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

Peer-reviewed author version

VAN PASSEL, Steven; Massetti, Emanuele & Mendelsohn, Robert (2017) A Ricardian Analysis of the Impact of Climate Change on European Agriculture. In: ENVIRONMENTAL & RESOURCE ECONOMICS, 67(4), p. 725-760.

DOI: 10.1007/s10640-016-0001-y
Handle: http://hdl.handle.net/1942/24460

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

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 41,030 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 impacts from +5% to -32% by 2100 depending on the climate scenario. Farms in Southern Europe are predicted to be particularly sensitive, suffering losses of -5% to -9% per degree Celsius.

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

JEL: Q54, Q51, Q15

Introduction

Although there have been several economic analyses of the impact of climate change on American agriculture (Mendelsohn et al. 1994; Mendelsohn and Dinar 2003; Schlenker et al. 2005; Deschênes and Greenstone 2007), there have been few studies in Europe. Because data collected by countries across Europe was traditionally incompatible, European Ricardian studies were long limited to single country analyses such as in Germany (Lang 2007; Lippert et al. 2009) and Great Britain (Maddison 2000). Previous studies of the impact of climate change on European-wide agriculture relied on crop models (e.g. Ciscar *et al.*, 2011). These crop studies carefully describe how climate affects many crops but usually assume limited and exogenous adaptations by farmers. Crop studies also leave out impacts to livestock. The crop studies may thus underestimate the adaptation potential in agriculture.

This study addresses these shortcomings in the literature by analysing EU-wide farm level data. The data set is collected by the European Union (EU) to administer farm policies. This data set contains individual data about farms in small geographic units (similar to US counties) across Europe. The study relies on a sample of over 41,000 farms that have been selected by the European Union to be representative of the agricultural sector in the EU-15 (Western Europe). A recent study by Moore and Lobell (2014) has also relied on this data source to study farm adaptation. This study estimates the impact of climate on farmland values.

The Ricardian method estimates the long-run relationship between agricultural land values and climate (Mendelsohn et al. 1994). The Ricardian model captures the underlying productivity of land, the annual net revenue that land generates. The model tests whether climate explains why some land is more productive than others. With competitive land markets, agricultural land productivity is capitalized into the value of land (Ricardo 1817). A complementary view is that the Ricardian method is an hedonic model of farmland value that explains what fraction of value is due to climate.

The Ricardian approach captures two phenomena. On the one hand, the model captures the direct effect of climate on individual crops. This corresponds to the results of crop experiments and crop models that predict changes in yields for specific crops as climate changes. The model also captures how climate affects the climate-sensitive choices of farmers. Research studies have found that crop choice (Seo and Mendelsohn 2008; Wang et al. 2009; Kurukulasuriya et al. 2011), livestock choice (Seo and Mendelsohn 2008), and irrigation are all climate sensitive choices. Unfortunately, many crop modelling exercises fail to capture this second effect and so overestimate the likely damages associated with climate change. One of the strengths of the Ricardian model is its ability to reflect endogenous adaptation.

One of the important insights of agronomic research on crop yields is that the climate response of most crops is hill-shaped. In order to capture this nonlinearity, the Ricardian method has tested nonlinear climate response functions. Agronomy also suggests that the climate sensitivity of crops varies with their stage of development. It is therefore important to test for seasonal climate effects. Unfortunately, this complexity makes the climate response model difficult to interpret. The literature consequently evaluates Ricardian models by showing marginal impacts, the effect of changing climate just slightly from observed values, and by estimating nonmarginal impacts, exploring how the Ricardian model responds to very different climates. We follow this tradition and show the response to both small and large changes in both temperature and precipitation. In order to examine realistic climates, we turn to a range of climate predictions made by climate models for 2100. Note that this exercise is not intended to be a forecast of outcomes in 2100, which would require extensive knowledge of other factors that may be very different by that time.

One of the advantages of this study is that there are so many observations being examined. In order to take advantage of all this micro data, the paper explores quantile regressions to estimate the Ricardian model. The quantile regression offers some advantages over the more traditional OLS regression by separating out the behaviour of different segments of the farm sector. For example, the quantile regressions reveal how climate affects the more marginal farms of Europe as well as the most valuable. The quantile regressions thus permit a closer view of how the huge diversity of farms in Europe (from vineyards to grazing) will respond to climate change.

There is an extensive literature that has used the Ricardian method to study the climate sensitivity of agriculture in 32 countries around the world (Mendelsohn and Dinar 2009). There is also a rich literature examining possible weaknesses of the Ricardian technique. 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 causes 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 exogenously using the results of crop experiments. The Ricardian approach is a comparative static analysis of long run equilibriums. It does not capture the cost or the dynamics of moving from one equilibrium to another (Kelly et al. 2005). Intertemporal analyses of weather are much more appropriate tools for capturing the short run dynamics associated with weather changes (Deschênes and Greenstone (2007).

There has also been an extensive debate concerning whether the Ricardian technique properly accounts for irrigation (Schlenker et al. 2005). Some Ricardian studies have carefully controlled for the availability of surface and groundwater (Mendelsohn and Dinar 2003; Kurukulasuriya et al. 2011; Massetti and Mendelsohn 2011). Unfortunately, such data are not available for this study. We do examine the climate response function of both rainfed versus irrigated farms in order to demonstrate how important these choices are to farm outcomes. As shown in the literature for Africa (Kurukulasuriya et al. 2011; Kala et al. 2012), South America (Seo and Mendelsohn 2008) and China (Wang et al. 2009), the climate response functions of rainfed and irrigated farms are different.

A special concern in Europe is whether the EU Common Agricultural Policy distorts climate sensitivities. For example, farm subsidies can hide (exaggerate) climate sensitivity if the subsidies are higher for farms in adverse (favourable) climates. We control for subsidies at the farm level. The analysis also includes country fixed effects to remove the influence of country level policies.

The paper is organized as follows. In section 1, we briefly explain the theory behind 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 measures of the impacts of different future climate scenarios by General Circulation Climate Models (GCM). The paper concludes with a summary of the results, policy conclusions, and limitations.

1. Methodology

The Ricardian model assumes that each farmer *i* chooses which output ($Q_{i,j}$) and how much inputs ($X_{i,k}$) to maximize net revenues (NR_i) each year:

$$NR_i = \sum_j \mathrm{P_j Q_{i,j}}(\mathrm{X_{i,k}}, \mathrm{Z_i}) - \sum_k \mathrm{M_k X_{i,k}} \quad (1)$$

where P_j is the market price of each output *j*,

$Q_{i,j}$ is the quantity of each output j at farm i, is a vector of purchased inputs k (other than land), M_k is a vector of input prices, and Z_i is a vector of exogenous variables at the farm. Farmers will choose both the type of output and their inputs to maximize net revenue given prices and exogenous factors. Looking at the final outcomes across a large set of farmers in different settings, net revenue will be a function of just the exogenous factors. Farmland value (V_i) is equal to the present value of future net revenue:

$$\mathrm{V}_i = \int_t^{\infty} NR_t \mathrm{e}^{-\varphi \mathrm{t}} \mathrm{dt} \quad (2)$$

where φ is the interest rate and V_i is therefore a function of only the exogenous variables:

$$\mathrm{V}_i = \mathrm{f}(Z_i) \,. \quad (3)$$

The cross sectional Ricardian regression estimates equation (3). Endogenous variables selected by the farmer such as fertilizer or crop choice should not be included as independent variables in the regression. When endogenous variables are included in the Ricardian regression, those factors are “controlled” or held fixed and not allowed to vary with climate. 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 use data on farmland value per hectare (V_i) from the FADN (Farm Accountancy Data Network). Farmland value is measured as the replacement value of agricultural land in owner occupation. The farm accountancy data are harmonized, applying the same bookkeeping and valuation principles across the entire sample.

Although we have tested a linear functional form, we find that a log-linear form fits the data best because land values are log-normally distributed (Schlenker et al. 2006; Massetti and Mendelsohn 2011)[1]. We use the climatology of each location (the 30 year average seasonal temperature and rainfall) to measure climate. We include four seasons because 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)). Some authors (e.g. Schlenker et al. (2006); Moore and Lobell (2014)) have promoted the idea of using just climate during the growing season. But perennials and winter crops are very relevant in Europe so that the growing season is all year long. Further, the climate during the "nongrowing season" has an impact on land value and is correlated with the climate during the growing season. Failure to include all seasons leads to biased climate coefficients. Finally, the agronomic and economic literature also suggests that the relationship between climate and land values is nonlinear (see review in Mendelsohn and Dinar (2009)). We therefore estimate the following model for each farm *i*:

$$\ln \mathrm{V_i} = \alpha + \beta_\mathrm{T}\mathrm{T_i} + \gamma_\mathrm{T}\mathrm{T_i^2} + \beta_\mathrm{R}\mathrm{R_i} + \gamma_\mathrm{R}\mathrm{R_i^2} + \eta\mathrm{E_i} + \xi\mathrm{D} + \mathrm{u_i} \tag{4}$$

where *T* and *R* are vectors reflecting seasonal temperatures and precipitations, *E* is a set of exogenous 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 cumulative distribution F $(F(y) = P(Y < y))$, the τ-th quantile is defined by $Q_y(\tau) = \inf\{y: F(y) \geq \tau\}$. The 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 4, we can run a quantile regression (Koenker and Bassett 1978) for each different value of τ:

$$Q_{\ln \mathrm{V_i}}(\tau|T,R,E,D) = \alpha(\tau) + \beta_\mathrm{T}(\tau)\mathrm{T_i} + \gamma_\mathrm{T}(\tau)\mathrm{T_i^2} + \beta_\mathrm{R}(\tau)\mathrm{R_i} + \gamma_\mathrm{R}(\tau)\mathrm{R_i^2} + \eta(\tau)\mathrm{E_i} + \xi(\tau)\mathrm{D} \tag{5}$$

The median quantile regression estimate is more robust against outliers compared to OLS 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 across the entire sample.

[1] 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.

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. Although in principle finer geographic controls for unmeasured spatial correlates, an overuse of fixed effects can significantly inflate the variability of the estimates of other covariate coefficients (Koenker 2004). The risk of ever-finer controls is a reduction in the climate variation within the sample. The climate signal becomes weaker with each additional layer of fixed effects. In the end, measurement error can dominate the results and bias the climate 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:

$$\left[\frac{\partial Q_{V_i}(\tau|\, T, R, E, D)}{\partial T_i}\right] = V_i(\tau)(\beta_T(\tau) + 2\gamma_T(\tau)T_i) \tag{6}$$

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:

$$MI_{T_r}(€) \stackrel{\text{def}}{=} \left[\frac{\partial Q_{V_{i,r}}(\tau|T, R, E, D)}{\partial T_{i,r}}\right] = \sum_{i=1}^{n} V_i(\tau)(\beta_T(\tau) + 2\gamma_T(\tau)T_i)\omega_i \tag{7}$$

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. One can also calculate the percentage change in land value associated with a small change in temperature:

$$MI_{T_r}(\%) \stackrel{\text{def}}{=} \left[\left[\frac{\partial Q_{V_{i,r}}(\tau|T, R, E, D)}{\partial T_{i,r}}\right] / V_{i,r}(\tau)\right] = \left[\sum_{i=1}^{n}(\beta_T(\tau) + 2\gamma_T(\tau)T_i)\omega_i\right] \tag{8}$$

In order to test the effect of very different climates, one can compare the predicted land value of a hypothetical climate (T_1, R_1) to the estimated value of land with the original climate (T_0, R_0):

$$\Delta W_r = \sum_{i=1}^{n}\left[Q_{V_i}(\tau)(T_1, R_1) - Q_{V_i}(\tau)(T_0, R_0)\right]\omega_i \tag{9}$$

where $Q_{V_i} = \exp(\alpha + \beta_T T_i + \gamma_T T_i^2 + \beta_R R_i + \gamma_R R_i^2 + \eta E_i + \xi D)$.

2. Data and model specifications

2.1. Data description

This is the first study that utilizes the FADN (farm accountancy data) across Western Europe to estimate a Ricardian model. The FADN data has also been used recently to estimate farm adaptation (Moore and Lobell (2014). The FADN data is a sample of farms drawn by the European Union to manage their agricultural policies. The 2007 sample of 58360 farms is designed to be representative of the underlying population of 15 million farms across Western Europe (EU 15) and includes population weights for each farm (EC 2009).[2] We have modified the FADN sample by removing greenhouses, farms with less than a hectare of owned land, and outliers, leaving a final sample of 41,030 farms.[3]

The FADN data set divides Western Europe into a set of geographic units called NUTS3 (Nomenclature of Territorial Units for Statistics) regions. The average area of each NUTS3 region is 3425 km^2 and there are 935 NUTS3 regions in the data set.

Each Member State conducts the survey using a consistent instrument. This has eliminated an earlier problem across Europe where each country collected slightly different farm data and used different definitions of key variables. The resulting farm data is exceptionally valuable. For example, the property value of each individual farm is measured consistently across countries from observed farmland sales. The farm data also provides information about the source of gross revenue on the farm. This information allows us to classify farms depending upon what source provides the largest share of gross revenue. We distinguish between four types of farms: irrigated versus rainfed and crops versus livestock. It is consequently possible to conduct distinct climate studies by farm type using the FADN data. In comparison, the US Census of Agriculture only reports aggregate land values for all types of farms in each county so that livestock and crop and rainfed and irrigated farm outcomes are often mixed together.

