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A Ricardian analysis of the impact of climate change on European agriculture

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

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6    **Abstract**

7    This research estimates the impact of climate on European agriculture using a continental scale Ricardian

8    analysis. Climate, soil, geography and regional socio-economic variables are matched with farm level data from

9    41,030 farms across Western Europe. We demonstrate that a median quantile regression outperforms OLS

10    given farm level data.  The results suggest that European farms are slightly more sensitive to warming than

11    American farms with impacts from +5% to -32% by 2100 depending on the climate scenario.  Farms in Southern

12    Europe are predicted to be particularly sensitive, suffering losses of -5% to -9% per degree Celsius.

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**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

79    Fisher et al. (2012), it is critical that climate is measured carefully. The Ricardian method does not measure

80    either price sensitivity (Cline 1996) or carbon fertilization since both prices and the level of carbon dioxide

81    remain the same across the entire sample. The absence of price effects causes the Ricardian method to

82    overestimate large global damages or global benefits of warming (Mendelsohn and Nordhaus 1996). The

83    beneficial effects from carbon dioxide fertilization (Kimball 2007) must be added exogenously using the results

84    of crop experiments. The Ricardian approach is a comparative static analysis of long run equilibriums. It does

85    not capture the cost or the dynamics of moving from one equilibrium to another (Kelly et al. 2005).

86    Intertemporal analyses of weather are much more appropriate tools for capturing the short run dynamics

87    associated with weather changes (Deschênes and Greenstone (2007).

88    There has also been an extensive debate concerning whether the Ricardian technique properly accounts for

89    irrigation (Schlenker et al. 2005). Some Ricardian studies have carefully controlled for the availability of surface

90    and groundwater (Mendelsohn and Dinar 2003; Kurukulasuriya et al. 2011; Massetti and Mendelsohn 2011).

91    Unfortunately, such data are not available for this study. We do examine the climate response function of both

92    rainfed versus irrigated farms in order to demonstrate how important these choices are to farm outcomes. As

93    shown in the literature for Africa (Kurukulasuriya et al. 2011; Kala et al. 2012), South America (Seo and

94    Mendelsohn 2008) and China (Wang et al. 2009), the climate response functions of rainfed and irrigated farms

95    are different.

96    A special concern in Europe is whether the EU Common Agricultural Policy distorts climate sensitivities. For

97    example, farm subsidies can hide (exaggerate) climate sensitivity if the subsidies are higher for farms in adverse

98    (favourable) climates. We control for subsidies at the farm level. The analysis also includes country fixed effects

99    to remove the influence of country level policies.

100   The paper is organized as follows. In section 1, we briefly explain the theory behind the Ricardian analysis.

101   Section 2 presents the data and the model specifications of the Ricardian model using farm level data. In

102   section 3 the empirical findings are presented as well as measures of the impacts of different future climate

103   scenarios by General Circulation Climate Models (GCM). The paper concludes with a summary of the results,

104   policy conclusions, and limitations.

105    **1. Methodology**

106    The Ricardian model assumes that each farmer $i$ chooses which output ($Q_{i,j}$) and how much inputs ($X_{i,k}$) to

107    maximize net revenues ($NR_i$) each year:

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

109    where $P_j$ is the market price of each output $j$,

110    $Q_{i,j}$ is the quantity of each output $j$ at farm $i$, is a vector of purchased inputs $k$ (other than land), $M_k$ is a

111    vector of input prices, and $Z_i$ is a vector of exogenous variables at the farm. Farmers will choose both the type

112    of output and their inputs to maximize net revenue given prices and exogenous factors. Looking at the final

113    outcomes across a large set of farmers in different settings, net revenue will be a function of just the

114    exogenous factors.   Farmland value ($V_i$) is equal to the present value of future net revenue:

115    $$V_i = \int_t^\infty NR_t e^{-\varphi t} dt \tag{2}$$

116    where $\varphi$ is the interest rate and $V_i$ is therefore  a function of only the exogenous variables:

117    $$V_i = f(Z_i) . \tag{3}$$

118    The cross sectional Ricardian regression estimates equation (3). Endogenous variables selected by the farmer

119    such as fertilizer or crop choice should not be included as independent variables in the regression. When

120    endogenous variables are included in the Ricardian regression, those factors are "controlled" or held fixed and

121    not allowed to vary with climate. Exogenous variables can be grouped into different subgroups: climate

122    variables (temperature, *T*, and rainfall, *R*), and exogenous control variables (*E*) such as geographic, soil

123    variables, and socio-economic variables including market access (which may proxy for price variation).

