

4 Results

Section 3.1 presents the regression results across Western European farms. The first regressions use the entire sample in order to understand the impact climate has on the entire sector. A set of subsamples (rainfed and irrigated farms and cropland and livestock farms) is also analysed to understand different components of European agriculture. Section 3.2 utilizes the median regression of all farms to calculate marginal impacts. The expected nonmarginal impacts of future climate scenarios are calculated in Section 3.3. Section 3.4 analyses the robustness of the Ricardian regressions.

4.1 Ricardian regressions

Table 2 shows the coefficients and standard errors of the log-linear regression of the entire sample of farms. Both OLS and median quantile regressions are shown. In the quantile regression, twelve of the sixteen seasonal climate coefficients are statistically significant revealing that climate has a significant impact on the value of European farmland. Only one of the squared temperature coefficients is significant implying that seasonal temperature generally has a linear effect on land value across the data. Land values fall with warmer winter and summer temperatures but they increase with warmer spring and autumn temperatures. This is exactly the same qualitative result found in US studies (Mendelsohn et al. 1994, Mendelsohn and Dinar 2003, Massetti and Mendelsohn 2011a). Colder winters are beneficial because they kill pests, warmer springs and autumns are valuable because they lengthen the growing season, and warmer summers are harmful because they stress crops. The squared term for summer temperature is negative implying summer temperature has a hill-shaped relationship with farmland value. Dividing the linear coefficient by twice the squared coefficient reveals that the peak of the summer temperature function is at 9.5°C. Because most European farms are warmer than this peak, warmer summer temperatures are generally harmful in Europe.

Precipitation also significantly affects land values. All the squared terms of the median regression for seasonal precipitation are significant. The seasonal squared terms are generally negative except for spring, which is positive. Except for spring, precipitation has a hill-shaped relationship. More rainfall is good up to a point but then becomes harmful. The peak monthly precipitation is 37, 15, and 2 cm for winter, summer, and autumn respectively. This implies that in all regions of the EU-15 more winter rain is good (allowing farmers to start their season with moist soils) and more autumn rain is harmful because autumn rain damages many crops. For most regions of the EU-15 more summer rain is also beneficial. Spring precipitation has a U-shaped effect on land value, making it quite different from the other seasons. Increased spring rainfall is harmful at first and becomes beneficial only once it exceeds 8.8 cm/month.

Several of the control variables in the median regression are also significant. Gravel soils tend to be harmful. A higher pH (more alkaline soil) increases land value. Higher population density increases land values, which makes sense because higher density implies land is scarce. Greater distance to markets reduces land value whether it is to large cities or ports. The coefficient is twice as large for ports as cities suggesting ports (and therefore exports) lead to more valuable markets for farmers. Higher elevation is harmful. Generally, higher elevation farms must cope with harmful diurnal temperature variance. Increased longitude is harmful implying that there are disadvantages to being in a continental climate. Increased latitude is also harmful because it implies a reduction in solar radiation. Country fixed effects are generally significant implying higher average land values in Denmark, Ireland, West Germany, Italy, Sweden and the Netherlands, but lower values in Austria, France, East Germany, and especially Portugal.

Table 2 also compares the results of the median regression and an identical OLS regression using the whole sample. The coefficients from both models are quite similar and there are no changes in sign. The median regression leads to a flatter overall climate response function than the OLS. The extreme data points that tend to have more influence in the OLS regression lead to a slightly more sensitive response function. We use the Morgan-Granger-Newbold (MGN) significance test to compare the forecasting accuracy of the median regression and OLS models (Diebold and Mariano 2002). We use a random sample of 80% of our farms to estimate the Ricardian function and we forecast land values of the remaining 20% farms. We repeat the MGN test 500 times. We reject the null hypothesis of equal forecasting accuracy in favour of the median regression model in 44.6% of the repetitions but in favour of the OLS regression model in only 3.4% of the repetitions. These results suggest that the median regression model outperforms the OLS regression. We consequently present only the median results in the remainder of the paper.

Irrigation is an important adaptation of farmers to local climate. Irrigation reduces the dependency on rainfall and also reduces heat stress by supplying sufficient moisture to plants even in hot temperatures. However, irrigation is an endogenous decision and thus should not be included among the explanatory variables in the Ricardian model. Schlenker et al. (2005) and Kurukulasuriya et al. (2011) suggest estimating a separate Ricardian function for irrigated and rainfed farms. Such separate regressions are shown in Table 3. The regression in the first column in Table 3 is estimated only on rainfed farms. The second regression in Table 3 is estimated only on irrigated farms. Comparing the two regressions reveals that the coefficients for the irrigated farms are quite different from the coefficients of the rainfed farms. For example, the coefficients of the linear and squared terms of seasonal temperature are larger and more significant in the irrigated farm regression compared to the rainfed farm regression. The peak summer temperature for irrigated farms (17.7°C) is higher than for rainfed farms (13.7°C). Irrigation appears to increase the tolerance of plants to higher temperatures. The shape of the relationship between land value and seasonal precipitation is also quite different for rainfed versus irrigated farms as the two regressions often have different signs for the coefficients of the linear and squared precipitation variables.

The control variables also have different coefficients for irrigated versus rainfed farms. Gravel soils and increased latitude are harmful for rainfed farms and beneficial to irrigated farms. Higher latitude irrigated farms are more valuable but it should be understood that almost all of the irrigated farms are in the southern half of the EU-15. Higher longitude is more harmful to irrigated farms than rainfed farms. Sand and silt soils and rented land are harmful to irrigated farms but have no effect on rainfed farms. The sand results can be explained by an aversion to losing irrigation water. Irrigation involves expensive capital that renters may not take care of. Population density, higher pH, a wider range of elevation (hilliness), lower elevation, and access to ports are more beneficial to rainfed farms than irrigated farms. Access to cities is equally beneficial to both rainfed and irrigated farms.

Table 2: EU-15 Ricardian regressions

	EU-15 (median regression)		EU-15 (OLS regression)	
	coef	se	coef	se
Temperature winter	-0.267***	0.025	-0.271***	0.022
Temp. winter sq	0.001	0.002	0.008***	0.001
Temperature spring	0.370***	0.047	0.307***	0.043
Temp. spring sq	0.001	0.002	0.011***	0.002
Temperature summer	0.228***	0.079	0.092	0.075
Temp. summer sq	-0.012***	0.002	-0.011***	0.002
Temperature autumn	0.184**	0.084	0.520***	0.068
Temp. autumn sq	-0.004	0.003	-0.022***	0.003
Precipitation winter	0.149***	0.015	0.093***	0.015
Prec. winter sq	-0.002***	0.001	0.001**	0.001
Precipitation spring	-0.333***	0.029	-0.382***	0.029
Prec. spring sq	0.019***	0.002	0.017***	0.002
Precipitation summer	0.150***	0.020	0.121***	0.020
Prec. summer sq	-0.005***	0.001	-0.002	0.001
Precipitation autumn	0.025	0.017	0.067***	0.015
Prec. autumn sq	-0.007***	0.001	-0.009***	0.001
Gravel (t_gravel)	-0.047***	0.004	-0.055***	0.003
Sand (t_sand)	-0.004	0.003	-0.012***	0.002
Silt (t_silt)	-0.003*	0.002	-0.010***	0.001
pH	0.286***	0.017	0.300***	0.015
Rented land	-0.009	0.018	0.058***	0.018
Population density (Pdnsty)	0.320***	0.028	0.304***	0.025
Distance to cities (Cities500k)	-0.658***	0.098	-0.631***	0.084
Distance to ports (PortsML)	-1.199***	0.080	-1.184***	0.074
Elevation mean	-0.522***	0.058	-0.602***	0.063
Elevation range	0.055***	0.013	0.101***	0.012
Latitude	-0.040***	0.007	-0.066***	0.007
Longitude	-0.029***	0.003	-0.022***	0.003
Austria (AT)	-2.199***	0.065	-2.419***	0.062
Belgium (BE)	0.031	0.047	0.159***	0.055
Denmark (DK)	0.938***	0.063	1.088***	0.050
Spain (ES)	-0.712***	0.063	-0.658***	0.056
Finland (FI)	0.049	0.099	0.134	0.100
France (FR)	-1.276***	0.049	-1.127***	0.041
Greece (GR)	0.566***	0.102	0.546***	0.095
Ireland (IE)	1.104***	0.032	1.017***	0.030
Italy (IT)	0.924***	0.071	0.983***	0.059
Luxembourg (LU)	-0.312***	0.054	-0.197***	0.054
Netherlands (NL)	1.056***	0.045	1.097***	0.041
Portugal (PT)	-2.229***	0.079	-2.298***	0.064
Sweden (SE)	0.221***	0.076	0.418***	0.067
West Germany (WDE)	0.410***	0.047	0.387***	0.040
East Germany (EDE)	-0.965***	0.066	-1.118***	0.053
United Kingdom (UK)	(omitted)		(omitted)	
Constant	5.929***	0.683	8.237***	0.669
Number of observations	37612		37612	