---

[2] FADN is well documented on http://ec.europa.eu/agriculture/rica/index.cfm. and the information about weighting can be found on http://ec.europa.eu/agriculture/rica/methodology3_en.cfm

[3] The following farms are removed: 2230 duplicates, 654 farms in out or range islands (e.g. Azores, Tenerife, Madeira), 1700 farms with missing spatial information, 3203 farms under glass, 8864 farms with less than 1 hectare land in ownership, 597 farms with low total land value (<50 €), and 82 outliers (e.g. farms without zero output or with a high output with (nearly) no farmland)

The observed 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, mean elevation) were matched to each NUTS3 region.

Table A.1 in the Appendix shows the descriptive statistics of our model variables for the entire sample. The average farm level land value is nearly 16,000 Euro per hectare but there is a wide range in values. The amount of land actively farmed exceeds the amount of land owned. Many farmers in Europe rent land from landowners, a practice which varies by country.

It is helpful to understand how farm types vary across Europe. The mean values of some key characteristics of farms are reported in Table A.2 for each farm type. Note that the value of irrigated land is generally much higher than rainfed land. The active size of rainfed farms, in contrast, is much higher than for irrigated farms. The optimal size to operate a farm is larger for rainfed farms. Irrigated farms tend to be located in warmer regions of Europe. Livestock farms are also quite different from crop farms. The utilized agricultural area of livestock is larger. Moreover, specialised livestock farms are located in cooler and wetter areas.

2.2 Model specifications

We explore a number of different analyses to test the robustness of our results. We estimate both OLS and quantile regression models of the entire sample to measure the overall climate sensitivity of European farms. We also estimate separate regressions for subsamples of rainfed, irrigated, crop and livestock farms.

In all regressions, we weight each farm within the sample using total owned agricultural land in that farm to control for heteroscedasticity. We also test for aggregation bias by comparing the results using the micro data versus the aggregate data for each NUTS3 region.

It is not possible to correct for spatial correlation with the micro data because we do not know the precise location of each farm. However, we do apply controls for spatial correlation using the aggregate data. Treating each NUTS3 region as an observation, we follow Schlenker and Roberts (2009) and apply the Conley (1999) non-parametric method to correct the matrix of covariances for spatial dependence among observations.

We then interpret the coefficients of the Ricardian models by first calculating the marginal impacts of small changes in temperature and precipitation change (away from the current climate). Because the model is nonlinear, these marginal effects change with large changes in climate. In order to learn how the Ricardian model responds to very different climates, we then calculate the consequence of predicted climate outcomes in 2100 for three different climates predicted by General Circulation Climate Models (GCMs): Hadley CM3 (Gordon et al. 2000), ECHO-G (Legutke and Voss 1999), and NCAR PCM (Washington et al. 2000). These specific climate scenarios are based on the A2 SRES (Special Report on Emissions Scenarios) emissions scenario (Nakićenović et al. 2000). Note that our purpose in choosing these three climate scenarios is not to predict realistic outcomes in 2100 but simply to show what the Ricardian model predicts would happen with a range of plausible climate scenarios. .

We interpolate from the climate grids of the GCMs to each NUTS3 region centroid using inverse distance weights to the four nearest grid points.[4] The absolute change of temperature and the percentage change in precipitation are defined as the difference in the climate model's predictions for 2071-2100 versus 1961-1990. These changes are then applied to the CRU 1961-1990 observed climate data for each NUTS3 region.

Across Western Europe, the Hadley CM3 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 NCAR PCM model predicts a warming of 2.8°C with a 5% loss of precipitation by 2100. The three climate scenarios effectively represent a severe, moderate, and mild possible outcome, respectively. However, the precise climate change for each country in Europe varies across the scenarios so that some parts of Europe are predicted to warm or dry at different rates. The mean temperature and precipitation in each member state for each scenario can be found in Appendix B.

[4] The grid sizes for the three climate models are considerably larger than the NUTS3 regions. The statistical downscaling we rely on generates a smooth prediction across space. It should be understood that these local predictions are plausible but highly uncertain.

3. Results

Section 3.1 presents the regression results across Western European farms. The first set of regressions use the entire sample in order to understand the impact climate has on the entire farm sector (Equation 4). A second set of regressions focuses on subsamples (rainfed and irrigated farms and cropland and livestock farms) to understand the climate sensitivity of different components of European agriculture. The third set of regressions uses quantile regression to examine each quintile of the sample (Equation 5). The expected nonmarginal impacts of future climate scenarios are calculated in Section 3.2. Section 3.3 analyses the robustness of the Ricardian regressions.

3.1 Ricardian regressions

Table 1 compares the coefficients and standard errors using both OLS and median quantile regressions for the entire sample of farms. In the median quantile regression, fourteen of the sixteen seasonal climate coefficients are statistically significant revealing that climate has a significant impact on the value of European farmland. The coefficients of squared temperature and precipitation (except summer precipitation) are significant implying effects are nonlinear. While Table 1 only reports the median quantile regression, we also estimate quantile regressions for the lowest 10%, lower 25%, upper 75%, and upper 10% of the distribution (shown in Table C.1 in Appendix C).

Insert Table 1

In order to interpret the coefficients in Table 1, we first analyse the impact of a small (marginal) change from the current climate. We later address the nonlinearity of the climate function by examining larger movements away from the current climate. Figure 1 reveals the marginal percentage effects of seasonal temperature and precipitation across Western Europe for each of the five quantile regressions. The marginals were calculated using the climate coefficients in Tables 12 and C.1. The temperature marginals reflect the percentage change in farmland value per °C and the precipitation marginals reflect the percentage change in farmland value per cm/month. Across all the quantiles, land values fall with warmer winter and summer temperatures and they increase with warmer spring temperatures. The top two quantiles have significantly stronger positive and negative responses to spring and summer temperature respectively compared to the rest of the sample. The marginal impacts of autumn temperature are generally positive but not for the two lowest quantiles. These general seasonal results mirror the results from US studies (Mendelsohn et al. 1994; Mendelsohn and Dinar 2003; Massetti and Mendelsohn 2011). A colder winter is beneficial because cold limits pests, a warmer spring and autumn are valuable because they lengthen the growing season, and a warmer summer is harmful because the high temperatures stress crops.

Insert Figure 1

Precipitation also significantly affects land values. For the median EU farm, rain is beneficial in winter and summer but harmful in spring and fall. There is adequate rainfall already in the spring and fall in Europe, so that more rainfall only diminishes much needed solar radiation. In contrast, there is not currently enough rainfall in summer to compensate for the heat, and so more rainfall is beneficial. More rainfall in the winter can lead to plentiful soil moisture for the beginning of growing season. These seasonal patterns for marginal changes are similar to American results. Figure 1 shows the impact of spring precipitation has especially wide ranging marginal effects across quantiles ranging from -23% in the 10^{th} percentile to +7% in the 90^{th} percentile.

Looking across all of Europe, one can summarize the annual marginal effects of both temperature and precipitation. The median regression of the entire sample of farms (Table 1) reveals that a uniform increase of 1°C in the EU-15 increases farmland value +8.2% (482 €/ha) and a uniform increase of 1 cm per month of precipitation increases farmland value +2.4% (143 €/ha). Marginal warming and marginal increases in precipitation are beneficial to EU-15 agriculture as a whole.

The marginal climate effects, however, differ a great deal across member countries within the EU-15 because each country has a different initial precipitation and temperature. A small warming (cooling) is beneficial (harmful) to cooler countries and harmful (beneficial) to warmer countries. A small increase (decrease) in precipitation is beneficial (harmful) to drier (wetter) countries and harmful (beneficial) to wetter countries. The marginal percentage change for each country is reported in the supplementary materials Table S.1 (equation 8), the absolute marginal values are reported in Table S.2 (equation 7), and Figures S.1 and S.2 map the temperature and precipitation marginal impacts at the NUTS3 level. A marginal increase in annual temperature has a beneficial effect on the northern countries: Austria, Belgium, Germany, Denmark, Finland, Ireland, Luxembourg, Netherlands, Sweden, and Great Britain and a negative 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 16% of land value, whereas the marginal loss is highest in Greece and Portugal which lose 9% of land value. A small increase in rainfall (see Figure S.2 in supplementary materials) is beneficial to Austria, Belgium, France, Germany, Luxembourg, Portugal, and Spain but harmful to Denmark, Finland, and Sweden.

Several of the control variables in Table 1 are also significant. Gravel soils tend to be harmful. Because neutral soils are more beneficial than either acidic or alkaline soils, soil pH has a concave impact on 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. Higher elevation may be harmful for many reasons including higher diurnal temperature variance, decreased access, or increased slope. Country fixed effects are generally significant implying higher average land values in Denmark, Ireland, West Germany, Italy, and the Netherlands, but lower values in Austria, France, East Germany, and Portugal.

Table 1 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. The median regression leads to a flatter overall climate response function (smaller marginal results) than the OLS regression. The extreme data points that tend to have more influence in the OLS regression lead to a slightly more sensitive climate 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 the land values of the remaining 20% of farms. We repeat the MGN test 1000 times and we reject the null hypothesis of equal forecasting accuracy in favour of the median regression in 99% of the repetitions. The median regression model outperforms the OLS model with an average t-statistic of 10.12. We consequently focus on the results of the median quantile regression in the remainder of the paper.

In addition to understanding how climate affects the entire farm sector, it is also helpful to estimate how climate affects subsamples of farms as shown in Table 2. The regression in the first column in Table 2 is estimated on only rainfed farms. The second column shows the results for irrigated farms. The climate coefficients for the irrigated farms are quite different from the climate coefficients of the rainfed farms. Irrigation allows farms to exist in dryer locations, as can be seen in Europe (Table A-2). However, irrigation also affects temperature sensitivity. The optimal summer temperature for irrigated farms (14.5°C) is higher than the optimal temperature for rainfed farms (13.6°C). As both agronomic and economic studies have previously shown, irrigation increases the tolerance of plants to higher temperatures (Mendelsohn and Dinar 2003; Elliott et al. 2014; Nendel et al. 2014). Figure 2 presents the marginal climate results for Table 2. A marginal increase in warming increases the value of irrigated farms slightly more than rainfed farms. A slight increase in precipitation, however, has a powerful positive marginal effect on irrigated farms and only a small effect on rainfed farms. Partly, this is because irrigated farms are located in the driest and warmest part of Europe so added rainfall is particularly valuable. However, controlling for climate, the net revenues of irrigated farms are clearly more sensitive to precipitation than rainfed farms.

Rainfed and irrigated farms also have different seasonal responses. Warmer temperatures in winter and spring benefit rainfed more than irrigated farms but warmer autumn temperatures are especially beneficial to irrigated farms. Irrigated farms respond especially well to wetter springs but especially poorly to wetter autumns compared to rainfed farms. These seasonal differences could be caused by the different crops that each type of farm is growing.

Insert Table 2

Insert Figure 2

The coefficients of the control variables in Table 2 are also quite different for irrigated versus rainfed farms. Gravel soils are only harmful to rainfed farms. Irrigated farms have a much higher negative reaction to sandy soils. This is probably because such soils cannot hold irrigated water and the water just seeps through. A higher share of rented land increases the land value of rainfed farms but decreases the land value of irrigated land. Renters have less long run incentive to invest in the capital required for irrigation compared to landowners. Access to ports is more beneficial to irrigated farms but access to cities is more beneficial to rainfed farms. One explanation is that irrigated farms could be growing crops directly for export whereas rainfed farms are selling more of their output to nearby cities.

Another important distinction between farms is whether they grow crops or raise livestock. The third and fourth columns in Table 2 are regressions on subsamples of crop farms and livestock farms. The seasonal temperature coefficients have similar patterns for both crops and livestock. However, examining the magnitude of marginal climate responses in Figure 2 reveals that warming is more beneficial to livestock than crop farms. This is especially clear in spring.

Some of the crop and livestock coefficients of the control variables are also different. Gravel soils are more harmful to crops but sandy soils and high elevation are more harmful to livestock. Alkaline soils, population density, and being closer to cities are more beneficial to crops whereas being closer to ports is more beneficial to livestock. The livestock may be dependent on the import of feed (e.g. soya) from the ports.

3.2 Alternative climates

In this section, we examine the impact of alternative climates that are quite different from the current climate. Because the Ricardian model is nonlinear, it predicts different outcomes as climate changes dramatically. We use three different climate models (Hadley CM3, ECHO-G and NCAR PCM) to select a range of plausible future climates. All three climate scenarios were based on the SRES A2 (no mitigation) GHG emission scenario.

We use the coefficients from the estimated median quantile regression of all farms (Table 1) to calculate the land values in each NUTS3 region for each climate scenario (including the current climate). . Subtracting the land values of the current climate from the three climate scenarios provides a measure of the welfare change. The calculation takes into account changes 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 9).

Table 3 reports the change in aggregate farmland value for Western Europe. The Hadley CM3 scenario generates a loss of 32% of farmland value by 2100. The ECHO-G scenario generates a loss of 16% and NCAR PCM generates a 5% gain. These impact estimates are calculated keeping the rest of the model constant. This is consequently not a forecast of the future but simply a measure of what climate might do if it alone changed. We also do not consider carbon fertilization. If carbon dioxide concentrations double between now and 2100 (from 400 ppm to 800 ppm), crop yields are expected to increase by 30% (Kimball 2007). Carbon fertilization would moderate the results reported in Table 3.