124    We use data on farmland value per hectare ($V_i$) from the FADN (Farm Accountancy Data Network). Farmland

125    value is measured as the replacement value of agricultural land in owner occupation. The farm accountancy

126    data are harmonized, applying the same bookkeeping and valuation principles across the entire sample.

127  Although we have tested a linear functional form, we find that a log-linear form fits the data best because land

128  values are log-normally distributed (Schlenker et al. 2006; Massetti and Mendelsohn 2011)[1]. We use the

129  climatology of each location (the 30 year average seasonal temperature and rainfall) to measure climate. We

130  include four seasons because agronomic and Ricardian studies reveal that seasonal differences in temperature

131  and precipitation have a significant impact on farmland productivity (see review in Mendelsohn and Dinar

132  (2009)). Some authors (e.g. Schlenker et al. (2006); Moore and Lobell (2014)) have promoted the idea of using

133  just climate during the growing season. But perennials and winter crops are very relevant in Europe so that the

134  growing season is all year long. Further, the climate during the "nongrowing season" has an impact on land

135  value and is correlated with the climate during the growing season. Failure to include all seasons leads to

136  biased climate coefficients. Finally, the agronomic and economic literature also suggests that the relationship

137  between climate and land values is nonlinear (see review in Mendelsohn and Dinar (2009)). We therefore

138  estimate the following model for each farm $i$:

139  $$\ln V_i = \alpha + \beta_T T_i + \gamma_T T_i^2 + \beta_R R_i + \gamma_R R_i^2 + \eta E_i + \xi D + u_i \tag{4}$$

140  where $T$ and $R$ are vectors reflecting seasonal temperatures and precipitations, $E$ is a set of exogenous control

141  variables; $D$ is a set of country fixed effects and $u_i$ is a random error term which is assumed not to be

142  correlated with climate.

143  For a random variable $Y$ with cumulative distribution $F$ ($F(y) = P(Y < y)$), the τ-th quantile is defined by

144  $Q_y(\tau) = \inf\{y : F(y) \geq \tau\}$. The most frequently examined quantiles are the median (τ=0.5), the first and last

145  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

146  quantile regression (Koenker and Bassett 1978) for each different value of τ:

147  $$Q_{\ln V_i}(\tau | T, R, E, D) = \alpha(\tau) + \beta_T(\tau) T_i + \gamma_T(\tau) T_i^2 + \beta_R(\tau) R_i + \gamma_R(\tau) R_i^2 + \eta(\tau) E_i + \xi(\tau) D \tag{5}$$

148  The median quantile regression estimate is more robust against outliers compared to OLS because the effect of

149  the outliers is relegated to the extreme quantiles. In contrast, OLS regressions can be strongly influenced by

150  extreme observations because the regression is minimizing squared errors across the entire sample.

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[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.

151    Although the entire sample is subject to the rules and regulations of the European Union, these rules are often

152    applied in a different fashion by each country. We control for country specific factors that affect farms by using

153    country fixed effects. Although in principle finer geographic controls for unmeasured spatial correlates, an

154    overuse of fixed effects can significantly inflate the variability of the estimates of other covariate coefficients

155    (Koenker 2004). The risk of ever-finer controls is a reduction in the climate variation within the sample. The

156    climate signal becomes weaker with each additional layer of fixed effects. In the end, measurement error can

157    dominate the results and bias the climate coefficients towards zero (Fisher et al. 2012).

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

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

160    Note that the marginal impacts may differ over quantiles (i.e. different values of $\tau$) and that we use a quadratic

161    specification of climate variables. Temperature and precipitation marginals consequently vary depending on

162    both the underlying land value and climate. In order to calculate the marginal impact of warming across all of

163    Europe (or a particular member state), one must sum the effects at every farm:

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

165    with *n* the total number of sampled farms in region *r* and where $\omega_i$ is a weight that reflects the total amount of

166    farmland that each farm represents. This expression evaluates a small change in $T_i$ at each region *r* and reports

167    the expected response across all regions. One can also calculate the percentage change in land value

168    associated with a small change in temperature:

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

170    In order to test the effect of very different climates, one can compare the predicted land value of a

171    hypothetical climate $(T_1, R_1)$ to the estimated value of land with the original climate $(T_0, R_0)$:

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

173    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.