*** p<0.01, ** p<0.05, * p<0.1

Table 3: EU-15 Ricardian median regressions with only rainfed farms, only irrigated farms, only specialized field crops and only specialized grazing livestock

	EU-15 (only rainfed)		EU-15 (only irrigation)		EU-15 (only crop farms)		EU-15 (only grazing)	
	coef	se	coef	se	coef	se	coef	se
Temp. winter	-0.137***	0.026	-0.486***	0.003	-0.334***	0.029	-0.342***	0.032
Temp. winter sq	0.004**	0.002	0.015***	0.000	-0.021***	0.002	-0.006***	0.002
Temp. spring	0.357***	0.047	-1.168***	0.007	-0.582***	0.064	-0.079	0.059
Temp. spring sq	-0.003	0.003	0.045***	0.000	0.046***	0.003	0.043***	0.004
Temp. summer	0.301***	0.080	1.097***	0.009	1.042***	0.113	1.061***	0.106
Temp. summer sq	-0.011***	0.002	-0.031***	0.000	-0.038***	0.003	-0.047***	0.003
Temp. autumn	0.019	0.082	1.323***	0.012	0.002	0.105	0.513***	0.105
Temp. autumn sq	-0.005	0.003	-0.022***	0.000	0.021***	0.005	-0.010**	0.004
Prec. winter	0.059***	0.016	-0.120***	0.001	0.225***	0.026	-0.019	0.021
Prec. winter sq	0.001	0.001	0.016***	0.000	-0.005***	0.001	0.004***	0.001
Prec. spring	-0.296***	0.032	0.606***	0.003	-0.054	0.041	-0.131***	0.035
Prec. spring sq	0.016***	0.002	-0.044***	0.000	-0.012***	0.002	0.007***	0.002
Prec. summer	0.130***	0.021	0.134***	0.002	0.129***	0.029	0.007	0.023
Prec. summer sq	-0.004***	0.001	0.003***	0.000	0.000	0.001	0.005***	0.001
Prec. autumn	0.076***	0.017	-0.287***	0.002	-0.283***	0.032	0.054***	0.019
Prec. autumn sq	-0.009***	0.001	0.010***	0.000	0.013***	0.002	-0.009***	0.001
t_gravel	-0.046***	0.004	0.006***	0.000	-0.074***	0.005	-0.028***	0.005
t_sand	0.001	0.003	-0.033***	0.000	-0.011***	0.004	-0.021***	0.004
t_silt	-0.003	0.002	-0.022***	0.000	-0.007***	0.002	-0.010***	0.002
pH	0.238***	0.017	0.064***	0.001	0.271***	0.022	0.107***	0.023
Rented land	0.027	0.018	-0.057***	0.001	-0.046**	0.019	0.210***	0.023
Pdnsty	0.255***	0.027	0.195***	0.003	0.256***	0.033	0.167***	0.033
Cities500k	-0.746***	0.100	-0.940***	0.008	-1.022***	0.112	-0.427***	0.131
PortsML	-1.299***	0.082	-0.743***	0.008	-0.691***	0.101	-1.175***	0.110
Elevation mean	-0.784***	0.063	-0.377***	0.004	-0.444***	0.074	-0.871***	0.076
Elevation range	0.038***	0.014	0.024***	0.001	0.220***	0.014	0.218***	0.023
Latitude	-0.063***	0.007	0.024***	0.001	-0.038***	0.009	-0.059***	0.010
Longitude	-0.031***	0.003	-0.058***	0.000	-0.076***	0.004	-0.035***	0.004
AT	-1.941***	0.065	-0.766***	0.012	-1.483***	0.079	-2.839***	0.079
BE	0.123***	0.045	1.329***	0.013	0.386***	0.070	-0.174***	0.053
DK	1.116***	0.062	0.771***	0.008	0.727***	0.075	0.932***	0.081
ES	-0.886***	0.063	-0.160***	0.014	-1.111***	0.078	-1.278***	0.074
FI	0.232**	0.096			-0.075	0.123	0.679***	0.118
FR	-1.242***	0.048	-0.666***	0.013	-1.165***	0.058	-1.594***	0.057
GR	0.500***	0.106	1.469***	0.014	1.053***	0.116	0.534***	0.136
IE	1.002***	0.030			1.636***	0.058	1.052***	0.033
IT	0.806***	0.074	1.641***	0.012	1.145***	0.091	1.010***	0.081
LU	-0.110**	0.053			0.307***	0.100	-0.279***	0.061
NL	1.149***	0.044			1.176***	0.053	1.011***	0.052
PT	-2.215***	0.080	-2.437***	0.014	-2.634***	0.109	-2.949***	0.098
SE	0.339***	0.072			0.528***	0.092	0.302***	0.091
WDE	0.578***	0.046	1.891***	0.013	0.639***	0.060	0.154***	0.058
EDE	-0.820***	0.063			-0.838***	0.072	-1.187***	0.083
UK	(omitted)		0.553***	0.013	(omitted)		(omitted)	
cons	7.689***	0.698	-5.019***	0.109	4.566***	0.977	3.033***	0.904
number obs.	28792		8820		8812		12575	

*** p<0.01, ** p<0.05, * p<0.1 Irrigated farms are classified as farms with at least 20% irrigated agricultural area. Crops farms are classified as specialized field crops (including cereals, root crops, field vegetables and various field crops). Grazing farms are classified as specialized grazing livestock (including dairying, sheep, goats, cattle rearing and fattening) (http://ec.europa.eu/agriculture/rica/).

Another important distinction between farms is whether they grow crops or raise livestock. The third and fourth columns in Table 3 are regressions on subsamples of only farms with crops and only farms with livestock. Although the winter and summer temperature coefficients for both groups are very similar, the spring and autumn temperature coefficients are significantly different. What is perhaps most striking, however, are the precipitation coefficients for the two land uses. They have completely different responses to precipitation.

Some of the control variables are also different between crop and livestock farms. Gravel soils are more harmful to crops, sandy soils, high elevation, and latitude are more harmful to livestock, alkaline soils, population density, less longitude (being closer to the Atlantic Ocean), and access (less distance) to cities are more beneficial to crops and access (less distance) to ports is more beneficial to livestock. The coefficients for the remaining control variables are similar. For example, the countries with relatively low valued cropland (Austria, Spain, France, Portugal and East Germany) also have low valued grazing land (although Austria's grazing land is worth a lot less than its cropland). The countries with high valued cropland (Greece, Ireland, Italy, Netherlands, and Denmark) also have high valued grazing land. Some of these control variables, such as elevation and longitude, may reflect omitted climate variables such as diurnal temperature variation (which increases with elevation) or interannual temperature variance (which increases with distance from oceans).

4.2 Marginal Analysis

The quadratic climate coefficients presented in Tables 2 and 3 are not straightforward to interpret because the marginal consequences depend on both the linear and squared coefficients and the point of comparison. In order to provide an easy interpretation of climate sensitivity at different climates, Table 4 presents the seasonal and annual marginal effects (Equation 7) of both temperature and precipitation using the median regression on the entire sample of farms (Table 2). Values are calculated at the median temperature and precipitation level for each country as well as for the EU-15 as a whole. Table 4 presents the percentage change in land values per °C of warming and per cm per month of additional precipitation. Table 5 presents the absolute marginal change in land value in €/ha/°C or €/ha/cm/mo (Equation 6).

For the EU-15 as a whole, temperature and precipitation have significantly different marginal effects on farmland value across seasons. Warmer winter and summer temperatures are harmful and warmer spring and fall temperatures are beneficial. These effects mirror results from the United States (see review Mendelsohn and Dinar (2009)). More precipitation in winter and summer is beneficial but more precipitation in spring and fall is harmful. The seasonal precipitation effects differ from the United States but the difference in seasonal precipitation patterns can explain this. Summing the seasonal temperature effects across the year suggests that the marginal effect of annual temperature is not different from zero for the EU-15 as a whole. Summing the marginal effect of seasonal precipitation across the year reveals that a marginal increase in annual precipitation increases farmland value in the EU-15.