Insert Table 3

In order to quantify the uncertainty surrounding the welfare estimates in Table 3, 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 1,000 times to generate 1,000 values for each climate scenario. The results illustrate that the damage predicted in the ECHO-G and Hadley CM3 scenarios is significantly different from zero at EU-15 level while the gain of the NCAR PCM scenario is not significant different from zero. The uncertainty across the climate models is large as one can see from the results across three climate models. The uncertainty of the Ricardian model is also large.

It is also important to note that the impact of temperature and precipitation change is not at all uniform across the EU-15. Figures 3, 4, and 5 present maps of the impacts of each climate scenario on each NUTS3 region. Several countries are damaged by future temperature and precipitation changes. Only Belgium, Germany, Denmark, the Netherlands, United Kingdom, and especially Ireland benefit in the NCAR PCM climate scenario. Denmark, Finland, Ireland, Sweden, and the UK benefit slightly in the ECHO-G climate scenario, and only Ireland and the UK show a benefit in the Hadley CM3 climate scenario. Italy has the largest aggregate loss of farmland value. Italy loses € 120 billion (-71%) of farmland value in the Hadley CM3 scenario, € 101 billion (-60%) in the ECHO-G scenario, and € 58 billion (-34%) in the NCAR PCM climate scenario. The future climate scenarios, in general, are beneficial to agriculture in northern countries and harmful in southern countries. But the effect is not uniform across the future scenarios because the magnitude of annual climate change varies and because there are important seasonal changes. For example, the Ricardian model predicts Finland to be harmed by warming because the winter temperature there increases by 8°C in some scenarios. This effect is predicted to be more harmful than the gains from warming in the other seasons.

Insert Figure 3

Insert Figure 4

Insert Figure 5

3.3 Robustness checks

We estimate a number of alternative regressions as a robustness check. We look at regressions with and without country fixed effects (see Table C.2 in Appendix C). Dropping the country fixed effects causes the climate coefficients to change. s. The annual marginal temperature effect in the EU-15 drops from +8.2% (with country fixed effects) to +5.7% (without country fixed effects) while the annual marginal precipitation effect increases from +2.4% to +11.5%.

We also examine what happens when even more refined spatial fixed effects are included. Instead of using 15 country dummies, we include 63 regional dummies to capture broad regions within each country. The results are reported in Appendix C in Table C.2. With more spatial fixed effects, there is less remaining variation in climate. This magnifies measurement error biasing the climate coefficients towards zero. All the climate coefficients drift towards zero with the regional dummies. This same phenomenon can be seen in the panel regression results of Deschênes and Greenstone (2007). If fixed effects remove too much of the climate signal, measurement error begin to dominate the results leading the coefficients to be biased towards zero (Fisher et al. 2012). We consequently advise against using the regional fixed effects.

We test whether aggregation has a significant effect on the results. We aggregate the data on all farms to the NUTS3 region. This effectively treats each NUTS3 region as an observation, dropping all the information on the individual farm. The result reported in Table C.2 in Appendix C reveals that the temperature coefficients remain stable but the significance of the coefficients declines. With the aggregated data, spring and autumn temperature and winter and autumn precipitation have a significant impact on farmland value. The annual marginal temperature effect using the aggregate data is comparable with the marginal effect using the farm level data: 7.2% versus 8.2%. However, the aggregate annual precipitation marginal effect is clearly different (-4.0% versus +2.4%) and is only significant at the 10% level. The aggregation affects the measurement of the effect of precipitation (a similar result was found for England by Fezzi and Bateman (2015)).

Using this aggregate data, we also explore the importance of spatial correlation using the Conley (1999) non-parametric method. Controlling for spatial correlation does not change the coefficients but it reduces the t-statistics. Only the coefficients of spring temperature and autumn precipitation remain significant. A similar test using individual farm data is not possible because the location of each farm within a NUTS3 region is not known.

4. Conclusion

This study utilizes farmland data for Western Europe to understand the role that climate plays in determining the value of current European farmland. Utilizing a number of different regressions, we estimate the impact of seasonal temperature and precipitation on current farmland values. Seasonal climatic variables have a strong influence on European farmland values. Farms with warmer autumn and spring temperature, and cooler summer and winter temperature have higher values (ceteris paribus). Similarly, farms with wetter winter and summers and drier spring and autumns also have higher values (ceteris paribus).

The research provides indications of how changes in climate would affect European farms in the future. Marginal temperature increases from current levels in spring and autumn would increase farmland values but similar increases in summer and winter temperature would reduce farmland value. Adding together these marginal seasonal effects yields a significant annual marginal benefit of +8% in Western Europe. Marginal precipitation increases in spring and autumn are harmful but marginal precipitation increases in winter and summer are beneficial. Summing these seasonal effects across the year reveals that a marginal increase in annual precipitation would also be beneficial (+2%) for Western European agriculture. However, 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 the Scandinavian countries.

These results are consistent with the results found in country level 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) whereas analyses of Italy suggest a harmful effect (Bozzola et al. 2014). The crop model studies also 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). Ricardian studies in the United States also find similar patterns of seasonal effects (e.g. Mendelsohn et al. (1994); Massetti and Mendelsohn (2011)). Regional effects within the US also vary in a similar way as warming is beneficial in northern states and harmful 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 shows that the climate effects are similar across the sector though not identical.

In order to measure the climate sensitivity of the entire agricultural sector, it is important to estimate a Ricardian model with all farms included. The climate sensitivity of irrigated farms is not the same as the climate sensitivity of rainfed farms. The climate sensitivity of rainfed farms cannot be used to predict the climate outcome of the entire agricultural system (as suggested by Schlenker et al. (2005) and Schlenker et al. (2006)). Irrigated farms are less temperature sensitive than rainfed farms and whether a farm is irrigated or not is climate sensitive. The analysis also suggests that the climate sensitivity of crops and livestock are different. These results for Europe are similar to results found in studies across the world (Mendelsohn and Dinar (2009)).

The climate coefficients suggest that climate has a large impact on farmland in Europe now. Further, climate change is going to have a strong influence on future farmland values in Europe. The results suggest that warmer temperature and precipitation changes by 2100 will generally be harmful to European agriculture. The impacts range from a +5% gain with the NCAR PCM climate model, to a -16% loss with the ECHO-G climate model, to a -32% loss with the Hadley CM3 climate model. Including the likely benefit (30% gain) that farmers will experience by 2100 from carbon fertilization, however, the net effect of greenhouse gases is more ambiguous and may even be beneficial

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.

We assume in this analysis that the only thing that changes over time is climate. Of course, many things may change. Prices may be very different in the future. That applies to both the prices of agricultural outputs as well as inputs. Technology and infrastructure may also change. Finally, government policies may change. This is especially important given the strong role of current EU farm policy. But this also applies to the role that government may play to develop new farm technologies, crops and breeds. The government is also responsible for managing water, which is a key input to agriculture. In several countries, the government also regulates how land can be used. Changes in government policy can therefore play a large role in helping farmers adapt to climate change. Hopefully, governments will be careful to avoid policies that actually make adapting to climate change more difficult.

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 already 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 wide array of climate models and emission scenarios.

5. References

Bozzola M, Capitanio F, Massetti E, Mendelsohn R (2014) A Ricardian Analysis of the Impact of Climate Change on Italian Agriculture. manuscript

Ciscar JC, Iglesias A, Feyen L, Szabo L, Van Regemorter D, Amelung B, Nicholls R, Watkiss P, Christensen OB, Dankers R, Garrote L, Goodess CM, Hunt A, Moreno A, Richards J, Soria A (2011) Physical and economic consequences of climate change in Europe. Proc Natl Acad Sci U S A 108(7): 2678-2683

Cline WR (1996) The Impact of Global Warming of Agriculture: Comment. The American Economic Review 86(5): 1309-1311

Conley TG (1999) GMM estimation with cross sectional dependence. Journal of Econometrics 92(1): 1-45

Deschênes O, Greenstone M (2007) The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather. American Economic Review 97(1): 354-385

Diebold FX, Mariano RS (2002) Comparing Predictive Accuracy. Journal of Business & Economic Statistics 20(1): 134-144

EC (2009) COUNCIL REGULATION (EC) No 1217/2009 of 30 November 2009 setting up a network for the collection of accountancy data on the incomes and business operation of agricultural holdings in the European Community.

Elliott J, Deryng D, Müller C, Frieler K, Konzmann M, Gerten D, Glotter M, Flörke M, Wada Y, Best N, Eisner S, Fekete BM, Folberth C, Foster I, Gosling SN, Haddeland I, Khabarov N, Ludwig F, Masaki Y, Olin S, Rosenzweig C, Ruane AC, Satoh Y, Schmid E, Stacke T, Tang Q, Wisser D (2014) Constraints and potentials of future irrigation water availability on agricultural production under climate change. Proceedings of the National Academy of Sciences 111(9): 3239-3244

Fezzi C, Bateman IJ (2015) The impact of climate change on agriculture: nonlinear effects and aggregation bias in Ricardian models of farmland value. Journal of the Association of Environmental and Resource Economists 2: 57-92

Fisher AC, Hanemann WM, Roberts MJ, Schlenker W (2012) The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Comment. American Economic Review 102(7): 3749-3760

Gordon C, Cooper C, Senior CA, Banks H, Gregory JM, Johns TC, Mitchell JFB, Wood RA (2000) The simulation of SST, sea ice extents and ocean heat transports in a version of the Hadley Centre coupled model without flux adjustments. Climate Dynamics 16(2): 147-168

Kala N, Kurukulasuriya P, Mendelsohn R (2012) The impact of climate change on agro-ecological zones: evidence from Africa. Environment and Development Economics 17(06): 663-687

Kelly DL, Kolstad CD, Mitchell GT (2005) Adjustment costs from environmental change. Journal of Environmental Economics and Management 50(3): 468-495

Kimball Bruce A (2007) Plant Growth and Climate Change. Biological Sciences Series. Edited by James I L Morison and Michael D Morecroft. The Quarterly Review of Biology 82(4): 436-437

Koenker R (2004) Quantile regression for longitudinal data. Journal of Multivariate Analysis 91(1): 74-89

Koenker R, Bassett G (1978) REGRESSION QUANTILES. Econometrica 46(1): 33-50

Kurukulasuriya P, Kala N, Mendelsohn R (2011) Adaptation and climate change impacts: a structural Ricardian model of irrigation and farm income in Africa. Climate Change Economics 02(02): 149-174

Lang G (2007) Where are Germany's gains from Kyoto? Estimating the effects of global warming on agriculture. Climatic Change 84(3): 423-439

Legutke S, Voss R. 1999. The Hamburg Atmosphere-Ocean Coupled Circulation Model ECHO-G.Hamburg, Germany.

Lippert C, Krimly T, Aurbacher J (2009) A Ricardian analysis of the impact of climate change on agriculture in Germany. Climatic Change 97(3): 593-610

Maddison D (2000) A hedonic analysis of agricultural land prices in England and Wales. European Review of Agricultural Economics 27(4): 519-532

Massetti E, Mendelsohn R (2011) Estimiting Ricardian models with panel data. Climate Change Economics (CCE) 02(04): 301-319

Massetti E, Mendelsohn R 2011. The impact of climate change on US agriculture: a repeated cross-sectional Ricardian analysis. In: Handbook on Climate Change and Agriculture. Dinar, A and Mendelsohn, R. Edward Elgar. Cheltenham, UK, Northampton, MA, USA.

Mendelsohn R, Dinar A (2003) Climate, Water, and Agriculture. Land Economics 79(3): 328-341

Mendelsohn R, Dinar A 2009. Climate Change and Agriculture: An Economic Analysis of Global Impacts, Adaptation and Distributional Effects. In. England, Edward Elgar Publishing.

Mendelsohn R, Nordhaus WD (1996) The Impact of Global Warming on Agriculture: Reply. The American Economic Review 86(5): 1312-1315

Mendelsohn R, Nordhaus WD, Shaw D (1994) The Impact of Global Warming on Agriculture: A Ricardian Analysis. The American Economic Review 84(4): 753-771

Moore FC, Lobell DB (2014) Adaptation potential of European agriculture in response to climate change. Nature Clim Change 4(7): 610-614

Nakićenović Na, Alcamo J, Davis G, de Vries B, Fenhann J, Gaffin S, Gregory K, Grübler A, Jung TY, Kram T, Lebre La Rovere E, Michaelis L, Mori S, Morita T, Pepper W, Pitcher H, Price L, Riahi K, Roehri A, Rogner H-H, Sankovski A, Schlesinger M, Shukla P, Smith S, Swart R, van Rooijen S, Victor N, Dadi Z 2000. Special report on emissions scenarios : a special report of Working Group III of the Intergovernmental Panel on Climate Change. In. Cambridge ; New York, Cambridge University Press. 599 p.

Nendel C, Kersebaum KC, Mirschel W, Wenkel KO (2014) Testing farm management options as climate change adaptation strategies using the MONICA model. European Journal of Agronomy 52, Part A(0): 47-56

New M, Lister D, Hulme M, Makin I (2002) A high-resolution data set of surface climate over global land areas. Climate Research 21(1): 1-25

Ricardo D 1817. On the principles of political economy and taxation. In, Batoche Books, Ontaria, Canada.