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[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)

196   The observed climate data for each NUTS3 region was derived from the Climatic Research Unit (CRU) CR 2.0

197   dataset (New et al. 2002). The climatologies for temperature and precipitation rely on measurements from

198   1961 to 1990. Soil data are from the harmonized world soil database, a partnership between the Food and

199   Agriculture Organization (FAO) and the European Soil Bureau Network. An overview and detailed description of

200   all model variables and sources can be found in Appendix A. Additional socioeconomic (population density) and

201   geographic variables (e.g., distance from urban areas, distance from ports, mean elevation) were matched to

202   each NUTS3 region.

203   Table A.1 in the Appendix shows the descriptive statistics of our model variables for the entire sample. The

204   average farm level land value is nearly 16,000 Euro per hectare but there is a wide range in values.  The amount

205   of land actively farmed exceeds the amount of land owned. Many farmers in Europe rent land from

206   landowners, a practice which varies by country.

207   It is helpful to understand how farm types vary across Europe. The mean values of some key characteristics of

208   farms are reported in Table A.2 for each farm type. Note that the value of irrigated land is generally much

209   higher than rainfed land.  The active size of rainfed farms, in contrast, is much higher than for irrigated farms.

210   The optimal size to operate a farm is larger for rainfed farms.  Irrigated farms tend to be located in warmer

211   regions of Europe. Livestock farms are also quite different from crop farms. The utilized agricultural area of

212   livestock is larger. Moreover, specialised livestock farms are located in cooler and wetter areas.

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214   2.2 Model specifications

215   We explore a number of different analyses to test the robustness of our results. We estimate both OLS and

216   quantile regression models of the entire sample to measure the overall climate sensitivity of European farms.

217   We also estimate separate regressions for subsamples of rainfed, irrigated, crop and livestock farms.

218   In all regressions, we weight each farm within the sample using total owned agricultural land in that farm to

219   control for heteroscedasticity.  We also test for aggregation bias by comparing the results using the micro data

220   versus the aggregate data for each NUTS3 region.

221 It is not possible to correct for spatial correlation with the micro data because we do not know the precise

222 location of each farm. However, we do apply controls for spatial correlation using the aggregate data. Treating

223 each NUTS3 region as an observation, we follow Schlenker and Roberts (2009) and apply the Conley (1999)

224 non-parametric method to correct the matrix of covariances for spatial dependence among observations.

225 We then interpret the coefficients of the Ricardian models by first calculating the marginal impacts of small

226 changes in temperature and precipitation change (away from the current climate). Because the model is

227 nonlinear, these marginal effects change with large changes in climate. In order to learn how the Ricardian

228 model responds to very different climates, we then calculate the consequence of predicted climate outcomes

229 in 2100 for three different climates predicted by General Circulation Climate Models (GCMs): Hadley CM3

230 (Gordon et al. 2000), ECHO-G (Legutke and Voss 1999), and NCAR PCM (Washington et al. 2000). These specific

231 climate scenarios are based on the A2 SRES (Special Report on Emissions Scenarios) emissions scenario

232 (Nakićenović et al. 2000). Note that our purpose in choosing these three climate scenarios is not to predict

233 realistic outcomes in 2100 but simply to show what the Ricardian model predicts would happen with a range of

234 plausible climate scenarios. .

235 We interpolate from the climate grids of the GCMs to each NUTS3 region centroid using inverse distance

236 weights to the four nearest grid points.[4] The absolute change of temperature and the percentage change in

237 precipitation are defined as the difference in the climate model's predictions for 2071-2100 versus 1961-1990.

238 These changes are then applied to the CRU 1961-1990 observed climate data for each NUTS3 region.

239 Across Western Europe, the Hadley CM3 model predicts an average warming of 4.4°C with a 34% loss of annual

240 precipitation, the ECHO-G model predicts a warming of 4.3°C with a 21% loss of precipitation, and the NCAR

241 PCM model predicts a warming of 2.8°C with a 5% loss of precipitation by 2100. The three climate scenarios

242 effectively represent a severe, moderate, and mild possible outcome, respectively. However, the precise

243 climate change for each country in Europe varies across the scenarios so that some parts of Europe are

244 predicted to warm or dry at different rates. The mean temperature and precipitation in each member state for

245 each scenario can be found in Appendix B.