The marginal effects differ a great deal across member countries within the EU-15 because each country has a different initial precipitation and temperature. Annual temperature has a beneficial marginal effect on the northern countries: Austria, Belgium, Germany, Denmark, Finland, Ireland,

Table 4: Percentage Land Value Marginal Effects at Median Temperature and Precipitation (%/ha per °C or cm/mo)

	Temp. annual	Prec. annual	Temp. winter	Temp. spring	Temp. summer	Temp. autumn	Prec. winter	Prec. spring	Prec. summer	Prec. autumn
Austria	0.044 ***	0.032 ***	-0.272 ***	0.382 ***	-0.185 ***	0.119 ***	0.130 ***	-0.063 ***	0.042 ***	-0.078 ***
Belgium	0.039 ***	0.042 ***	-0.260 ***	0.384 ***	-0.188 ***	0.104 **	0.125 ***	-0.081 ***	0.083 ***	-0.085 ***
Germany	0.048 ***	0.029 ***	-0.266 ***	0.382 ***	-0.180 ***	0.112 ***	0.131 ***	-0.129 ***	0.084 ***	-0.058 ***
Denmark	0.078 ***	-0.038 ***	-0.266 ***	0.380 ***	-0.151 ***	0.116 ***	0.130 ***	-0.165 ***	0.091 ***	-0.094 ***
Spain	-0.095 ***	0.043 ***	-0.252 ***	0.388 ***	-0.305 ***	0.075	0.129 ***	-0.164 ***	0.131 ***	-0.054 ***
Finland	0.095 ***	-0.046 ***	-0.288 ***	0.374 ***	-0.144 ***	0.153 **	0.137 ***	-0.218 ***	0.092 ***	-0.057 ***
France	0.013	0.062 ***	-0.257 ***	0.385 ***	-0.211 ***	0.096 **	0.124 ***	-0.077 ***	0.099 ***	-0.083 ***
Greece	-0.133 ***	0.034 ***	-0.254 ***	0.389 ***	-0.337 ***	0.069	0.120 ***	-0.159 ***	0.127 ***	-0.054 ***
Ireland	0.111 ***	0.008	-0.254 ***	0.382 ***	-0.126 ***	0.109 ***	0.111 ***	-0.058 ***	0.085 ***	-0.130 ***
Italy	-0.093 ***	0.028 ***	-0.251 ***	0.388 ***	-0.304 ***	0.074	0.122 ***	-0.118 ***	0.118 ***	-0.095 ***
Luxembourg	0.046 ***	0.043 ***	-0.264 ***	0.383 ***	-0.185 ***	0.112 ***	0.119 ***	-0.068 ***	0.082 ***	-0.091 ***
Netherlands	0.056 ***	0.005	-0.260 ***	0.383 ***	-0.173 ***	0.107 ***	0.126 ***	-0.128 ***	0.088 ***	-0.081 ***
Portugal	-0.124 ***	0.058 ***	-0.240 ***	0.392 ***	-0.326 ***	0.049	0.112 ***	-0.113 ***	0.137 ***	-0.078 ***
Sweden	0.082 ***	-0.029 ***	-0.274 ***	0.378 ***	-0.153 ***	0.131 ***	0.133 ***	-0.183 ***	0.092 ***	-0.071 ***
UK	0.102 ***	0.017 **	-0.258 ***	0.382 ***	-0.133 ***	0.111 ***	0.118 ***	-0.088 ***	0.086 ***	-0.100 ***
EU-15	0.019	0.023 ***	-0.257 ***	0.384 ***	-0.209 ***	0.100 **	0.125 ***	-0.123 ***	0.097 ***	-0.076 ***

The percentage change in land value for an increase of 1°C or 1cm/mo. Reported values are weighted based on total farm utilized agricultural land and the number of farms represented by each farm. Significant different from 0 (no impact): *** p<0.01, ** p<0.05, * p<0.1

Luxembourg, Netherlands, Sweden, and Great Britain. In contrast, annual temperature has a negative marginal effect on the southern countries: Spain, Greece, Italy, and Portugal. The magnitude of the marginal effects varies by countries. The marginal benefit is the highest in Sweden and Finland which gain about 9% of land value per °C. Spain, Greece, Italy, and Portugal all lose about 10% of land value per °C.

A marginal increase in annual precipitation is beneficial to Austria, Belgium, France, Germany, Greece, Italy, Luxembourg, Portugal, and Spain. Additional precipitation is harmful to Denmark, Finland, and Sweden and has no significant effect on Ireland, the Netherlands, and Great Britain. The northern countries in Europe near the Atlantic currently are wetter than the rest of the EU-15 and consequently do not benefit from more rain. The countries that gain the most from more rain are Portugal, France and Spain which all gain about 6% of land value per cm/month. Finland loses about 5% of land value per cm/month.

The pattern of marginal effects across seasons is stable across all the countries of the EU-15. Warmer spring temperature is beneficial and warmer winter and summer temperatures are harmful for every country. Autumn temperature generally has a positive marginal effect but it is not significant in every country. The marginal seasonal precipitation effects are completely stable across countries, increasing land values in winter and summer, and decreasing land values in spring and fall.

In Table 5 we see that the absolute marginal impact of annual temperature across all of Western Europe is not significantly different from zero. But the marginal annual temperature impact for Greece and Italy is significantly negative at -1000 €/°C/ha and the marginal impact for Ireland and the Netherlands is significantly positive at +2000 €/°C/ha. Column 2 reveals the marginal impact of more rainfall for all of Western Europe is +137 €/ha/cm/mo. However, the marginal impact of annual precipitation is negative for Scandinavia.

Table 5: Absolute Marginal Effects at Median Temperature and Precipitation (Euro/ha)

	All farms		Only rainfed		Only irrigation		Only crop farms		Only grazing	
	Temp. annual	Prec. annual	Temp. annual	Prec. annual	Temp. annual	Prec. annual	Temp. annual	Prec. annual	Temp. annual	Prec. annual
Austria	44 ***	32 ***	18	16 *	53 ***	280 ***	67 **	-34	82 ***	42 ***
Belgium	534 ***	570 ***	214	241 **	2,709 ***	3,650 ***	-7	-138	1,304 ***	69
Germany	618 ***	367 ***	289 *	73	2,829 ***	4,384 ***	-266	-142	1,379 ***	-36
Denmark	1,103 ***	-536 ***	893 ***	-881 ***	-22 *	3,650 ***	-1,362 ***	875 ***	1,140 ***	-882 ***
Spain	-279 ***	125 ***	-337 ***	52 *	-54 ***	999 ***	-186 ***	-8	-403 ***	-113 ***
Finland	304 ***	-145 ***	247 ***	-218 ***			-748 ***	235 ***	42	-114 ***
France	34	163 ***	-19	93 ***	506 ***	492 ***	-72	-29	126 ***	6
Greece	-1,195 ***	306 ***	-1,000 ***	201 ***	-623 ***	3,134 ***	-295 **	-119	-1,452 ***	-125
Ireland	2,321 ***	161	2,134 ***	-138			-32	473	5,155 ***	-462 ***
Italy	-1,222 ***	364 ***	-1,282 ***	5	385 ***	5,545 ***	-55	527 ***	-1,496 ***	-466 ***
Luxembourg	373 ***	353 ***	167	202 ***			-162	-196 **	1,002 ***	60
Netherlands	1,836 ***	178	1,187 **	-501 *			-579	900 **	4,258 ***	-725 **
Portugal	-146 ***	69 ***	-159 ***	52 ***	1,029 ***	1,241 ***	157 ***	-34	-90 ***	-27 ***
Sweden	361 ***	-129 ***	296 ***	-227 ***	-447 ***	2,004 ***	-1,176 ***	378 ***	92 *	-154 ***
UK	906 ***	147 **	835 ***	-13	1,476 ***	1,649 ***	-173	41	1,717 ***	-195 ***
EU-15	111	137 ***	102	16	162 ***	2,331 ***	-375 ***	28	555 ***	-43

Impact (in Euro/ha) of an increase of 1°C or 1cm/mo, reported values are weighted, based on total farm utilized agricultural land and the number of farms represented by each farm. Significance: *** p<0.01, ** p<0.05, * p<0.1

Table 5 also presents the absolute marginal effects for each of the subsamples explored in Table 3. The marginal results for rainfed land are similar to the results for all farms. The temperature and precipitation marginals for rainfed farms across all of Western Europe are not significant. However, Irish farms stand to gain +2000 €/ha/°C and Danish and Dutch farms stand to gain about +1000 €/ha/°C. In contrast, Italian and Greek farms stand to lose about -1000 €/ha/°C. The marginal impact of more rainfall for rainfed farms is similar to the results for all farms. Rainfall generally has a positive impact on country specific rainfed farms except for Ireland and the Scandinavian region.