Schlenker W, Hanemann WM, Fisher AC (2005) Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach. The American Economic Review 95(1): 395-406

Schlenker W, Hanemann WM, Fisher AC (2006) The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions. Review of Economics and Statistics 88(1): 113-125

Schlenker W, Roberts MJ (2009) Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. Proceedings of the National Academy of Sciences

Seo N, Mendelsohn R (2008) A Ricardian Analysis of the Impact of Climate Change on South American Farms. Chilean Journal Of Agricultural Research 68(1): 69-79

Seo SN, Mendelsohn R (2008) Measuring impacts and adaptations to climate change: a structural Ricardian model of African livestock management1. Agricultural Economics 38(2): 151-165

Wang J, Mendelsohn R, Dinar A, Huang J, Rozelle S, Zhang L (2009) The impact of climate change on China's agriculture. Agricultural Economics: The Journal of the International Association of Agricultural Economists 40(3): 323-337

Washington WM, Weatherly JW, Meehl GA, Semtner Jr AJ, Bettge TW, Craig AP, Strand Jr WG, Arblaster J, Wayland VB, James R, Zhang Y (2000) Parallel climate model (PCM) control and transient simulations. Climate Dynamics 16(10): 755-774

Table 1: EU-15 Ricardian regressions

	EU-15 (median regression)		EU-15 (OLS regression)	
	coef	se	coef	se
Temperature winter	-0.242***	0.023	-0.251***	0.021
Temp. winter sq	0.004**	0.002	0.008***	0.001
Temperature spring	0.375***	0.045	0.291***	0.042
Temp. spring sq	0.003	0.002	0.014***	0.002
Temperature summer	0.054	0.076	0.083	0.072
Temp. summer sq	-0.008***	0.002	-0.010***	0.002
Temperature autumn	0.363***	0.079	0.620***	0.066
Temp. autumn sq	-0.013***	0.003	-0.027***	0.003
Precipitation winter	0.110***	0.015	0.086***	0.016
Prec. winter sq	-0.001*	0.001	0.001**	0.001
Precipitation spring	-0.223***	0.027	-0.313***	0.028
Prec. spring sq	0.014***	0.001	0.015***	0.001
Precipitation summer	0.055***	0.020	0.003	0.019
Prec. summer sq	-0.001	0.001	0.004***	0.001
Precipitation autumn	0.060***	0.016	0.103***	0.015
Prec. autumn sq	-0.008***	0.001	-0.011***	0.001
Gravel (t_gravel)	-0.052***	0.004	-0.046***	0.003
Silt (t_silt)	-0.001	0.003	-0.008***	0.002
Sand (t_sand)	-0.007***	0.002	-0.013***	0.001
pH	0.774***	0.154	0.214*	0.117
pH squared	-0.041***	0.012	0.005	0.009
Rented land	0.065***	0.017	0.124***	0.018
Population density (Pdnsty)	0.340***	0.025	0.347***	0.023
Subsidies	0.294***	0.013	0.408***	0.015
Distance to cities (Cities500k)	-0.618***	0.090	-0.530***	0.082
Distance to ports (PortsML)	-1.075***	0.076	-1.110***	0.070
Elevation mean	-0.179***	0.046	-0.129***	0.048
Elevation range	0.023*	0.012	0.063***	0.012
Austria (AT)	-2.454***	0.054	-2.647***	0.051
Belgium (BE)	-0.096**	0.042	0.032	0.050
Denmark (DK)	0.846***	0.057	0.942***	0.044
Spain (ES)	-0.430***	0.056	-0.504***	0.053
Finland (FI)	-0.357***	0.086	-0.515***	0.086
France (FR)	-1.267***	0.044	-1.118***	0.039
Greece (GR)	0.117	0.073	-0.050	0.072
Ireland (IE)	1.155***	0.030	1.068***	0.029
Italy (IT)	0.807***	0.060	0.847***	0.051
Luxembourg (LU)	-0.417***	0.047	-0.353***	0.046
Netherlands (NL)	1.043***	0.040	1.017***	0.037
Portugal (PT)	-2.107***	0.074	-2.378***	0.062
Sweden (SE)	0.035	0.068	0.056	0.058
West Germany (WDE)	0.332***	0.041	0.307***	0.035
East Germany (EDE)	-0.898***	0.053	-0.914***	0.041
United Kingdom (UK)	(omitted)		(omitted)	
Constant	2.799***	0.646	4.156***	0.466
Pseudo R2 / Adj. R2	0.4439		0.6217	
Number of observations	41030		41030	

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

Table 2: 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
Temperature winter	-0.074***	0.024	-0.549***	0.027	-0.119***	0.035	-0.192***	0.037
Temp. winter sq	0.005***	0.002	0.026***	0.002	-0.008***	0.003	-0.004	0.003
Temperature spring	0.273***	0.046	-0.644***	0.060	-0.769***	0.084	-0.106	0.071
Temp. spring sq	0.003	0.002	0.034***	0.002	0.069***	0.004	0.042***	0.004
Temperature summer	0.244***	0.079	0.638***	0.086	0.536***	0.139	1.154***	0.130
Temp. summer sq	-0.009***	0.002	-0.022***	0.002	-0.025***	0.003	-0.045***	0.004
Temperature autumn	0.187**	0.079	1.302***	0.108	0.504***	0.132	0.460***	0.124
Temp. autumn sq	-0.013***	0.003	-0.031***	0.004	-0.019***	0.006	-0.016***	0.005
Precipitation winter	-0.040**	0.016	-0.176***	0.013	0.070**	0.034	0.030	0.026
Prec. winter sq	0.004***	0.001	0.017***	0.001	-0.000	0.002	0.002*	0.001
Precipitation spring	-0.074**	0.031	0.673***	0.031	0.130***	0.047	-0.117***	0.042
Prec. spring sq	0.005***	0.002	-0.043***	0.002	-0.020***	0.003	0.007***	0.002
Precipitation summer	0.009	0.020	-0.007	0.017	-0.014	0.036	-0.103***	0.029
Prec. summer sq	0.001	0.001	0.006***	0.001	0.009***	0.002	0.010***	0.001
Precipitation autumn	0.140***	0.016	-0.244***	0.019	-0.162***	0.039	0.074***	0.023
Prec. autumn sq	-0.010***	0.001	0.009***	0.001	0.009***	0.002	-0.009***	0.001
Gravel (t_gravel)	-0.051***	0.004	0.002	0.003	-0.069***	0.006	-0.022***	0.006
Silt (t_silt)	0.005*	0.003	-0.035***	0.002	-0.005	0.004	-0.020***	0.004
Sand (t_sand)	-0.007***	0.002	-0.021***	0.001	-0.008***	0.003	-0.016***	0.003
pH	1.008***	0.155	1.568***	0.129	1.648***	0.222	-0.325	0.300
pH squared	-0.065***	0.012	-0.120***	0.010	-0.111***	0.017	0.031	0.024
Rented land	0.111***	0.018	-0.070***	0.013	0.032	0.025	0.298***	0.028
Population density (Pdnsty)	0.283***	0.024	0.254***	0.025	0.285***	0.039	0.141***	0.036
Subsidies	0.363***	0.017	0.083***	0.006	0.201***	0.018	0.983***	0.021
Distance to cities (Cities500k)	-0.684***	0.093	-0.434***	0.075	-0.759***	0.140	-0.437***	0.145
Distance to ports (PortsML)	-1.056***	0.079	-1.394***	0.064	-0.673***	0.127	-1.240***	0.128
Elevation mean	-0.140***	0.048	-0.037	0.034	0.124	0.076	-0.221***	0.072
Elevation range	-0.030**	0.014	-0.011	0.008	0.112***	0.017	0.156***	0.027
Austria (AT)	-2.166***	0.055	-2.193***	0.085	-1.977***	0.093	-3.215***	0.078
Belgium (BE)	-0.063	0.042	0.569***	0.091	0.248***	0.086	-0.451***	0.060
Denmark (DK)	1.001***	0.057	0.176**	0.076	0.742***	0.090	0.696***	0.086
Spain (ES)	-0.687***	0.057	-0.591***	0.079	-0.381***	0.095	-1.195***	0.082
Finland (FI)	-0.179**	0.084			-0.542***	0.149	-0.628***	0.118
France (FR)	-1.278***	0.044	-1.289***	0.072	-1.157***	0.070	-1.594***	0.064
Greece (GR)	0.012	0.077	-0.463***	0.084	0.260**	0.118	-1.180***	0.126
Ireland (IE)	1.052***	0.029			1.571***	0.072	1.041***	0.038
Italy (IT)	0.600***	0.062	0.467***	0.074	0.930***	0.104	0.578***	0.085
Luxembourg (LU)	-0.232***	0.047			0.260**	0.127	-0.512***	0.066
Netherlands (NL)	1.170***	0.039			1.171***	0.065	0.779***	0.057
Portugal (PT)	-2.154***	0.077	-3.374***	0.085	-2.398***	0.132	-3.209***	0.119
Sweden (SE)	0.139**	0.066	-0.774***	0.109	0.352***	0.112	-0.144	0.097
West Germany (WDE)	0.503***	0.041	0.938***	0.086	0.540***	0.073	0.020	0.060
East Germany (EDE)	-0.744***	0.053	(omitted)		-0.735***	0.084	-1.202***	0.085
United Kingdom (UK)	(omitted)		(omitted)		(omitted)		(omitted)	
Constant	1.419**	0.664	-4.775***	0.597	0.780	1.010	0.194	1.183
Pseudo R2 / Adj. R2	0.4529		0.4954		0.4753		0.4948	
Number of observations	32013		9017		9608		13768	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$ 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/).

Table 3: 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	969	2310	-285	-678	-68	-162	-25	-60
			-422 -114	*-1020 -301*	*-166 105*	*-410 274*	*-115 98*	*-280 217*
Belgium	12389	14100	-3805	-4340	-1381	-1580	1138	1300
			-5524 -2054	*-6360 -2370*	*-2789 379*	*-3180 243*	*-249 2828*	*-359 3290*
Germany	10758	143000	-2951	-39200	363	4820	1403	18700
			-4273 -1376	*-56900 -18000*	*-939 2179*	*-13200 26500*	*122 3135*	*1370 39700*
Denmark	13862	30100	-1461	-3170	4018	8730	3362	7310
			-2843 106	*-6230 785*	*1535 6902*	*2980 15100*	*1574 5984*	*3030 13100*
Spain	2830	49100	-2143	-37200	-1854	-32100	-1068	-18500
			-2457 -1798	*-42500 -30200*	*-2142 -1548*	*-37200 -26100*	*-1294 -812*	*-22600 -14100*
Finland	2982	5950	-190	-379	585	1170	-871	-1740
			-612 413	*-1170 881*	*198 1270*	*336 2450*	*-1214 -278*	*-2440 -500*
France	2652	32200	-1549	-18800	-1077	-13100	-350	-4250
			-1845 -1291	*-22400 -15600*	*-1343 -795*	*-16300 -9870*	*-611 -72*	*-7370 -1060*
Greece	8810	23300	-7229	-19100	-5394	-14300	-5381	-14300
			-8165 -6117	*-21700 -16000*	*-6505 -4155*	*-17500 -10800*	*-6281 -4548*	*-16700 -11900*
Ireland	21875	98800	4486	20300	3502	15800	13289	60000
			1020 8508	*4860 39500*	*535 7497*	*1690 33500*	*9153 18035*	*40600 83900*
Italy	16599	169000	-11767	-120000	-9957	-101000	-5698	-57900
			-13498 -9746	*-137000 -99800*	*-11629 -8049*	*-118000 -81300*	*-7207 -4004*	*-72800 -41600*
Luxembourg	8096	1050	-3060	-395	-1540	-199	838	108
			-4126 -1910	*-546 -248*	*-2390 -471*	*-319 -74*	*-125 2031*	*-20 266*
Netherlands	32035	55000	-4734	-8130	1060	1820	6620	11400
			-8797 -80	*-15000 148*	*-2905 6541*	*-5570 10500*	*2494 11920*	*3560 20700*
Portugal	742	1210	-457	-742	-529	-859	-303	-492
			-597 -322	*-951 -516*	*-690 -416*	*-1120 -648*	*-418 -202*	*-685 -328*
Sweden	4431	8590	-761	-1480	2883	5590	116	226
			-1249 -221	*-2460 -271*	*1956 4135*	*3690 8050*	*-459 1053*	*-847 2080*
UK	7703	82300	639	6820	855	9130	3453	36900
			-491 1868	*-6280 22400*	*-75 2102*	*-1590 22900*	*2288 4715*	*23500 53100*
EU-15	**8534**	**716000**	**-2696**	**-226000**	**-1388**	**-116000**	**461**	**38700**
			-3422 -1847	*-287000 -156000*	*-2128 -373*	*-179000 -36100*	*-252 1397*	*-26400 121000*

The confidence intervals (95%) are based on bootstrap estimation with 1000 repetitions.