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[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

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273    general seasonal results mirror the results from US studies (Mendelsohn et al. 1994; Mendelsohn and Dinar

274    2003; Massetti and Mendelsohn 2011).  A colder winter is beneficial because cold limits pests, a warmer spring

275    and autumn are valuable because they lengthen the growing season, and a warmer summer is harmful because

276    the high temperatures stress crops.

277    Insert Figure 1

278    Precipitation also significantly affects land values. For the median EU farm, rain is beneficial in winter and

279    summer but harmful in spring and fall. There is adequate rainfall already in the spring and fall in Europe, so that

280    more rainfall only diminishes much needed solar radiation. In contrast, there is not currently enough rainfall in

281    summer to compensate for the heat, and so more rainfall is beneficial. More rainfall in the winter can lead to

282    plentiful soil moisture for the beginning of growing season. These seasonal patterns for marginal changes are

283    similar to American results. Figure 1 shows the impact of spring precipitation has especially wide ranging

284    marginal effects across quantiles ranging from -23% in the 10th percentile to +7% in the 90th percentile.

285    Looking across all of Europe, one can summarize the annual marginal effects of both temperature and

286    precipitation.  The median regression of the entire sample of farms (Table 1) reveals that a uniform increase of

287    1°C in the EU-15 increases farmland value +8.2% (482 €/ha) and a uniform increase of 1 cm per month of

288    precipitation increases farmland value +2.4% (143 €/ha). Marginal warming and marginal increases in

289    precipitation are beneficial to EU-15 agriculture as a whole.

290    The marginal climate effects, however, differ a great deal across member countries within the EU-15 because

291    each country has a different initial precipitation and temperature. A small warming (cooling) is beneficial

292    (harmful) to cooler countries and harmful (beneficial) to warmer countries.  A small increase (decrease) in

293    precipitation is beneficial (harmful) to drier (wetter) countries and harmful (beneficial) to wetter countries.

294    The marginal percentage change for each country is reported in the supplementary materials Table S.1

295    (equation 8), the absolute marginal values are reported in Table S.2 (equation 7), and Figures S.1 and S.2 map

296    the temperature and precipitation marginal impacts at the NUTS3 level.  A marginal increase in annual

297    temperature has a beneficial effect on the northern countries: Austria, Belgium, Germany, Denmark, Finland,

298    Ireland, Luxembourg, Netherlands, Sweden, and Great Britain and a negative effect on the southern countries:

299    Spain, Greece, Italy, and Portugal. The magnitude of the marginal effects varies by countries. The marginal

300 benefit is the highest in Sweden and Finland which gain about 16% of land value, whereas the marginal loss is

301 highest in Greece and Portugal which lose 9% of land value. A small increase in rainfall  (see Figure S.2 in

302 supplementary materials) is beneficial to Austria, Belgium, France, Germany, Luxembourg, Portugal, and Spain

303 but harmful to Denmark, Finland, and Sweden.

304 Several of the control variables in Table 1 are also significant. Gravel soils tend to be harmful. Because neutral

305 soils are more beneficial than either acidic or alkaline soils, soil pH has a concave impact on land value.. Higher

306 population density increases land values, which makes sense because higher density implies land is scarce.

307 Greater distance to markets reduces land value whether it is to large cities or ports. The coefficient is twice as

308 large for ports as cities suggesting ports (and therefore exports) lead to more valuable markets for farmers.

309 Higher elevation is harmful. Higher elevation may be harmful for many reasons including higher diurnal

310 temperature variance, decreased access, or increased slope. Country fixed effects are generally significant

311 implying higher average land values in Denmark, Ireland, West Germany, Italy, and the Netherlands, but lower

312 values in Austria, France, East Germany, and Portugal.

313 Table 1 also compares the results of the median regression and an identical OLS regression using the whole

314 sample. The coefficients from both models are quite similar. The median regression leads to a flatter overall

315 climate response function (smaller marginal results) than the OLS regression. The extreme data points that

316 tend to have more influence in the OLS regression lead to a slightly more sensitive climate response function.

317  We use the Morgan-Granger-Newbold (MGN) significance test to compare the forecasting accuracy of the

318 median regression and OLS models (Diebold and Mariano 2002). We use a random sample of 80% of our farms

319 to estimate the Ricardian function and we forecast the land values of the remaining 20% of farms. We repeat

320 the MGN test 1000 times and we reject the null hypothesis of equal forecasting accuracy in favour of the

321 median regression in 99% of the repetitions. The median regression model outperforms the OLS model with an

322 average t-statistic of 10.12.   We consequently focus on the results of the median quantile regression in the

323 remainder of the paper.