The marginal climate impacts in irrigated farms are different. For one thing, irrigated farms are concentrated in southern Europe. Finland, Ireland, Luxembourg and the Netherlands have no irrigated farms. Across all the countries with irrigated farms, the marginal impact of temperature is +162 €/ha/°C. Belgium and Germany have temperature marginals of over +2500 €/ha/°C but these apply to only a small number of farms. Greece and Sweden have negative temperature marginals for irrigated land of -623 €/°C/ha and -227€/°C/ha. It is not clear what explains the Swedish results as there are few irrigated farms in Sweden. The precipitation marginal is significantly higher for irrigated farms than rainfed farms. Irrigation is often used in semi-arid locations, where precipitation is more valuable. Further, across a sample of irrigated farms, wetter places need less irrigation water. Italy has the highest precipitation marginal for irrigated land of +5545 €/ha/cm/mo. The lowest precipitation marginals are in Austria and France with +282 and +490 €/ha/cm/mo respectively.

Looking at farms that grow just crops reveals yet another distinction amongst farms. Across all of Europe, the temperature marginal for crops is negative and equal to -375 €/°C/ha. A surprising result, however, is that Denmark and Sweden (-1100 €/°C/ha) and Finland and the Netherlands all have large negative marginals. Given the cold temperatures of all these countries, it was expected that the temperature marginal would be positive.

The final result in Table 5 concerns the climate marginals of livestock farms. Across Western Europe the temperature marginal for livestock farms is +555 €/ha/°C. Livestock farms increase in value with warming while crop farms decrease. Livestock farms can clearly tolerate higher temperatures. The largest marginals are in Ireland and the Netherlands with +5155 and +4258 €/ha/°C. But the marginal temperature impacts in Belgium, Germany, Denmark, Luxembourg and the United Kingdom are all over +1000 €/°C/ha. The only countries with large negative temperature marginals for livestock are Greece and Italy. In general, livestock farms can also tolerate drier conditions relative to crop farms. However, many livestock farms are already in a dry location. So the precipitation marginal for livestock for all of Western Europe is not significantly different from zero. The precipitation marginal is only positive for Austria and it is just +60 €/ha/cm/mo. In contrast, most of the countries with negative precipitation marginals are wetter. Denmark and the Netherlands have negative precipitation marginals of -882 and -725 €/ha/cm/mo respectively but Finland, Ireland, Sweden, and the United Kingdom all have negative precipitation marginals for livestock. Curiously, both Spain and Italy also have negative precipitation marginals, which imply that although the countries are not wet, the livestock farms are in wet regions.

4.3 Nonmarginal climate projections

In this section, we examine the impact of the nonmarginal climate changes in 2100 predicted by each climate model: (i) Hadley CM3 (Had3), (ii) ECHO-G (ECHO) and, (iii) NCAR PCM (PCM) for the A2 (no mitigation) emission scenario. We use the coefficients from the estimated median quantile regression of all farms (Table 2) to measure the consequence of these future climate scenarios. We begin by calculating what the regression model predicts the current farmland value is in the EU-15. We then calculate what the model predicts the future farmland value will be given the new climate scenario. The calculation takes into account the predicted change in both temperature and precipitation at each NUTS3 location. The effects are then aggregated across space to measure country impacts and EU-15 impacts (Equation 8). The first two columns in Table 6 show the estimated current farmland value per hectare as well as the aggregate farmland value for each country and the EU-15 as a whole. The remaining columns show the change in land value per hectare and the change in aggregate land value associated with each climate scenario. For the EU-15 as a whole, land value per hectare falls in all three climate scenarios. The change in land value per hectare is -900 €/ha, -3200 €/ha, and -5000 €/ha for the PCM, ECHO, and Had3 scenarios respectively. The aggregate lost farmland value in the EU-15 is € -63 billion, € -232 billion, and € -364 billion, respectively. This is a capital loss and not an annual loss of net revenue. The damage reflects an aggregate loss of 8%, 28%, and 44% of farmland value respectively.

The effect is not at all uniform across the EU-15 and across climate scenarios. Denmark, the Netherlands, United Kingdom, and especially Ireland benefit in the PCM climate scenario. The farm values increase by 45% in Ireland. Denmark, Ireland, Sweden, and Great Britain benefit slightly in the ECHO climate scenario, and only Ireland shows a tiny benefit in the Had3 climate scenario. Italy has the largest aggregate losses with € -162 billion (-74%) in the Had3 scenario, € -143 billion (66%) in the ECHO scenario, and € -87 billion (-40%) in the PCM climate scenario.

Figures 1, 2 and 3 present maps of the percentage change in farmland value in each NUTS3 region for each climate scenario. All three climate scenarios show a negative impact of climate change on European agriculture. The impact is clearly worse moving from the PCM to the ECHO to the Had3 climate scenarios. With the PCM scenario, some regions in countries in the north gain (UK, Ireland, Denmark, Netherlands, Germany and Austria) whereas others in the south lose. For example, Portugal, Spain, Southern France, Italy and Greece all lose in the PCM scenario. With the ECHO

Table 6: Welfare change per hectare and total welfare change by 2100 by climate scenario

			Hadley CM3		ECHO-G		NCAR PCM	
	Land value (Euro/ha)	Total Land value (million Euro)	Impact (Euro/ha)	Total impact (million Euro)	Impact (Euro/ha)	Total impact (million Euro)	Impact (Euro/ha)	Total impact (million Euro)
Austria	1216	2510	-487	-1010	-270	-559	-168	-347
Belgium	16813	15100	-7409	-6640	-3724	-3340	-673	-604
Germany	16667	135000	-7493	-60700	-2234	-18100	-382	-3090
Denmark	18591	29800	-5273	-8450	2851	4570	1236	1980
Spain	3745	63800	-2928	-49900	-2563	-43700	-1619	-27600
Finland	3960	7000	-1406	-2480	-993	-1750	-1916	-3390
France	3486	36400	-2307	-24100	-1713	-17900	-722	-7550
Greece	10826	28400	-9148	-24000	-7051	-18500	-7333	-19200
Ireland	28124	123000	1598	7010	2520	11100	12615	55300
Italy	21794	218000	-16219	-162000	-14234	-143000	-8695	-87100
Luxembourg	10550	904	-5815	-498	-3667	-314	-531	-46
Netherlands	42063	60100	-13077	-18700	-3139	-4490	2235	3190
Portugal	1312	2070	-791	-1250	-927	-1460	-552	-869
Sweden	5790	10500	-2177	-3930	1524	2750	-1118	-2020
UK	10075	94600	-745	-7000	254	2390	3005	28200
EU-15	11303	828000	-4971	-364000	-3166	-232000	-861	-63100

Predicted current and future land values; all values are weighted to represent total farm utilized agricultural land

scenario, the damages get worse and the benefits shrink. With the Had3 scenario, the southern regions lose more than 60% of their land value and every country in Western Europe has a region that loses except Ireland. In contrast to other model approaches, our results show no uniform benefit in Northern Europe. Climate change can have a negative impact (e.g. in Finland). We predict damages in Finland from warming because the winter temperature increases by up to 8°C (see Appendix B). Depending on the climate scenario, in certain Northern regions the negative impact of increasing winter temperature dominates the other seasonal climate impacts.

In order to quantify the uncertainty surrounding the welfare estimates in Table 6, we build bootstrap confidence intervals. Samples were created using a random selection of farms with replacement. The median regression was then estimated for each sample. The impact of each climate scenario was then calculated. The process was then repeated 1000 times to generate 1000 values for each climate scenario. Figure 4 shows the results of the bootstrapping. The results illustrate that the ECHO and HAD3 unambiguously lead to harmful impacts on European agriculture by 2100. The milder PCM scenario is more likely to be harmful but there is a sizeable chance that it may be beneficial to European agriculture. The uncertainty across the climate models is quite large. There are two sources of uncertainty revealed in Figure 4. The uncertainty of the economic model is certainly large. However, the uncertainty from the climate models is also quite large (the uncertainty surrounding future cumulative emissions was not examined). The results reveal why it is important to examine more than a single climate model in economic analyses. Combining the two sources of uncertainty, it is not possible to rule out that climate change may be beneficial to European agriculture. However, the weight of the evidence definitely suggests there will be a sizable damage to European agriculture by 2100 if greenhouse gas emissions remain unchecked for the remainder of the century.