Appendix A: Overview of the model variables and descriptive statistics

Table A.1: Descriptive statistics all farms

variable		mean	min	max	sd
		Farm specific socio-economic variables			
Agricultural land value	Euro/ha	15616.38	3.28	498991.10	25379.04
Land owned	ha	37.36	1.00	2695.53	72.81
Utilized agricultural area	ha	78.24	1.00	7845.25	197.13
Farms represented	number	56.59	1.00	10550.00	203.68
Subsidies	Euro/ha	443.91	0.00	9820.98	523.12
Share rented land	ha/ha	0.32	0.00	1.00	0.33
		Regional socio-economic variables			
Pdnsty	Cap/km²	156.73	2.00	3048.00	212.43
		Regional specific climatic variables			
Temp. winter	°C	3.47	-14.94	12.01	4.02
Temp. spring	°C	9.54	-2.77	15.96	2.93
Temp. summer	°C	18.47	6.83	26.15	3.27
Temp. autumn	°C	11.78	-1.81	19.67	3.46
Prec. winter	10mm	7.09	1.89	25.54	2.82
Prec. spring	10mm	6.27	2.08	17.06	2.26
Prec. summer	10mm	5.77	0.15	20.98	3.40
Prec. autumn	10mm	7.43	3.56	28.71	2.49
		Regional specific soil characteristics			
t_gravel	(%vol)	9.17	2.44	18.35	2.74
t_silt	(%wt)	31.54	10.83	45.99	6.00
t_sand	(%wt)	46.27	28.25	83.02	9.72
t_clay	(%wt)	21.32	5.79	40.22	4.81
pH		6.28	4.18	7.88	0.70
		Regional specific geographic variables			
Cities500k	km	115.56	0.97	842.84	81.29
PortsML	km	162.52	0.91	536.51	109.40
Elevation mean	m	382.26	0.01	2091.87	330.08
Elevation range	m	1144.81	1.00	4255.00	905.78
Latitude	°	46.22	35.14	67.71	6.08
Longitude	°	7.52	-9.19	29.97	8.86
		Total owned land	Total farmland		Total land represented
Austria	ha	49826	76456		2378137
Belgium	ha	13400	46278		1140623
Germany	ha	248350	1134656		13300000
Denmark	ha	142743	203360		2172787
Spain	ha	240442	334755		17300000
Finland	ha	35230	55407		1995606
France	ha	70516	263091		12100000
Greece	ha	15868	35297		2648096
Ireland	ha	49299	60832		4517713
Italy	ha	269483	405861		10200000
Luxembourg	ha	20449	42346		129084
Netherlands	ha	30323	48993		1718364
Portugal	ha	33364	40702		1624416
Sweden	ha	47127	82076		1938696
United Kingdom	ha	266603	380125		10700000
EU-15	ha	1533024	3210235		83900000

Table A.2: Descriptive statistics of farm types

variable		All farms	Rainfed	Irrigation	Crops	Grazing
Farm specific socio-economic variables						
Agricultural land value	Euro/ha	15616.38	12715.60	25915.03	13867.45	11297.84
Land owned	ha	37.36	42.79	18.09	46.57	42.32
Utilized agricultural area	ha	78.24	92.19	28.71	98.69	79.63
Farms represented	number	56.59	53.33	68.16	50.46	40.06
Subsidies	Euro/ha	443.91	425.87	507.99	447.17	578.47
Share rented land	ha/ha	0.32	0.35	0.25	0.36	0.38
Regional socio-economic variables						
Pdnsty	Cap/km²	156.73	155.76	160.16	148.57	145.66
Regional specific climatic variables						
Temp. winter	°C	3.47	3.09	4.83	3.43	2.73
Temp. spring	°C	9.54	9.15	10.92	9.85	8.51
Temp. summer	°C	18.47	17.95	20.31	19.10	16.97
Temp. autumn	°C	11.78	11.30	13.50	12.08	10.65
Prec. winter	10mm	7.09	6.95	7.59	6.27	8.16
Prec. spring	10mm	6.27	6.16	6.66	5.67	7.12
Prec. summer	10mm	5.77	5.98	5.04	5.15	6.90
Prec. autumn	10mm	7.43	7.33	7.77	6.78	8.38
Regional specific soil characteristics						
t_gravel	(%vol)	9.17	8.76	10.65	9.30	8.71
t_silt	(%wt)	31.54	31.59	31.37	31.51	31.63
t_sand	(%wt)	46.27	46.83	44.26	45.96	46.94
t_clay	(%wt)	21.32	20.94	22.68	21.96	20.57
pH		6.28	6.19	6.63	6.47	5.97
Regional specific geographic variables						
Cities500k	km	115.56	115.42	116.07	110.47	131.15
PortsML	km	162.52	164.58	155.20	149.66	157.05
Elevation mean	m	382.26	348.98	500.38	343.52	398.40
Elevation range	m	1144.81	968.92	1769.30	1091.53	1096.42
Latitude	°	46.22	47.39	42.06	45.93	48.02
Longitude	°	7.52	6.70	10.44	9.00	5.31
Number of observations		41030	32013	9017	9608	13768

Table A.3: Overview of the model variables

Variable	Description	Source
	Farm specific socio-economic variables	
Agricultural land value (Euro/ha)	The replacement value of agricultural land per utilized agricultural area in owner occupation.	FADN
Rented land (ha/ha)	Total leased land per total utilized agricultural land	FADN
Subsidies (Euro/ha)	Total farm subsidies per utilized agricultural area	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
Country dummies	AT (Austria), BE (Belgium), WDE (West-Germany), EDE (East-Germany), 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

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	-2.0	1.2	2.7	2.4	6.8	9.1	11.0	10.9	15.6	18.3	20.6	21.7	7.9	11.1	12.7	13.0
Belgium	2.5	5.3	5.9	5.7	8.6	10.7	11.8	11.7	16.6	18.5	21.0	21.4	10.2	13.2	14.5	14.7
Germany	0.3	3.6	4.2	4.4	7.9	10.2	11.4	11.4	16.6	18.5	20.5	21.3	9.2	12.2	13.5	13.8
Denmark	0.3	4.4	3.7	4.3	6.3	9.0	9.5	9.7	15.4	17.2	18.6	19.4	9.0	12.0	13.1	13.1
Spain	6.3	8.7	10.0	9.5	11.7	14.2	15.6	15.9	21.5	25.1	27.3	29.5	14.4	17.6	19.5	19.6
Finland	-8.0	0.1	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	9.9
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	19.8	20.4
Ireland	4.8	7.2	7.1	6.9	7.9	10.0	9.9	9.9	13.9	15.4	16.8	16.4	9.7	12.3	12.9	12.4
Italy	5.6	8.2	9.2	9.0	11.4	13.7	15.3	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	12.7	12.1	13.4	15.7	17.3	18.0	21.5	24.7	27.0	28.3	16.2	19.2	21.3	21.1
Sweden	-3.1	2.5	1.5	2.0	4.5	7.4	8.6	8.4	14.9	16.9	18.1	19.9	6.6	10.1	11.0	11.4
UK	3.5	6.2	6.3	6.0	7.4	9.7	9.9	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	5.9	6.4	6.4	7.3	8.0	9.3	8.0	9.0	11.9	11.6	11.4	8.6	7.6	7.2	7.2	7.0
Belgium	7.2	7.5	9.0	8.8	6.8	7.8	7.0	7.1	7.5	6.9	5.8	4.1	7.7	7.0	7.7	7.7
Germany	4.9	5.7	6.8	5.9	5.4	6.7	5.9	6.5	7.2	7.5	6.3	4.2	5.3	5.0	6.0	5.1
Denmark	5.4	6.7	8.3	6.7	4.5	5.3	5.4	5.4	6.4	7.2	6.4	5.1	7.8	7.9	9.8	8.5
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	5.2	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	8.2	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	6.5	6.7	5.3	5.3	4.9	4.3	3.9	3.0	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	7.6	5.5	6.4	5.9	6.1	6.9	6.8	5.7	4.4	7.0	6.4	7.7	7.4
Portugal	10.2	10.0	8.3	9.6	6.1	5.5	4.5	3.4	1.7	0.9	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	8.2	7.1
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.

Appendix C: Additional regression estimates

Table C.1: 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**
Temperature winter	-0.132***	0.038	-0.074**	0.032	-0.242***	0.023	-0.249***	0.025	-0.222***	0.038
Temp. winter sq	-0.003	0.003	0.001	0.002	0.004**	0.002	-0.003**	0.002	0.004	0.003
Temperature spring	-0.040	0.081	0.104	0.065	0.375***	0.045	0.181***	0.047	0.363***	0.069
Temp. spring sq	0.027***	0.004	0.019***	0.003	0.003	0.002	0.019***	0.002	0.013***	0.003
Temperature summer	1.160***	0.126	0.792***	0.106	0.054	0.076	0.093	0.082	-0.535***	0.129
Temp. summer sq	-0.038***	0.003	-0.027***	0.003	-0.008***	0.002	-0.013***	0.002	0.003	0.003
Temperature autumn	0.426**	0.171	0.262**	0.127	0.363***	0.079	0.295***	0.078	0.443***	0.124
Temp. autumn sq	-0.019***	0.007	-0.017***	0.005	-0.013***	0.003	-0.006*	0.003	-0.016***	0.005
Precipitation winter	-0.070**	0.028	-0.087***	0.022	0.110***	0.015	0.127***	0.016	0.037	0.025
Prec. winter sq	0.007***	0.001	0.008***	0.001	-0.001*	0.001	-0.003***	0.001	-0.002*	0.001
Precipitation spring	-0.549***	0.039	-0.305***	0.034	-0.223***	0.027	-0.134***	0.029	0.065	0.049
Prec. spring sq	0.028***	0.002	0.014***	0.002	0.014***	0.001	0.008***	0.002	0.000	0.003
Precipitation summer	-0.024	0.029	-0.017	0.025	0.055***	0.020	0.065***	0.021	-0.019	0.031
Prec. summer sq	0.008***	0.001	0.007***	0.001	-0.001	0.001	-0.002*	0.001	-0.000	0.001
Precipitation autumn	0.307***	0.023	0.206***	0.022	0.060***	0.016	0.039**	0.016	0.046*	0.025
Prec. autumn sq	-0.020***	0.001	-0.015***	0.001	-0.008***	0.001	-0.006***	0.001	-0.005***	0.001
Gravel (t_gravel)	-0.032***	0.006	-0.042***	0.005	-0.052***	0.004	-0.037***	0.004	-0.035***	0.006
Silt (t_silt)	0.010*	0.005	0.014***	0.004	-0.001	0.003	0.007***	0.003	0.002	0.004
Sand (t_sand)	-0.008**	0.004	-0.002	0.003	-0.007***	0.002	-0.003	0.002	0.002	0.002
pH	-0.131	0.307	0.514*	0.269	0.774***	0.154	1.023***	0.136	0.791***	0.198
pH squared	0.027	0.024	-0.022	0.021	-0.041***	0.012	-0.068***	0.011	-0.044***	0.016
Rented land	0.157***	0.028	0.078***	0.024	0.065***	0.017	0.073***	0.017	0.061**	0.027
Population density (Pdnsty)	0.220***	0.056	0.289***	0.042	0.340***	0.025	0.385***	0.022	0.334***	0.030
Subsidies	0.368***	0.028	0.346***	0.022	0.294***	0.013	0.202***	0.011	0.218***	0.018
Distance to cities	0.583***	0.145	-0.164	0.126	-0.618***	0.090	-0.515***	0.092	-0.669***	0.152

(Cities500k)										
Distance to ports (PortsML)	-0.680***	0.121	-1.020***	0.111	-1.075***	0.076	-0.749***	0.077	-0.524***	0.129
Elevation mean	-0.601***	0.072	-0.247***	0.066	-0.179***	0.046	-0.200***	0.049	-0.187**	0.080
Elevation range	-0.110***	0.020	-0.015	0.018	0.023*	0.012	0.115***	0.012	0.221***	0.016
Austria (AT)	-2.876***	0.083	-2.704***	0.074	-2.454***	0.054	-2.326***	0.052	-2.127***	0.084
Belgium (BE)	-0.187***	0.056	-0.142**	0.055	-0.096**	0.042	0.051	0.041	0.184***	0.067
Denmark (DK)	0.409***	0.085	0.759***	0.077	0.846***	0.057	0.893***	0.057	1.105***	0.086
Spain (ES)	-0.957***	0.092	-0.793***	0.078	-0.430***	0.056	-0.119**	0.055	-0.184**	0.092
Finland (FI)	-0.890***	0.137	-0.387***	0.115	-0.357***	0.086	-0.104	0.089	0.406***	0.141
France (FR)	-1.706***	0.065	-1.420***	0.059	-1.267***	0.044	-1.190***	0.041	-1.080***	0.066
Greece (GR)	-0.275**	0.135	0.199*	0.105	0.117	0.073	0.167**	0.072	0.129	0.118
Ireland (IE)	0.942***	0.060	1.122***	0.044	1.155***	0.030	1.071***	0.031	0.766***	0.049
Italy (IT)	0.491***	0.099	0.763***	0.083	0.807***	0.060	0.793***	0.058	0.820***	0.096
Luxembourg (LU)	-0.175**	0.074	-0.140**	0.065	-0.417***	0.047	-0.512***	0.046	-0.375***	0.074
Netherlands (NL)	0.709***	0.055	0.898***	0.053	1.043***	0.040	1.049***	0.037	0.993***	0.055
Portugal (PT)	-3.901***	0.136	-2.507***	0.107	-2.107***	0.074	-1.635***	0.073	-1.203***	0.119
Sweden (SE)	-1.031***	0.111	-0.411***	0.093	0.035	0.068	0.193***	0.068	0.783***	0.108
West Germany (WDE)	-0.095	0.061	0.191***	0.055	0.332***	0.041	0.432***	0.039	0.722***	0.061
East Germany (EDE)	-1.540***	0.076	-1.103***	0.069	-0.898***	0.053	-0.696***	0.051	-0.342***	0.074
United Kingdom (UK)	(omitted)		(omitted)		(omitted)		(omitted)		(omitted)	
Constant	-2.493**	1.026	-1.375	1.160	2.799***	0.646	2.621***	0.556	7.540***	0.819
Pseudo R2	0.4636		0.4571		0.4439		0.4140		0.3734	
Number of observations	41030		41030		41030		41030		41030	