324 In addition to understanding how climate affects the entire farm sector, it is also helpful to estimate how

325 climate affects subsamples of farms as shown in Table 2. The regression in the first column in Table 2 is

326 estimated on only rainfed farms. The second column shows the results for irrigated farms. The climate

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327    coefficients for the irrigated farms are quite different from the climate coefficients of the rainfed farms.

328    Irrigation allows farms to exist in dryer locations, as can be seen in Europe (Table A-2). However, irrigation also

329    affects temperature sensitivity.  The optimal summer temperature for irrigated farms (14.5°C) is higher than

330    the optimal temperature for rainfed farms (13.6°C). As both agronomic and economic studies have previously

331    shown, irrigation increases the tolerance of plants to higher temperatures (Mendelsohn and Dinar 2003; Elliott

332    et al. 2014; Nendel et al. 2014).  Figure 2 presents the marginal climate results for Table 2. A marginal increase

333    in warming increases the value of irrigated farms slightly more than rainfed farms. A slight increase in

334    precipitation, however, has a powerful positive marginal effect on irrigated farms and only a small effect on

335    rainfed farms. Partly, this is because irrigated farms are located in the driest and warmest part of Europe so

336    added rainfall is particularly valuable. However, controlling for climate, the net revenues of irrigated farms are

337    clearly more sensitive to precipitation than rainfed farms.

338    Rainfed and irrigated farms also have different seasonal responses.  Warmer temperatures in winter and spring

339    benefit rainfed more than irrigated farms but warmer autumn temperatures are especially beneficial to

340    irrigated farms. Irrigated farms respond especially well to wetter springs but especially poorly to wetter

341    autumns compared to rainfed farms. These seasonal differences could be caused by the different crops that

342    each type of farm is growing.

343    Insert Table 2

344    Insert Figure 2

345    The coefficients of the control variables in Table 2 are also quite different for irrigated versus rainfed farms.

346    Gravel soils are only harmful to rainfed farms. Irrigated farms have a much higher negative reaction to sandy

347    soils.  This is probably because such soils cannot hold irrigated water and the water just seeps through.  A

348    higher share of rented land increases the land value of rainfed farms but decreases the land value of irrigated

349    land. Renters have less long run incentive to invest in the capital required for irrigation compared to

350    landowners. Access to ports is more beneficial to irrigated farms but access to cities is more beneficial to

351    rainfed farms. One explanation is that irrigated farms could be growing crops directly for export whereas

352    rainfed farms are selling more of their output to nearby cities.

353    Another important distinction between farms is whether they grow crops or raise livestock. The third and

354    fourth columns in Table 2 are regressions on subsamples of crop farms and livestock farms. The seasonal

355    temperature coefficients have similar patterns for both crops and livestock. However, examining the

356    magnitude of marginal climate responses in Figure 2 reveals that warming is more beneficial to livestock than

357    crop farms. This is especially clear in spring.

358    Some of the crop and livestock coefficients of the control variables are also different.  Gravel soils are more

359    harmful to crops but sandy soils and high elevation are more harmful to livestock. Alkaline soils, population

360    density, and being closer to cities are more beneficial to crops whereas being closer to ports is more beneficial

361    to livestock.  The livestock may be dependent on the import of feed (e.g. soya) from the ports.

362    **3.2 Alternative climates**

363    In this section, we examine the impact of alternative climates that are quite different from the current climate.

364    Because the Ricardian model is nonlinear, it predicts different outcomes as climate changes dramatically.  We

365    use three different climate models (Hadley CM3, ECHO-G and NCAR PCM) to select a range of plausible future

366    climates. All three climate scenarios were based on the SRES A2 (no mitigation) GHG emission scenario.

367    We use the coefficients from the estimated median quantile regression of all farms (Table 1) to calculate the

368    land values in each NUTS3 region for each climate scenario (including the current climate). . Subtracting the

369    land values of the current climate from the three climate scenarios provides a measure of the welfare change.

370    The calculation takes into account changes in both temperature and precipitation at each NUTS3 location. The

371    effects are then aggregated across space to measure country impacts and EU-15 impacts (Equation 9).

372    Table 3 reports the change in aggregate farmland value for Western Europe. The Hadley CM3 scenario

373    generates a loss of 32% of farmland value by 2100. The ECHO-G scenario generates a loss of 16% and NCAR

374    PCM generates a 5% gain. These impact estimates are calculated keeping the rest of the model constant. This is

375    consequently not a forecast of the future but simply a measure of what climate might do if it alone changed.