Figure 1: Percentage change in farmland values predicted by Hadley CM3 climate scenario (2100)

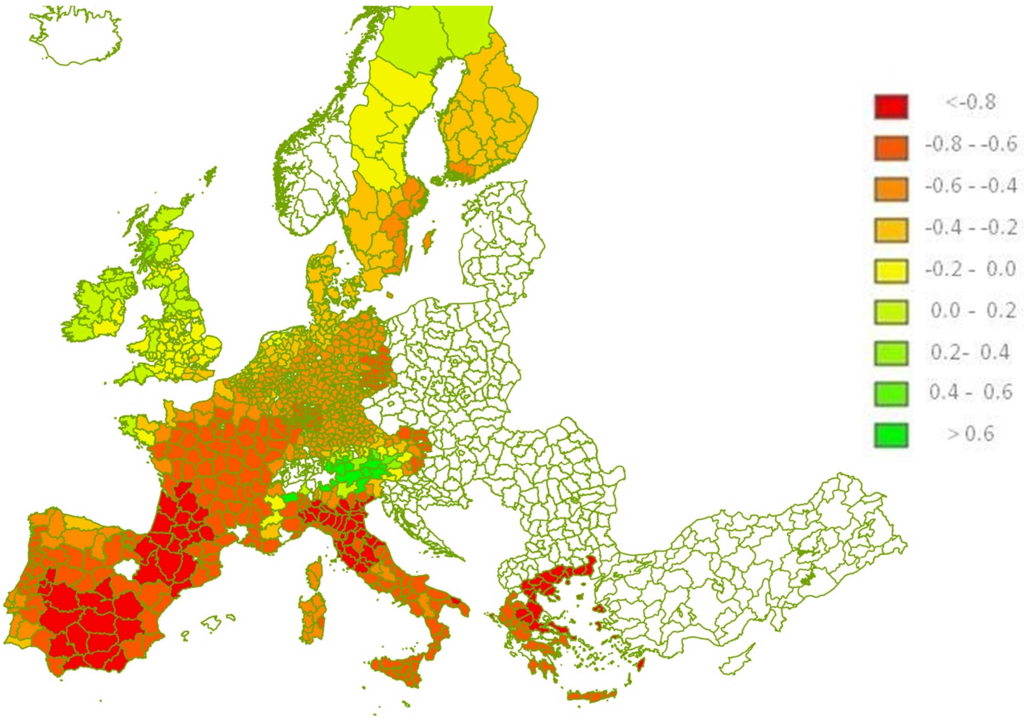


Figure 2: Percentage change in farmland values predicted by ECHO-G climate scenario (2100)

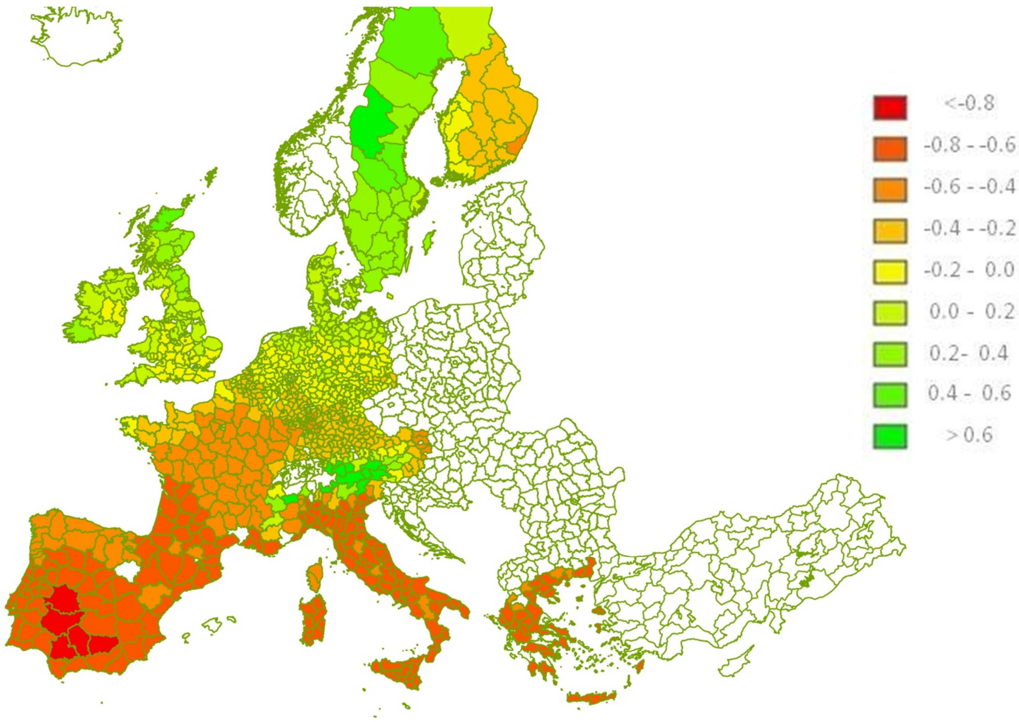


Figure 3: Percentage change in farmland values predicted by NCAR PCM climate scenario (2100)

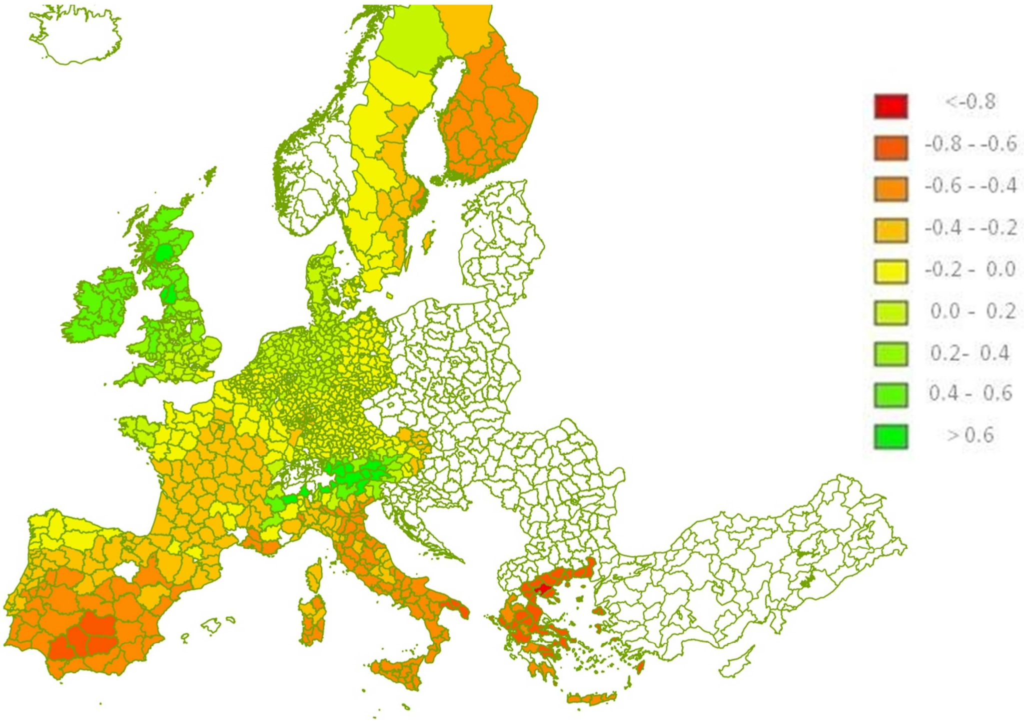
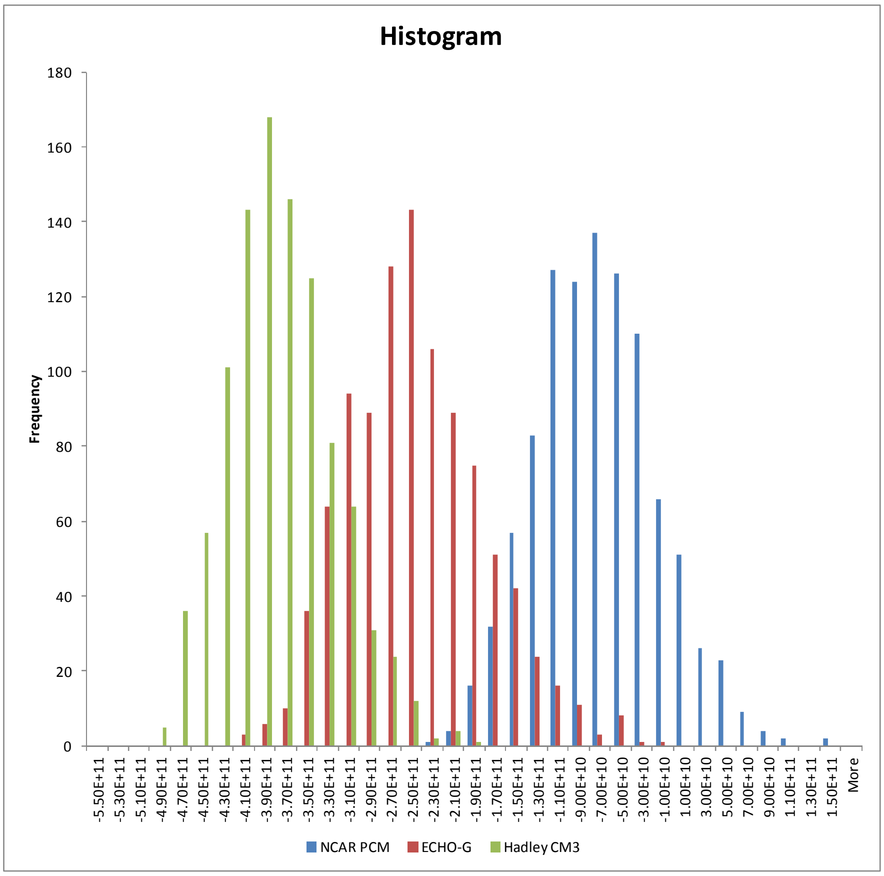


Figure 4: Probability distribution of farm impacts by climate scenario



Based on bootstrap estimation with 1000 repetitions.