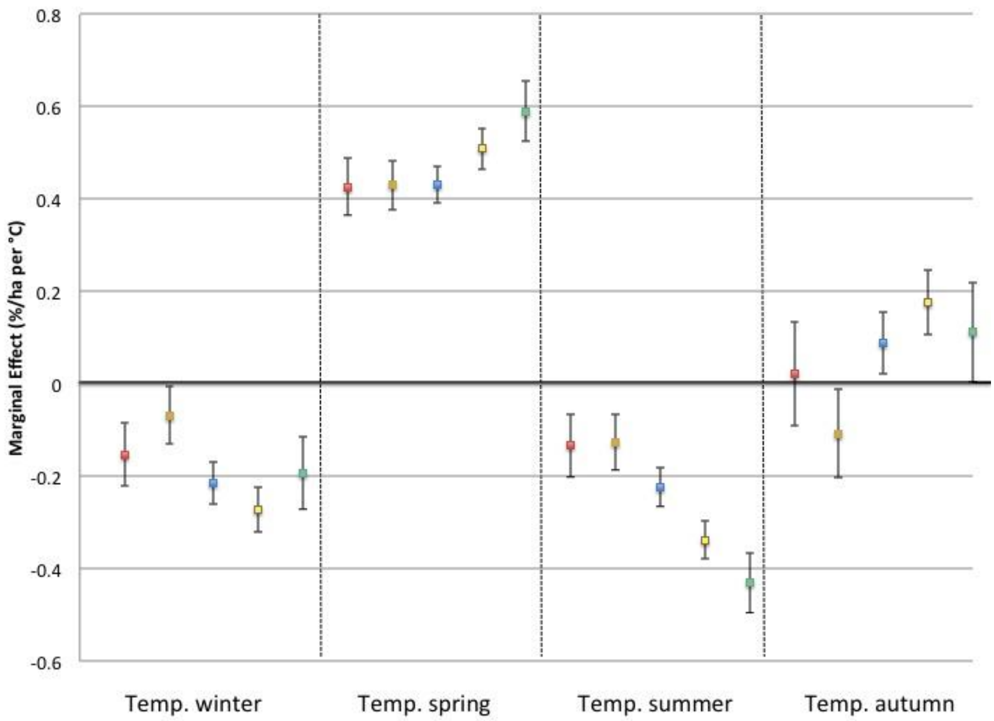
*** p<0.01, ** p<0.05, * p<0.1

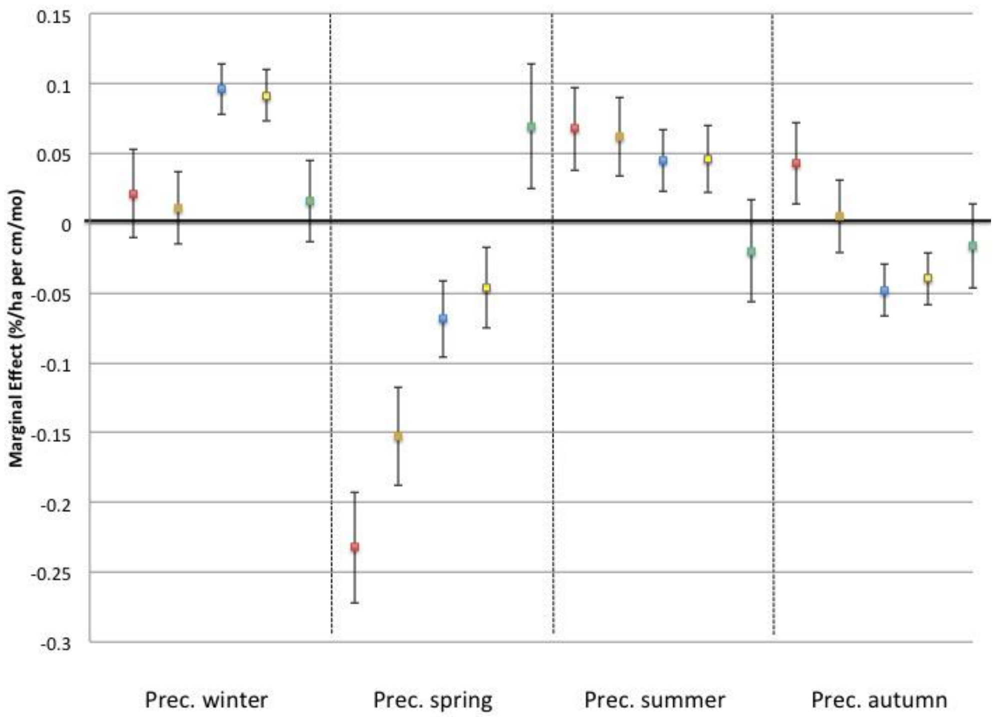
Table C.2: Alternative EU-15 Ricardian regressions

	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
Temperature winter	0.020	0.026	0.172***	0.020	-0.113	0.075	0.100
Temp. winter sq	-0.005***	0.002	0.000	0.001	0.003	0.005	0.008
Temperature spring	0.802***	0.062	0.466***	0.039	0.073	0.157	0.223
Temp. spring sq	-0.042***	0.003	-0.017***	0.002	0.026***	0.009	0.013
Temperature summer	-0.231**	0.094	0.464***	0.060	-0.043	0.269	0.444
Temp. summer sq	0.008***	0.002	-0.011***	0.001	-0.010	0.007	0.012
Temperature autumn	-0.612***	0.105	-0.710***	0.058	0.471*	0.247	0.331
Temp. autumn sq	0.027***	0.004	0.011***	0.002	-0.022**	0.010	0.015
Precipitation winter	0.268***	0.020	0.263***	0.013	-0.122**	0.058	0.086
Prec. winter sq	-0.010***	0.001	-0.004***	0.000	0.005*	0.002	0.003
Precipitation spring	-1.282***	0.038	-0.276***	0.021	-0.135	0.097	0.143
Prec. spring sq	0.071***	0.002	0.002*	0.001	0.008	0.005	0.008
Precipitation summer	0.706***	0.027	0.061***	0.015	0.031	0.071	0.092
Prec. summer sq	-0.038***	0.001	0.003***	0.001	0.000	0.003	0.004
Precipitation autumn	0.443***	0.020	-0.026*	0.014	0.139**	0.058	0.079
Prec. autumn sq	-0.018***	0.001	-0.004***	0.000	-0.009***	0.002	0.003
Gravel (t_gravel)	-0.051***	0.005	-0.059***	0.003	-0.019*	0.011	0.015
Silt (t_silt)	-0.025***	0.004	0.007***	0.002	0.013*	0.007	0.008
Sand (t_sand)	-0.012***	0.003	-0.005***	0.001	-0.004	0.004	0.005
pH	3.045***	0.211	0.581***	0.110	1.244***	0.430	0.768
pH squared	-0.191***	0.017	-0.027***	0.009	-0.086**	0.035	0.062
Rented land	-0.167***	0.027	0.086***	0.011	-0.749***	0.148	0.191
Population density (Pdnsty)	0.706***	0.037	0.215***	0.018	0.438***	0.085	0.076
Subsidies	0.389***	0.019	0.300***	0.008	0.503***	0.119	0.176
Distance to cities (Cities500k)	0.984***	0.124	-1.494***	0.065	-0.614**	0.307	0.403
Distance to ports (PortsML)	-0.489***	0.111	-0.549***	0.065	-0.155	0.242	0.354
Elevation mean	-0.596***	0.060	-0.376***	0.037	-0.134	0.163	0.198
Elevation range	0.061***	0.018	-0.017*	0.009	0.074*	0.044	0.068
Austria (AT)					-2.392***	0.191	0.230
Belgium (BE)					0.499***	0.169	0.175
Denmark (DK)					1.187***	0.163	0.201
Spain (ES)					-0.118	0.187	0.269
Finland (FI)					0.214	0.312	0.341
France (FR)					-0.736***	0.142	0.180
Greece (GR)					0.656**	0.272	0.410
Ireland (IE)					0.815***	0.127	0.172
Italy (IT)					1.193***	0.186	0.287
Luxembourg (LU)					0.158	0.169	0.181
Netherlands (NL)					1.262***	0.144	0.131
Portugal (PT)					-1.229***	0.238	0.409
Sweden (SE)					0.335	0.213	0.266
West Germany (WDE)					0.799***	0.133	0.151
East Germany (EDE)					-0.007	0.163	0.196
United Kingdom (UK)					(omitted)		
Regional dummies			not reported				
Constant	-0.893	0.928	6.083***	0.537	3.490**	1.780	3.079
Pseudo R2 / Adj. R2	0.2703		0.4767		0.8108		
Number of obs.	41060		41060		935		

*** p<0.01, ** p<0.05, * p<0.1; the spatial standard errors are based on the Conley routine (http://economics.uwo.ca/people/conley_docs/code_to_download_gmm.html)

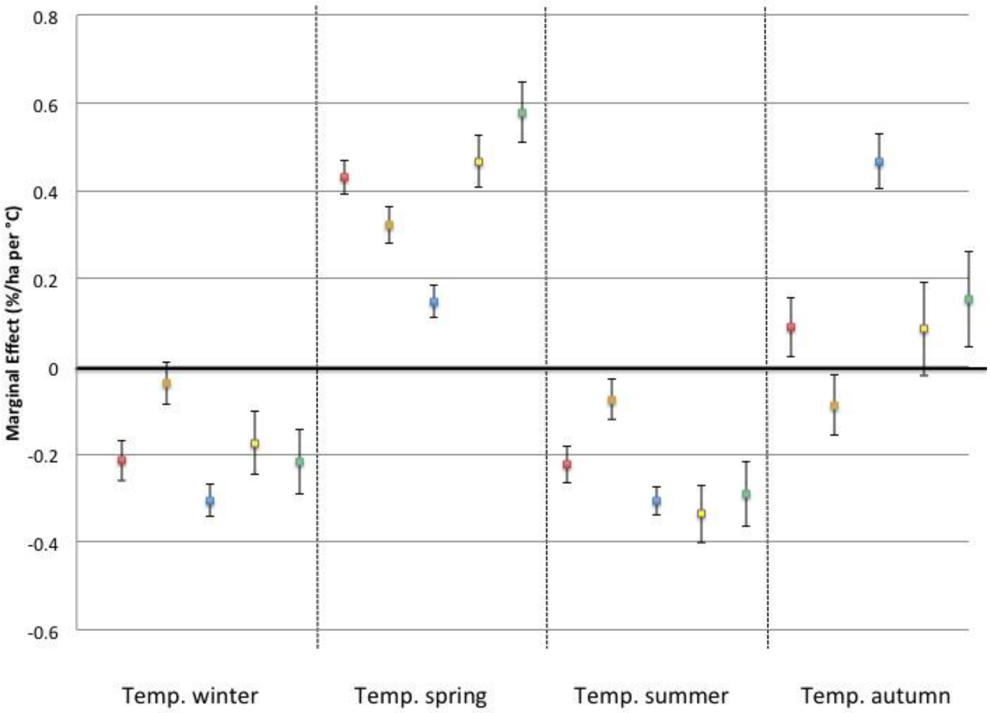
Figure 1: Marginal Impact in Percentage of Land Value of Temperature and Precipitation across quantiles