376    We also do not consider carbon fertilization.  If carbon dioxide concentrations double between now and 2100

377    (from 400 ppm to 800 ppm), crop yields are expected to increase by 30% (Kimball 2007). Carbon fertilization

378    would moderate the results reported in Table 3.

379    Insert Table 3

380  In order to quantify the uncertainty surrounding the welfare estimates in Table 3, we build bootstrap

381  confidence intervals. Samples were created using a random selection of farms with replacement. The median

382  regression was then estimated for each sample. The impact of each climate scenario was then calculated. The

383  process was then repeated 1,000 times to generate 1,000 values for each climate scenario. The results

384  illustrate that the damage predicted in the ECHO-G and Hadley CM3 scenarios is significantly different from

385  zero at EU-15 level while the gain of the NCAR PCM scenario is not significant different from zero. The

386  uncertainty across the climate models is large as one can see from the results across three climate models. The

387  uncertainty of the Ricardian model is also large.

388  It is also important to note that the impact of temperature and precipitation change is not at all uniform across

389  the EU-15.  Figures 3, 4, and 5 present maps of the impacts of each climate scenario on each NUTS3 region.

390  Several countries are damaged by future temperature and precipitation changes. Only Belgium, Germany,

391  Denmark, the Netherlands, United Kingdom, and especially Ireland benefit in the NCAR PCM climate scenario.

392  Denmark, Finland, Ireland, Sweden, and the UK benefit slightly in the ECHO-G climate scenario, and only Ireland

393  and the UK show a benefit in the Hadley CM3 climate scenario. Italy has the largest aggregate loss of farmland

394  value. Italy loses € 120 billion (-71%) of farmland value in the Hadley CM3 scenario, € 101 billion (-60%) in the

395  ECHO-G scenario, and € 58 billion (-34%) in the NCAR PCM climate scenario. The future climate scenarios,  in

396  general, are beneficial to agriculture in northern countries  and harmful in southern countries.  But the effect is

397  not uniform across the future scenarios because the magnitude of annual climate change varies and because

398  there are important seasonal changes.  For example, the Ricardian model predicts Finland to be harmed by

399  warming because the winter temperature there increases by 8°C in some scenarios. This effect is predicted to

400  be more harmful than the gains from warming in the other seasons.

401  Insert Figure 3

402  Insert Figure 4

403  Insert Figure 5

404  **3.3 Robustness checks**

405  We estimate a number of alternative regressions as a robustness check. We look at regressions with and

406  without country fixed effects (see Table C.2 in Appendix C). Dropping the country fixed effects causes the

407   climate coefficients to change. s. The annual marginal temperature effect in the EU-15 drops from +8.2% (with

408   country fixed effects) to +5.7% (without country fixed effects) while the annual marginal precipitation effect

409   increases from +2.4% to +11.5%.

410   We also examine what happens when even more refined spatial fixed effects are included. Instead of using 15

411   country dummies, we include 63 regional dummies to capture broad regions within each country. The results

412   are reported in Appendix C in Table C.2. With more spatial fixed effects, there is less remaining variation in

413   climate. This magnifies measurement error biasing the climate coefficients towards zero. All the climate

414   coefficients drift towards zero with the regional dummies. This same phenomenon can be seen in the panel

415   regression results of Deschênes and Greenstone (2007).  If fixed effects remove too much of the climate signal,

416   measurement error begin to dominate the results leading the coefficients to be biased towards zero (Fisher et

417   al. 2012).  We consequently advise against using the regional fixed effects.

418   We test whether aggregation has a significant effect on the results. We aggregate the data on all farms to the

419   NUTS3 region. This effectively treats each NUTS3 region as an observation, dropping all the information on the

420   individual farm. The result reported in Table C.2 in Appendix C reveals that the temperature coefficients remain

421   stable but the significance of the coefficients declines.  With the aggregated data, spring and autumn

422   temperature and winter and autumn precipitation have a significant impact on farmland value. The annual

423   marginal temperature effect using the aggregate data is comparable with the marginal effect using the farm

424   level data: 7.2% versus 8.2%. However, the aggregate annual precipitation marginal effect is clearly different (-

425   4.0% versus +2.4%) and is only significant at the 10% level. The aggregation affects the measurement of the

426   effect of precipitation (a similar result was found for England by Fezzi and Bateman (2015)).