4.4 Robustness checks

While Table 2 only showed the median and OLS regression, a range of quantile regressions are presented in Table 7. Quantile regressions reveal that climate has a different impact on low and high farmland values. For example, although higher temperatures in summer decrease agricultural land value in all quantiles, the squared term is higher when farms have lower land values. The squared summer temperature is not significant in the highest quantile. This implies that the concavity of summer temperature is decreasing with increasing farmland values. Similar differences can be found with regard to autumn temperature. The peak autumn temperature is low for low farmland values and high for median and high farmland values. As a result, warmer autumn temperatures are beneficial for farms with median and high farmland values but harmful for farms with lower land values. The impact of precipitation is different across different quantiles as well. Farms in the highest quantile are generally less sensitive to rainfall than other farms. One possible explanation is that these high valued farms incorporate other activities such as food processing or tourism that are less sensitive to climate.

In Table 8, we present a set of alternative regressions as a robustness check. The first column presents the median quantile regression without country fixed effects. Dropping the country fixed effects implies unmeasured country level effects are no longer controlled. However, the absence of controls allows there to be more variation in climate.

In the second column, we go in the opposite direction and add even more detailed spatial fixed effects. We include 63 regional dummies instead of the 15 country dummies in Table 2 to the medina quantile regression. Of course, the more fixed effects that are included, the less the remaining variation in climate. The removal of potential sources of bias is also removing the signal being tested, magnifying problems that arise from measurement error. All the climate coefficients drift towards zero as more and more controls are imposed. This same phenomenon can be seen in the panel regression results of Deschênes and Greenstone (2007) where the climate coefficients move towards zero as more and more controls remove the remaining variation of climate in the sample.

The third regression of Table 8 explores the role of spatial correlation in the analysis on an aggregated data sample of the 923 NUTS regions. In this analysis, we estimate the spatial standard errors following Conley (1999). Controlling spatial correlation has no effect on the magnitude or sign of the coefficients. However, it does tend to increase the standard error suggesting there are fewer degrees of freedom than the OLS model assumes. The mean farmland value per hectare of each region is the dependent variable and the average characteristics of each NUTS3 region are the independent variables. The coefficients have similar size but the standard errors are much larger because of the assumption of so much fewer observations.The coefficients of several climate variables are no longer significant. With the aggregated data, only winter, spring and autumn temperature and spring and autumn precipitation have a significant impact on farmland value.

Table 7: EU-15 Ricardian quantile regressions

	τ =0.1		τ =0.25		median regression τ = 0.50		τ =0.75		τ =0.90	
	coef	se	coef	se	coef	se	coef	se	coef	se
Temp. winter	-0.240***	0.018	-0.081***	0.010	-0.267***	0.025	-0.331***	0.016	-0.298***	0.029
Temp. winter sq	0.004***	0.001	0.001	0.001	0.001	0.002	-0.005***	0.001	0.002	0.002
Temp. spring	0.099**	0.043	0.063***	0.021	0.370***	0.047	0.207***	0.028	0.330***	0.046
Temp. spring sq	0.018***	0.002	0.023***	0.001	0.001	0.002	0.013***	0.001	0.010***	0.002
Temp. summer	0.877***	0.061	0.938***	0.032	0.228***	0.079	0.300***	0.050	-0.351***	0.096
Temp. summer sq	-0.033***	0.001	-0.032***	0.001	-0.012***	0.002	-0.018***	0.001	-0.001	0.003
Temp. autumn	0.498***	0.067	0.144***	0.041	0.184**	0.084	0.187***	0.053	0.435***	0.096
Temp. autumn sq	-0.019***	0.003	-0.016***	0.002	-0.004	0.003	0.005**	0.002	-0.008*	0.004
Prec. winter	-0.033***	0.012	-0.025***	0.006	0.149***	0.015	0.195***	0.009	0.048***	0.016
Prec. winter sq	0.006***	0.000	0.005***	0.000	-0.002***	0.001	-0.004***	0.000	-0.001	0.001
Prec. spring	-0.709***	0.025	-0.464***	0.012	-0.333***	0.029	-0.249***	0.019	0.062*	0.035
Prec. spring sq	0.034***	0.001	0.021***	0.001	0.019***	0.002	0.012***	0.001	0.001	0.002
Prec. summer	0.220***	0.017	0.078***	0.008	0.150***	0.020	0.161***	0.013	0.013	0.023
Prec. summer sq	-0.004***	0.001	0.003***	0.000	-0.005***	0.001	-0.006***	0.001	-0.001	0.001
Prec. autumn	0.244***	0.012	0.138***	0.007	0.025	0.017	0.000	0.011	0.046**	0.019
Prec. autumn sq	-0.018***	0.000	-0.012***	0.000	-0.007***	0.001	-0.005***	0.000	-0.006***	0.001
t_gravel	-0.051***	0.004	-0.052***	0.002	-0.047***	0.004	-0.044***	0.003	-0.043***	0.004
t_sand	0.006	0.003	0.005***	0.001	-0.004	0.003	-0.003*	0.002	-0.006**	0.003
t_silt	-0.002	0.002	0.001	0.001	-0.003*	0.002	-0.002	0.001	0.001	0.001
pH	0.221***	0.018	0.261***	0.008	0.286***	0.017	0.274***	0.010	0.333***	0.017
Rented land	0.055***	0.015	-0.013*	0.007	-0.009	0.018	0.042***	0.011	0.012	0.019
Pdnsty	0.137***	0.034	0.255***	0.015	0.320***	0.028	0.353***	0.015	0.356***	0.025
Cities500k	-0.137	0.085	-0.447***	0.040	-0.658***	0.098	-0.665***	0.064	-0.884***	0.120
PortsML	-0.574***	0.068	-1.133***	0.035	-1.199***	0.080	-0.862***	0.053	-0.427***	0.105
Elevation mean	-1.174***	0.053	-0.767***	0.026	-0.522***	0.058	-0.244***	0.037	-0.167**	0.069
Elevation range	-0.033***	0.011	0.071***	0.006	0.055***	0.013	0.122***	0.008	0.250***	0.012
Latitude	-0.113***	0.006	-0.064***	0.003	-0.040***	0.007	-0.013***	0.004	0.026***	0.007
Longitude	-0.050***	0.003	-0.022***	0.001	-0.029***	0.003	-0.035***	0.002	-0.024***	0.003
AT	-2.374***	0.057	-2.420***	0.028	-2.199***	0.065	-2.041***	0.040	-1.933***	0.074
BE	0.110***	0.034	0.064***	0.018	0.031	0.047	0.089***	0.030	0.191***	0.053
DK	0.955***	0.052	0.910***	0.026	0.938***	0.063	0.855***	0.038	0.956***	0.066
ES	-1.111***	0.053	-0.894***	0.026	-0.712***	0.063	-0.488***	0.038	-0.364***	0.070
FI	0.594***	0.093	0.081**	0.041	0.049	0.099	0.043	0.062	0.385***	0.112
FR	-1.558***	0.040	-1.358***	0.020	-1.276***	0.049	-1.209***	0.029	-1.021***	0.053
GR	1.119***	0.104	0.740***	0.044	0.566***	0.102	0.672***	0.064	0.627***	0.118
IE	0.674***	0.032	1.091***	0.015	1.104***	0.032	1.087***	0.020	0.854***	0.037
IT	1.059***	0.066	0.997***	0.029	0.924***	0.071	0.904***	0.045	0.928***	0.085
LU	0.210***	0.048	0.005	0.022	-0.312***	0.054	-0.514***	0.034	-0.340***	0.062
NL	1.142***	0.037	1.053***	0.019	1.056***	0.045	0.998***	0.027	1.015***	0.045
PT	-3.370***	0.071	-2.551***	0.033	-2.229***	0.079	-1.893***	0.047	-1.376***	0.082
SE	0.013	0.064	-0.043	0.031	0.221***	0.076	0.400***	0.047	0.820***	0.083
WDE	0.177***	0.040	0.303***	0.019	0.410***	0.047	0.491***	0.029	0.756***	0.051
EDE	-1.692***	0.057	-1.313***	0.026	-0.965***	0.066	-0.829***	0.040	-0.374***	0.068
UK	(omitted)		(omitted)		(omitted)		(omitted)		(omitted)	
cons	4.614***	0.560	3.424***	0.288	5.929***	0.683	4.172***	0.423	5.757***	0.717
number obs.	37612		37612		37612		37612		37612	