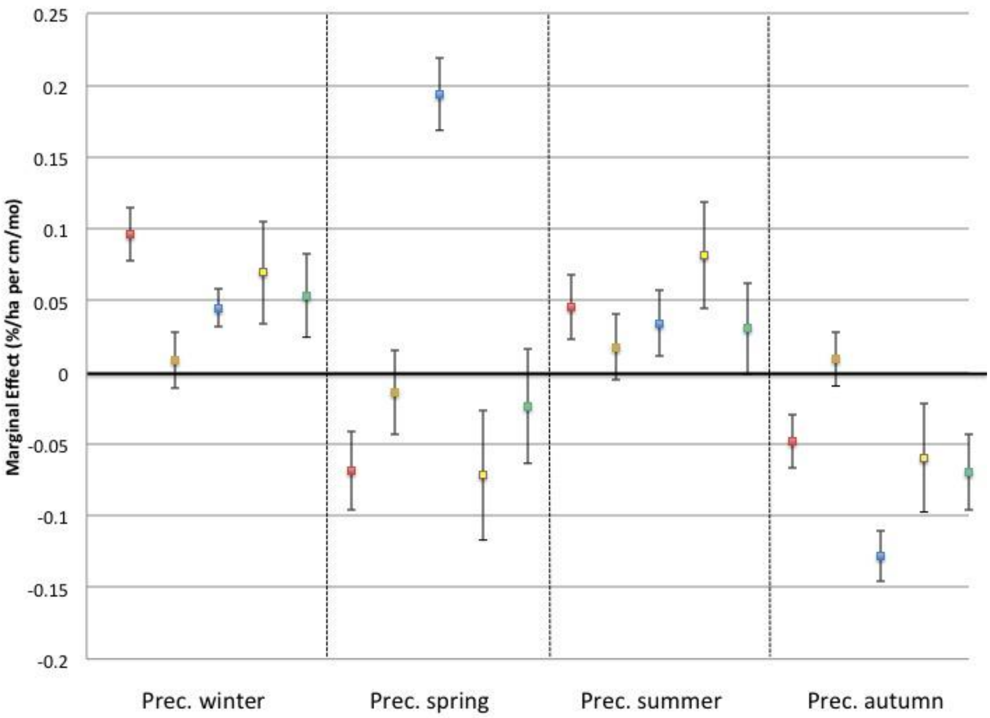




color coding: red (Q10), orange (Q25), blue (Q50), yellow (Q75) and green (Q90)

Figure 2: Percentage Land Value Marginal Effects at Temperature and Precipitation of all farms, only rainfed, only irrigated land, only crop farms and only grazing farms (median regressions)





color coding: red (all farms), orange (rainfed farms), blue (irrigated farms), yellow (crop farms) and green (grazing farms)

Figure 3: Percentage change in farmland values predicted by Hadley CM3 climate scenario (2100)

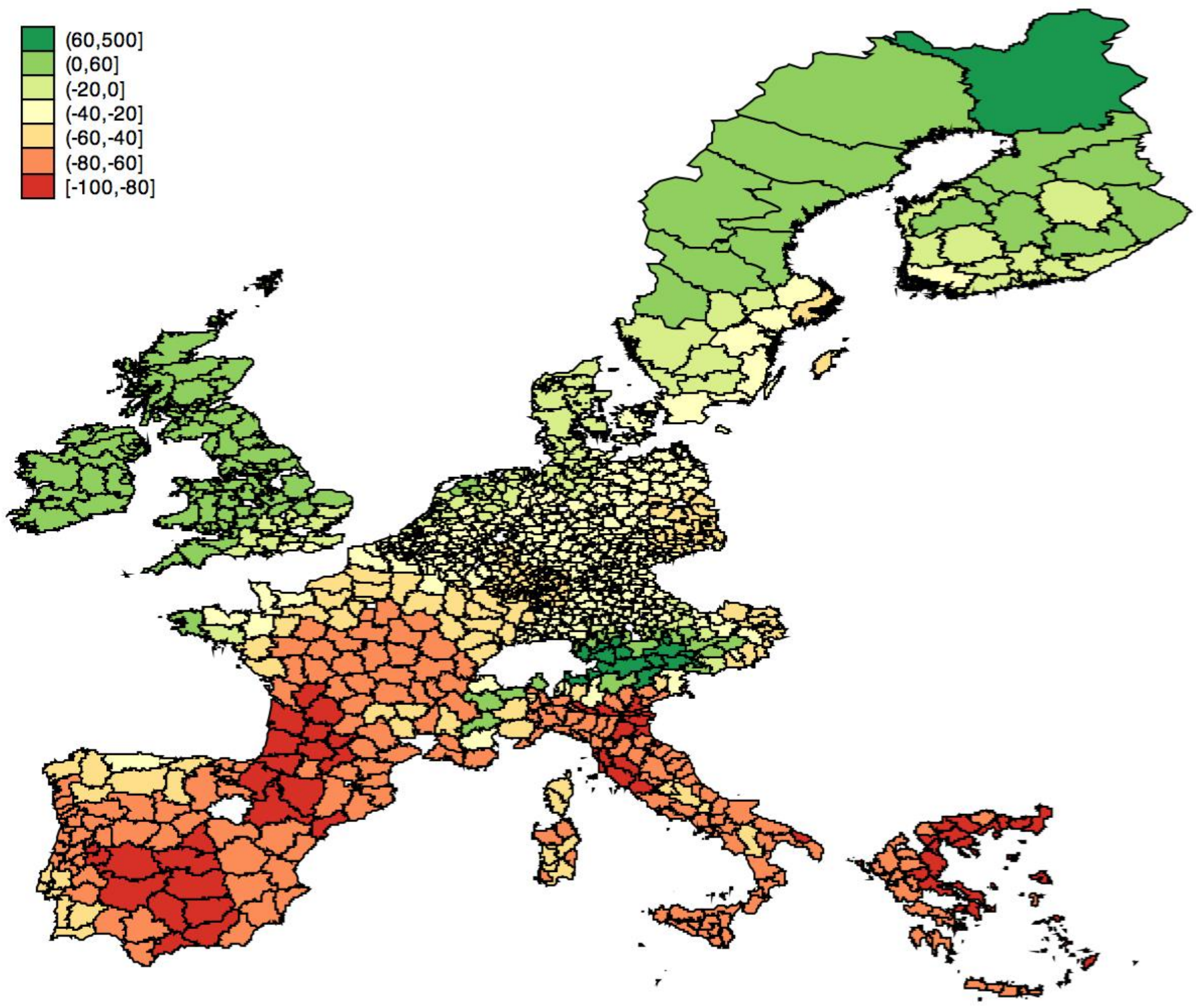


Figure 4: Percentage change in farmland values predicted by ECHO-G climate scenario (2100)

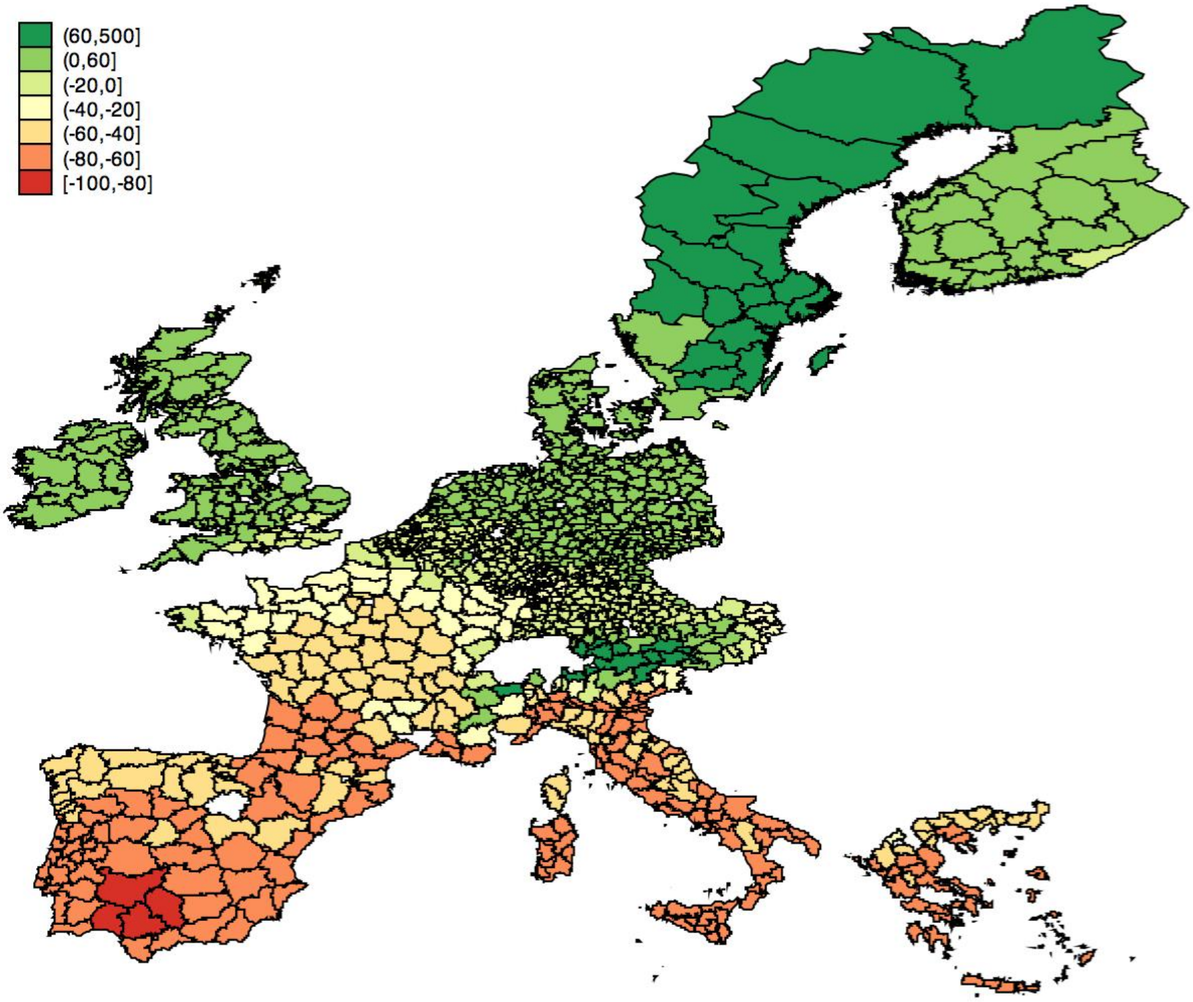
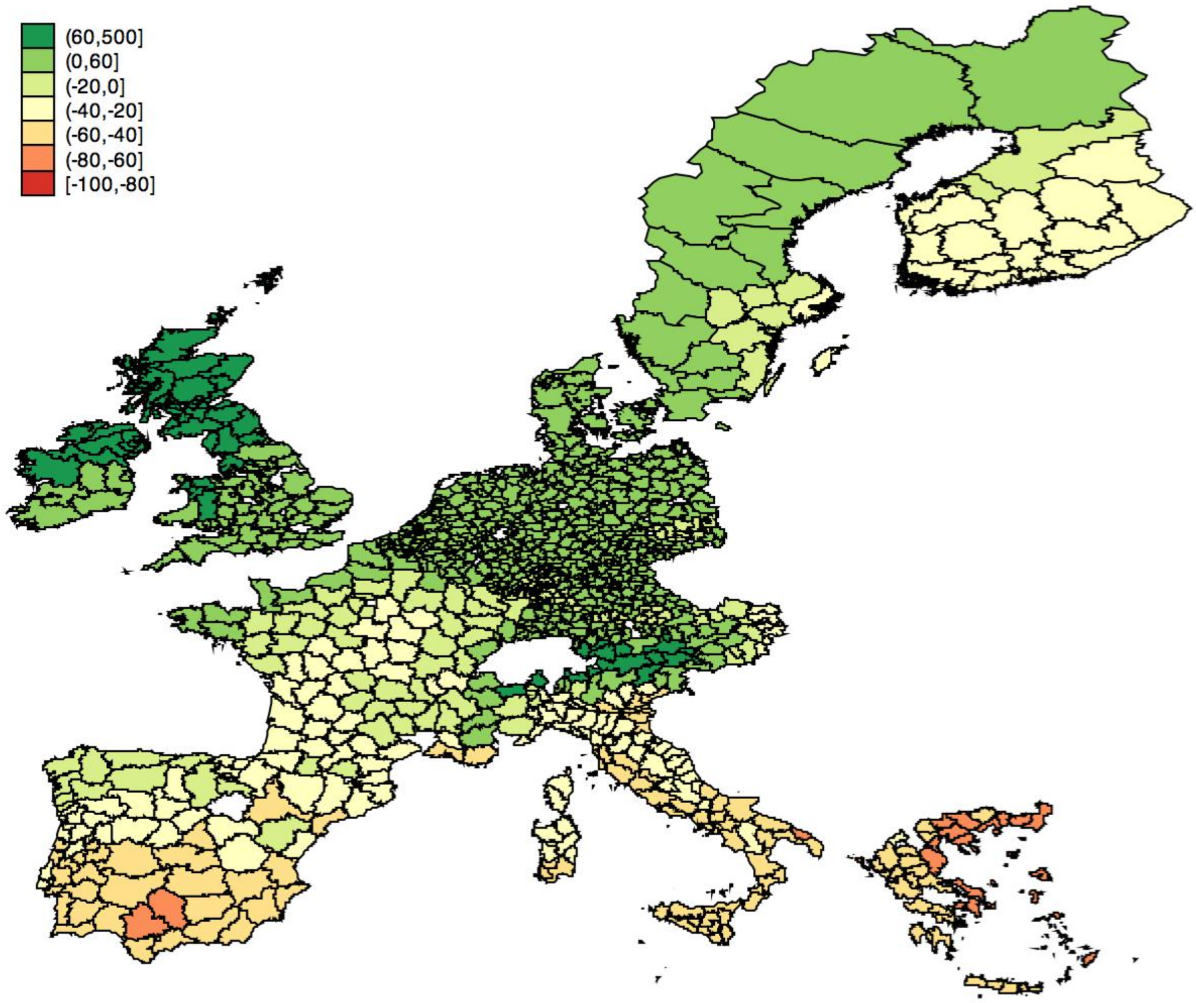


Figure 5: Percentage change in farmland values predicted by NCAR PCM climate scenario (2100)