427   Using this aggregate data, we also explore the importance of spatial correlation using the Conley (1999) non-

428   parametric method. Controlling for spatial correlation does not change the coefficients but it reduces the t-

429   statistics. Only the coefficients of spring temperature and autumn precipitation remain significant.  A similar

430   test using individual farm data is not possible because the location of each farm within a NUTS3 region is not

431   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

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459   quantile regression is less sensitive to extreme observations. Further, the full set of quantile regressions offer a

460   rich and varied view of the entire population of farms. It shows that the climate effects are similar across the

461   sector though not identical.

462   In order to measure the climate sensitivity of the entire agricultural sector, it is important to estimate a

463   Ricardian model with all farms included. The climate sensitivity of irrigated farms is not the same as the climate

464   sensitivity of rainfed farms. The climate sensitivity of rainfed farms cannot be used to predict the climate

465   outcome of the entire agricultural system (as suggested by Schlenker et al. (2005) and Schlenker et al. (2006)).

466   Irrigated farms are less temperature sensitive than rainfed farms and whether a farm is irrigated or not is

467   climate sensitive. The analysis also suggests that the climate sensitivity of crops and livestock are different.

468   These results for Europe are similar to results found in studies across the world (Mendelsohn and Dinar (2009)).

469   The climate coefficients suggest that climate has a large impact on farmland in Europe now. Further, climate

470   change is going to have a strong influence on future farmland values in Europe. The results suggest that

471   warmer temperature and precipitation changes by 2100 will generally be harmful to European agriculture. The

472   impacts range from a +5% gain with the NCAR PCM climate model, to a -16% loss with the ECHO-G climate

473   model, to a -32% loss with the Hadley CM3 climate model. Including the likely benefit (30% gain) that farmers

474   will experience by 2100 from carbon fertilization, however, the net effect of greenhouse gases is more

475   ambiguous and may even be beneficial

476   The impact of climate change is not uniform across Europe. With all three climate scenarios, the impact is more

477   severe in southern Europe, which is harmed in all cases. In contrast, with the two milder climate scenarios,

478   several northern European countries benefit from climate change.

479   We assume in this analysis that the only thing that changes over time is climate. Of course, many things may

480   change. Prices may be very different in the future. That applies to both the prices of agricultural outputs as well

481   as inputs. Technology and infrastructure may also change. Finally, government policies may change. This is

482   especially important given the strong role of current EU farm policy. But this also applies to the role that

483   government may play to develop new farm technologies, crops and breeds. The government is also responsible

484   for managing water, which is a key input to agriculture. In several countries, the government also regulates

485   how land can be used. Changes in government policy can therefore play a large role in helping farmers adapt to

486    climate change. Hopefully, governments will be careful to avoid policies that actually make adapting to climate

487    change more difficult.

488    There remain several promising topics for future research. It is important to understand how European farmers

489    can best cope with future climates. Estimating how farmers have already adapted to the different current

490    climates in Europe would provide valuable insights.  It would be desirable to expand this analysis to include the

491    new European member states of Eastern Europe. Future studies should also explore how future climates may

492    affect water supplies and how best to cope with these changes. Finally, both the impact and adaptation

493    research should examine a wide array of climate models and emission scenarios.

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**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 | |

603   *** p<0.01, ** p<0.05, * p<0.1 Irrigated farms are classified as farms with at least 20% irrigated agricultural
604   area. Crops farms are classified as specialized field crops (including cereals, root crops, field vegetables and
605   various field crops). Grazing farms are classified as specialized grazing livestock (including dairying, sheep,
606   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**

| | Land value (Euro/ha) | Total Land value (million Euro) | Hadley CM3 | | ECHO-G | | NCAR PCM | |
|---|---|---|---|---|---|---|---|---|
| | | | 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**

610  **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 |

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**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 |

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623 **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 |

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

**Appendix C: Additional regression estimates**

628    **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 | |

629

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

631 **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 | | |

632

633 *** p<0.01, ** p<0.05, * p<0.1; the spatial standard errors are based on the Conley routine