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Alternative EU-15 Ricardian regressions

	EU-15 (median) (no country dummies)		EU-15 (median) (regional dummies)		EU-15 (aggregated OLS) (country dummies)		
	coef	se	coef	se	coef	se	se corr
Temp. winter	0.064**	0.031	0.101***	0.004	-0.291***	0.077	0.113
Temp. winter sq	-0.001	0.002	-0.005***	0.000	0.005	0.005	0.009
Temp. spring	0.853***	0.064	0.570***	0.008	0.113	0.154	0.220
Temp. spring sq	-0.034***	0.003	-0.019***	0.000	0.022***	0.008	0.013
Temp. summer	-0.358***	0.095	0.664***	0.012	-0.058	0.265	0.445
Temp. summer sq	0.009***	0.002	-0.018***	0.000	-0.010	0.007	0.012
Temp. autumn	-0.491***	0.112	-0.812***	0.012	0.660***	0.240	0.351
Temp. autumn sq	0.012***	0.004	0.023***	0.000	-0.022**	0.010	0.016
Prec. winter	0.356***	0.020	0.281***	0.002	-0.010	0.055	0.094
Prec. winter sq	-0.012***	0.001	-0.004***	0.000	0.003	0.002	0.004
Prec. spring	-1.213***	0.044	-0.255***	0.004	-0.396***	0.102	0.149
Prec. spring sq	0.068***	0.002	0.001***	0.000	0.019***	0.005	0.008
Prec. summer	0.702***	0.029	0.066***	0.003	0.134*	0.072	0.095
Prec. summer sq	-0.037***	0.001	0.004***	0.000	-0.003	0.003	0.004
Prec. autumn	0.216***	0.023	-0.043***	0.003	0.113**	0.054	0.086
Prec. autumn sq	-0.011***	0.001	-0.004***	0.000	-0.010***	0.002	0.003
t_gravel	-0.047***	0.005	-0.064***	0.001	-0.032***	0.012	0.019
t_sand	-0.028***	0.004	-0.000	0.000	0.006	0.007	0.009
t_silt	-0.003	0.003	-0.006***	0.000	0.001	0.005	0.006
pH	0.672***	0.023	0.292***	0.002	0.289***	0.049	0.062
Rented land	-0.154***	0.027	0.013***	0.002	-0.599***	0.144	0.211
Pdnsty	0.543***	0.040	0.256***	0.004	0.390***	0.085	0.084
Cities500k	1.219***	0.128	-1.387***	0.013	-0.742**	0.307	0.427
PortsML	-1.247***	0.104	-0.323***	0.013	-0.474*	0.261	0.419
Elevation mean	-1.044***	0.090	-0.016**	0.008	-0.561***	0.215	0.287
Elevation range	0.082***	0.018	-0.010***	0.002	0.185***	0.042	0.075
Latitude	-0.055***	0.009	0.071***	0.001	-0.054**	0.024	0.038
Longitude	0.027***	0.002	-0.008***	0.001	-0.038***	0.011	0.018
AT					-2.221***	0.216	0.274
BE					0.509***	0.171	0.176
DK					1.115***	0.174	0.232
ES					-0.666***	0.188	0.268
FI					0.565*	0.336	0.385
FR					-0.914***	0.142	0.198
GR					0.941***	0.333	0.518
IE					0.829***	0.121	0.182
IT					1.116***	0.205	0.330
LU					0.189	0.182	0.179
NL					1.194***	0.148	0.132
PT					-1.780***	0.229	0.428
SE					0.563**	0.232	0.309
WDE					0.774***	0.141	0.167
EDE					-0.316*	0.182	0.232
UK						(omitted)	
regional dummies			(not reported)				
cons	10.675***	0.928	1.853***	0.108	8.383***	2.369	3.773
number obs.	37612		37612			923	

*** p<0.01, ** p<0.05, * p<0.1

5 Discussion and Conclusions

This study shows that current climate plays a role in determining the existing distribution of farmland values across Europe. Seasonal climatic variables have a strong influence on European farmland values. Farms with warmer spring temperature, cooler summer temperature, and more precipitation have higher values than other farms.

The research also provides indications of how changes in climate would affect European farms in the future. Marginal temperature increases in spring and autumn would increase farmland values but similar increases in summer and winter temperature would reduce farmland value. Adding these marginal seasonal effects yields an annual marginal effect, which is not significantly different from zero. Small changes in temperature will have no net effect on European agriculture. Marginal precipitation increases in spring and autumn are harmful but marginal precipitation increases in winter and summer are harmful. Summing these seasonal effects across the year reveals that a marginal increase in annual precipitation would be beneficial for Western European agriculture.

Marginal effects are not the same in each country. Warmer marginal temperatures are harmful in southern European countries whereas they are beneficial in northern European countries. A marginal increase in precipitation would benefit most European countries except for Ireland, Great Britain, and the Netherlands.

These results are consistent with the results found in other studies. Ricardian studies in Great Britain and Germany find similar positive marginal impacts of temperature in those countries (Maddison 2000, Lang 2007, Lippert et al. 2009). The crop model studies find similar patterns of marginal impacts across Western Europe with benefits in the northern countries and damages in the southern countries (Ciscar et al. 2011). US Ricardian studies also have similar patterns of seasonal effects (e.g. Mendelsohn et al. (1994); Massetti and Mendelsohn (2011b)). Effects within the US vary in a similar way with beneficial warming in northern states and harmful warming in southern states.

This study is the first Ricardian analysis to use quantile regressions. Using a Morgan-Granger-Newbold test, we found that the median quantile regression outperforms the more traditional OLS regression. The median quantile regression is less sensitive to extreme observations. Further, the full set of quantile regressions offer a rich and varied view of the entire population of farms. It provides a way to explore heterogeneity in response to climate change.

The climate sensitivity of irrigated farms is not the same as the climate sensitivity of rainfed farms. Rainfed farms cannot be used to predict the climate outcome of irrigated farms (and vice-versa). Irrigated farms are less temperature sensitive than rainfed farms. The analysis also suggests that the climate sensitivity of cropland and grazing land is different. Livestock farms are less temperature sensitive than crop farms. In order to measure the climate sensitivity of the entire agricultural sector, however, it is important to estimate a Ricardian model with both samples included. Analysing the impact of climatic variables on just crops or just livestock does not account for the endogenous choice of farm type.

The climate coefficients suggest that climate change is going to have a strong influence on future farmland values in Europe. The results suggest that climate change will be harmful to European agriculture by 2100. European agriculture is harmed in every tested climate scenario. The impacts are very different, however, for each climate scenario. With the milder climate scenario (NCAR PCM), European farms lose an average 8% of their value. With the more intermediate climate scenario (ECHO-G), European farms lose 28% of their value by 2100. Finally, with the more severe Hadley CM3 climate scenario, farms lose 44% of their value by 2100.

The impact of climate change is not uniform across Europe. With all three climate scenarios, the impact is more severe in southern Europe which is harmed in all cases. In contrast, with the two milder climate scenarios, several northern European countries benefit from climate change. Only Ireland appears to benefit in all three climate scenarios.

The Ricardian model captures adaptations that farmers can make with current crops, livestock, and technology. The analysis does not take into account adaptations that can be made with future breeds, varieties, and technologies. One important role of government is to conduct research and technology that might provide farmers with new opportunities to adapt to climate. Another important role of government is to manage surface and ground water supplies to increase their overall efficiency. Finally, governments have an important role to play in reforming agricultural policy to facilitate farm adaptation. They must be careful to avoid creating incentives that inadvertently discourage farmers from making efficient responses to climate change.

Note that we use the estimated Ricardian functional form to predict how future climate change might affect future agricultural land value, assuming that all other conditions are kept constant. In other words, we simply isolate the effect of climate change and we do not make a forecast of how farmland values change because of other factors. We do not take into account other likely changes in technology, prices, and capital. A major advantage of the Ricardian approach is that structural changes and farm responses are implicitly taken into account. Our study also takes into account all current major farming activities in Europe such as crop and livestock farms.

There remain several promising topics for future research. It is important to understand how European farmers can best cope with future climates. Estimating how farmers have in fact adapted to the different current climates in Europe would provide valuable insights. It would be desirable to expand this analysis to include the new European member states of Eastern Europe. Future studies should also explore how future climates may affect water supplies and how best to cope with these changes. Finally, both the impact and adaptation research should examine a wider array of climate models and emission scenarios.