Supplementary Materials:

Figure S.1: Percentage land value marginal effects (1°C increase) (median regression)

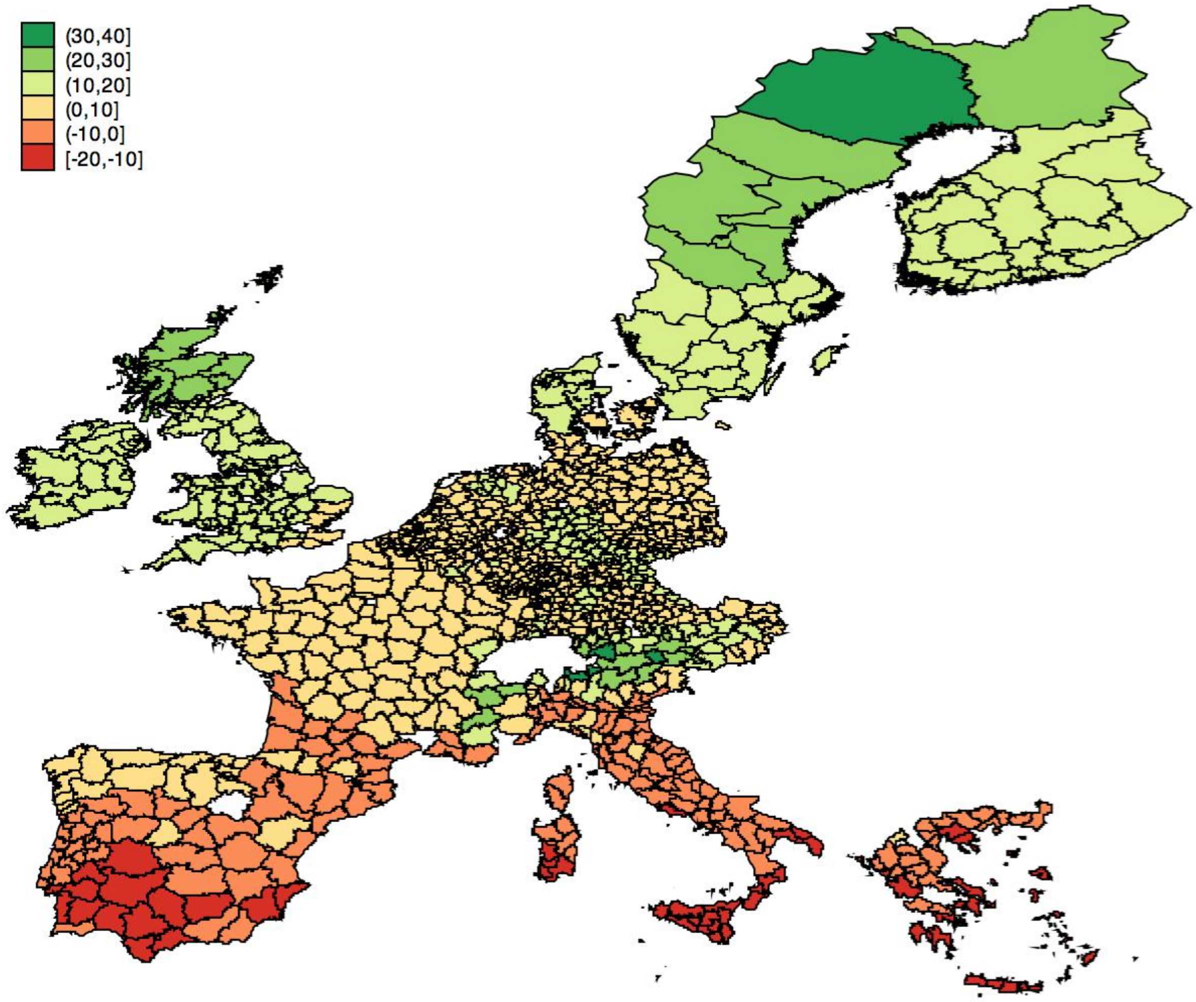


Figure S.2: Percentage land value marginal effects (10 mm/month increase) (median regression)

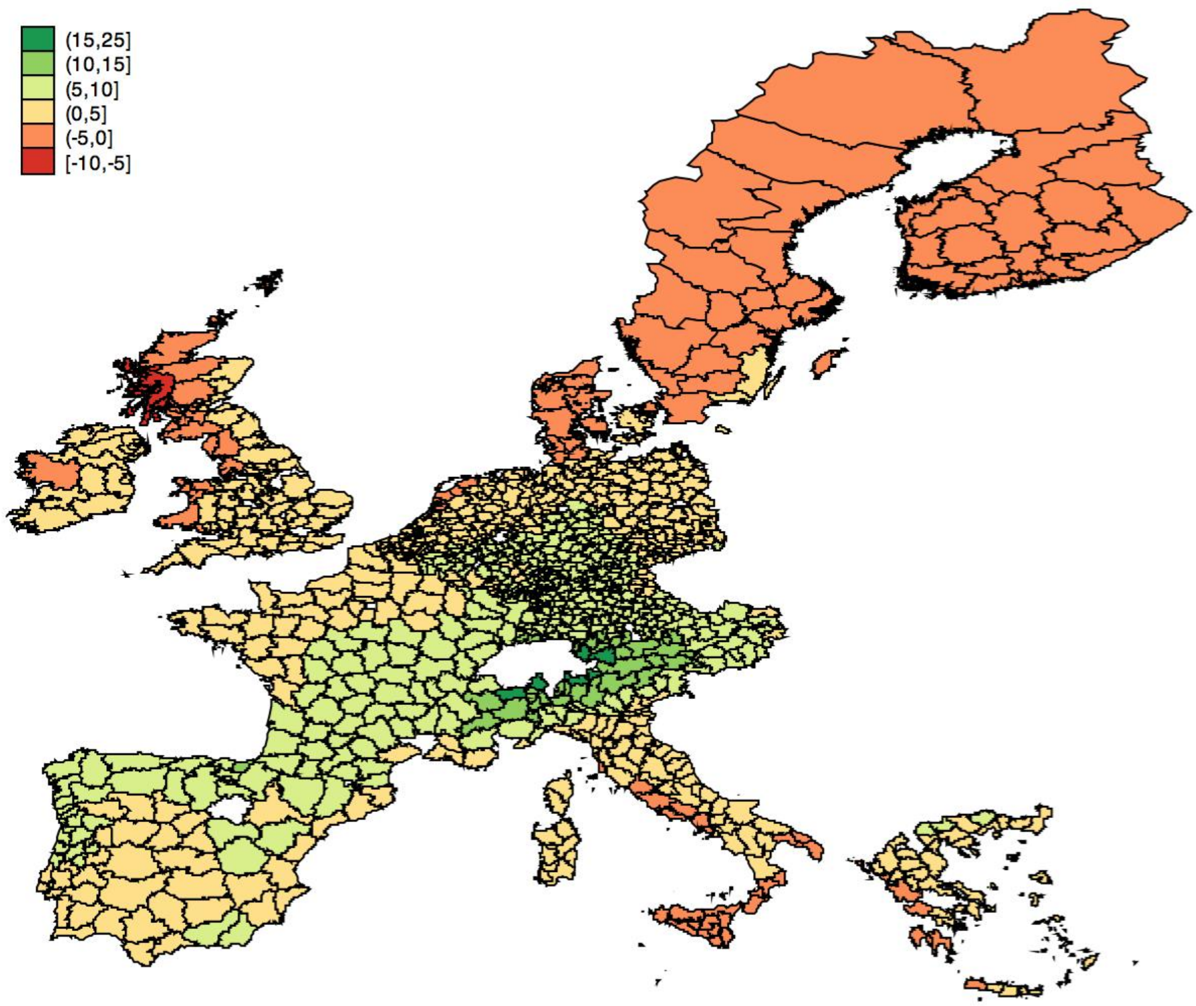


Table S.1: Percentage Land Value Marginal Effects at Median Temperature and Precipitation (%/ha per °C or cm/mo)

	Temp. annual		Prec. annual		Temp. winter		Temp. spring		Temp. summer		Temp. autumn		Prec. winter		Prec. spring		Prec. summer		Prec. autumn	
Austria	0.094	***	0.065	***	-0.252	***	0.425	***	-0.213	***	0.134	***	0.099	***	-0.022	*	0.036	***	-0.047	***
Belgium	0.085	***	0.044	***	-0.222	***	0.431	***	-0.215	***	0.092	***	0.096	***	-0.036	***	0.043	***	-0.059	***
Germany	0.092	***	0.045	***	-0.240	***	0.425	***	-0.212	***	0.119	***	0.100	***	-0.077	***	0.043	***	-0.021	*
Denmark	0.116	***	-0.024	**	-0.239	***	0.415	***	-0.192	***	0.131	***	0.099	***	-0.098	***	0.044	***	-0.069	***
Spain	-0.048	***	0.027	**	-0.200	***	0.448	***	-0.292	***	-0.005		0.098	***	-0.097	***	0.051	***	-0.026	**
Finland	0.163	***	-0.019	*	-0.300	***	0.391	***	-0.187	***	0.259	***	0.103	***	-0.137	***	0.044	***	-0.029	***
France	0.058	***	0.050	***	-0.212	***	0.436	***	-0.231	***	0.065	*	0.095	***	-0.033	***	0.046	***	-0.057	***
Greece	-0.088	***	0.024	**	-0.204	***	0.455	***	-0.312	***	-0.027		0.093	***	-0.094	***	0.051	***	-0.026	**
Ireland	0.154	***	0.004		-0.206	***	0.427	***	-0.175	***	0.108	***	0.088	***	-0.018		0.043	***	-0.109	***
Italy	-0.046	***	0.009		-0.197	***	0.452	***	-0.291	***	-0.010		0.094	***	-0.063	***	0.049	***	-0.071	***
Luxembourg	0.100	***	0.044	***	-0.233	***	0.428	***	-0.214	***	0.119	***	0.093	***	-0.026	**	0.043	***	-0.065	***
Netherlands	0.102	***	0.015	**	-0.222	***	0.428	***	-0.206	***	0.102	***	0.097	***	-0.070	***	0.044	***	-0.055	***
Portugal	-0.090	***	0.030	**	-0.165	***	0.468	***	-0.305	***	-0.088	*	0.089	***	-0.059	***	0.052	***	-0.051	***
Sweden	0.136	***	-0.010		-0.262	***	0.406	***	-0.193	***	0.184	***	0.100	***	-0.110	***	0.044	***	-0.044	***
UK	0.143	***	0.019	***	-0.216	***	0.423	***	-0.180	***	0.115	***	0.092	***	-0.041	***	0.043	***	-0.076	***
EU-15	0.082	***	0.024	***	-0.215	***	0.431	***	-0.223	***	0.089	***	0.096	***	-0.069	***	0.045	***	-0.048	***

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): *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table S.2: Absolute Marginal Effects at Median Temperature and Precipitation (Euro/ha)

	Temp. annual		Perc. annual		Temp. winter		Temp. spring		Temp. summer		Temp. autumn		Prec. winter		Prec. spring		Prec. summer		Prec. autumn	
Austria	101	***	70	***	-270	***	456	***	-229	***	144	***	106	***	-24	*	38	***	-51	***
Belgium	1,104	***	566	***	-2,866	***	5,570	***	-2,783	***	1,183	***	1,235	***	-461	***	554	***	-763	***
Germany	969	***	476	***	-2,530	***	4,485	***	-2,238	***	1,252	***	1,055	***	-817	***	459	***	-221	*
Denmark	1,625	***	-336	**	-3,338	***	5,810	***	-2,683	***	1,835	***	1,378	***	-1,374	***	620	***	-960	***
Spain	-139	***	76	**	-573	***	1,284	***	-835	***	-14		282	***	-279	***	147	***	-74	**
Finland	519	***	-60	*	-955	***	1,246	***	-596	***	824	***	328	***	-438	***	141	***	-91	***
France	149	***	128	***	-543	***	1,116	***	-590	***	166	*	244	***	-86	***	117	***	-147	***
Greece	-792	***	216	**	-1,836	***	4,105	***	-2,814	***	-247		837	***	-844	***	456	***	-233	**
Ireland	3,248	***	89		-4,350	***	9,012	***	-3,704	***	2,289	***	1,859	***	-390		912	***	-2,292	***
Italy	-609	***	114		-2,606	***	5,976	***	-3,842	***	-138		1,244	***	-834	***	648	***	-945	***
Luxembourg	829	***	365	***	-1,926	***	3,538	***	-1,765	***	981	***	765	***	-214	**	353	***	-539	***
Netherlands	3,329	***	493	**	-7,265	***	14,013	***	-6,743	***	3,324	***	3,160	***	-2,306	***	1,429	***	-1,790	***
Portugal	-64	***	22	**	-117	***	334	***	-217	***	-63	*	63	***	-42	***	37	***	-36	***
Sweden	609	***	-47		-1,173	***	1,821	***	-864	***	825	***	449	***	-495	***	199	***	-199	***
UK	1,262	***	169	***	-1,903	***	3,732	***	-1,584	***	1,017	***	811	***	-358	***	383	***	-666	***
EU-15	482	***	143	***	-1,254	***	2,520	***	-1,306	***	521	***	562	***	-401	***	264	***	-282	***

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