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Appendix A: Overview of the model variables

Variable	Description	Source
	Farm specific socio-economic variables	
Agricultural land value (Euro/ha)	The agricultural land is valued on the basis of prices (net of acquisition costs) applying in the region for non-rented land of similar situation and quality sold for agricultural purposes. The replacement value is divided by the utilized agricultural area in owner occupation.	FADN
Rented land (ha/ha)	Total leased land per total utilized agricultural land	FADN
	Regional socio-economic variables	
Pdnsty (1000 cap/km²)	The population density in 2010	ESRI, MBR and EuroGeographics
	Regional specific climatic variables	
Temp. winter(°C)	Average air temperature 1961-1990 during winter	CRU
Temp. spring(°C)	Average air temperature 1961-1990 during spring	CRU
Temp summer(°C)	Average air temperature 1961-1990 during winter	CRU
Temp. autumn(°C)	Average air temperature 1961-1990 during spring	CRU
Prec. winter(cm/mo)	Precipitation 1961-1990 during winter	CRU
Prec. spring(cm/mo)	Precipitation 1961-1990 during spring	CRU
Prec. summer(cm/mo)	Precipitation 1961-1990 during summer	CRU
Prec. autumn (cm/mo)	Precipitation 1961-1990 during autumn	CRU
	Regional specific soil characteristics	
t_gravel (%vol)	Volume percentage gravel (materials in a soil larger than 2mm) in the topsoil	World Soil database
t_sand (%wt)	Weight percentage sand content in the topsoil	World Soil database
t_silt (%wt)	Weight percentage silt content in the topsoil	World Soil database
t_clay(%wt)	Weight percentage clay content in the topsoil	World Soil database
pH	pH measured in a soil-water solution	World Soil database
	Regional specific geographic variables	
Cities500k (1000 km)	Distance from cities with population > 500 000	Natural Earth data
PortsML (1000 km)	Distance from medium and large ports	World port index
Elevation mean (km)	Mean level of elevation	ESRI
Elevation range (km)	Range of elevation	ESRI
Latitude (°)	Latitude	ESRI
Longitude (°)	Longitude	ESRI
Country dummies	AT (Austria), BE (Belgium), WDE (West-Germany), EDE (East-Germany)[5], DK (Denmark), ES (Spain), FI (Finland), FR (France), GR (Greece), IE (Ireland), IT (Italy), LU (Luxembourg), NL (Netherlands), PT (Portugal), SE (Sweden), UK (United Kingdom)	FADN

[5] We opt to divide Germany in two regions: West and (former) East Germany. Mapping residuals revealed high correlation between the NUTS3 regions of former Eastern Germany, if we only use one German country dummy. The average farm land value in West-Germany is 21475 Euro, while the average farm land value in East-Germany is only 6174 Euro.

Appendix B: Overview of the current climate and climate scenarios used (mean values)

	Temp. Winter (°C)				Temp. Spring (°C)				Temp. Summer (°C)				Temp. Autumn (°C)			
	B	1	2	3	B	1	2	3	B	1	2	3	B	1	2	3
Austria	-2.1	1.1	2.6	2.2	6.5	8.9	10.8	10.7	15.4	18.1	20.4	21.5	7.7	10.9	12.5	12.9
Belgium	2.5	5.3	5.9	5.8	8.6	10.7	11.8	11.7	16.6	18.5	21.0	21.4	10.3	13.2	14.5	14.7
Germany	0.3	3.5	4.2	4.4	7.8	10.2	11.3	11.4	16.4	18.4	20.5	21.2	9.1	12.2	13.5	13.8
Denmark	0.3	4.5	3.7	4.3	6.3	9.1	9.5	9.7	15.4	17.3	18.6	19.4	9.0	12.0	13.1	13.2
Spain	6.3	8.7	10.0	9.6	11.7	14.3	15.6	16.0	21.6	25.1	27.3	29.5	14.4	17.6	19.5	19.6
Finland	-7.9	0.2	0.3	-0.3	2.3	5.7	7.7	7.4	14.8	17.1	18.5	19.8	4.1	8.8	9.7	10.0
France	3.9	6.3	7.3	7.0	9.5	11.5	13.1	12.7	17.6	20.1	23.1	24.0	11.5	14.5	16.1	16.2
Greece	6.1	8.6	9.5	9.3	12.7	15.2	16.8	16.6	22.6	26.5	28.2	29.5	15.3	18.4	19.9	20.4
Ireland	4.8	7.2	7.1	6.9	7.9	10.0	9.9	9.9	13.9	15.5	16.8	16.4	9.7	12.3	12.9	12.5
Italy	5.6	8.2	9.2	9.1	11.4	13.7	15.4	14.9	20.8	23.9	26.7	27.0	14.2	17.2	19.0	19.0
Luxembourg	1.2	4.1	4.9	4.8	8.3	10.4	11.9	11.6	16.6	18.6	21.7	21.8	9.4	12.5	14.0	14.1
Netherlands	2.7	5.7	6.0	6.0	8.3	10.6	11.4	11.4	16.1	17.9	20.0	20.3	10.1	13.0	14.2	14.3
Portugal	9.0	11.1	12.8	12.1	13.5	15.8	17.3	18.1	21.6	24.8	27.0	28.3	16.2	19.2	21.3	21.1
Sweden	-3.2	2.5	1.5	1.9	4.5	7.4	8.6	8.4	14.9	16.9	18.1	19.9	6.5	10.1	11.0	11.4
UK	3.5	6.2	6.3	6.0	7.3	9.7	9.8	10.0	14.2	16.0	17.6	17.6	9.4	12.2	13.0	12.8
	Prec. Winter (cm)				Prec. Spring (cm)				Prec. Summer (cm)				Prec. Autumn (cm)			
	B	1	2	3	B	1	2	3	B	1	2	3	B	1	2	3
Austria	6.1	6.6	6.6	7.5	8.3	9.5	8.2	9.2	12.2	12.0	11.7	8.9	7.8	7.4	7.5	7.2
Belgium	7.2	7.5	8.9	8.7	6.8	7.7	6.9	7.1	7.4	6.9	5.7	4.1	7.6	6.9	7.7	7.7
Germany	5.2	6.0	7.1	6.3	5.7	7.0	6.2	6.8	7.7	7.8	6.7	4.6	5.7	5.3	6.3	5.5
Denmark	5.4	6.7	8.2	6.7	4.5	5.3	5.4	5.4	6.4	7.2	6.4	5.1	7.7	7.8	9.8	8.4
Spain	6.0	5.7	4.5	5.8	5.1	4.4	3.3	2.5	2.4	1.6	1.3	0.8	5.4	4.8	4.0	3.9
Finland	3.3	4.3	5.5	4.7	3.1	3.3	4.4	3.6	6.4	7.2	6.3	6.7	5.6	6.5	7.2	6.4
France	7.2	7.2	7.3	8.4	7.0	7.3	6.0	5.8	6.1	5.3	3.8	2.1	7.4	6.8	6.5	6.6
Greece	8.0	7.1	7.0	7.9	4.8	4.7	3.2	3.8	2.2	1.2	1.8	1.2	5.7	4.5	4.6	5.0
Ireland	10.9	12.3	12.8	12.9	7.8	8.4	8.5	8.1	7.3	7.2	6.1	5.1	10.9	11.2	11.0	11.4
Italy	7.4	7.1	6.7	7.9	6.4	6.7	5.3	5.3	4.9	4.3	3.9	2.9	8.4	7.6	7.6	7.1
Luxembourg	8.1	8.5	9.2	9.6	7.1	8.3	7.2	7.7	7.4	6.8	5.4	3.3	7.7	7.1	7.4	7.5
Netherlands	6.2	6.8	8.5	7.7	5.5	6.4	5.9	6.1	6.9	6.8	5.7	4.4	7.1	6.4	7.8	7.4
Portugal	10.2	10.0	8.2	9.6	6.0	5.5	4.4	3.4	1.7	0.8	0.7	0.8	7.0	5.9	4.9	5.3
Sweden	4.4	5.7	6.9	5.5	3.9	4.7	5.0	4.8	6.3	7.2	6.4	6.0	6.4	6.7	8.1	7.0
UK	9.7	10.5	12.1	11.1	7.3	7.7	7.8	7.4	7.4	7.3	6.3	4.8	10.0	9.8	10.9	10.4

Scenarios: B (CRU 1961-1990 climate data); 1 (NCAR PCM 2100); 2 (ECHO-G 2100); 3 (HADLEY CM3 2100); the temperature is given in °C and the precipitation in cm per month.