634 (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**
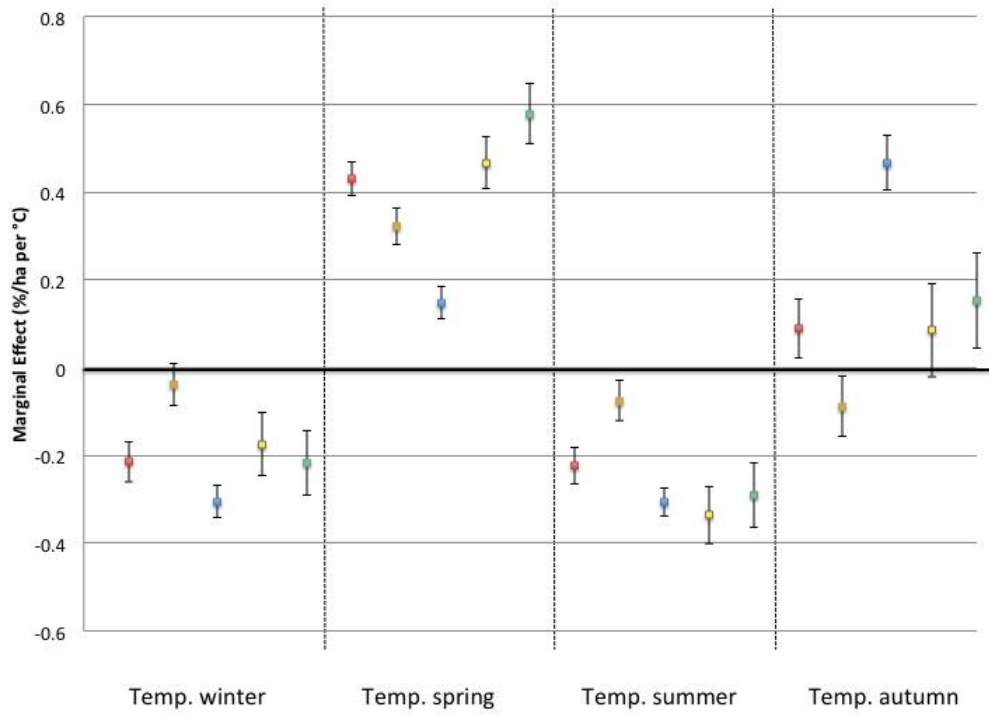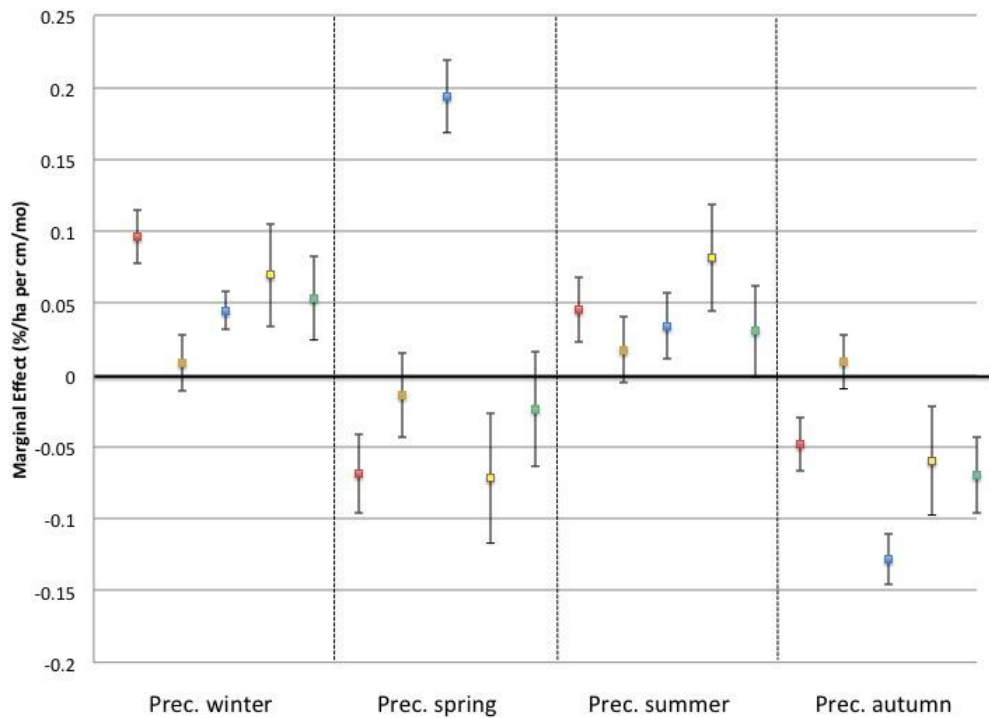
636 **quantiles**
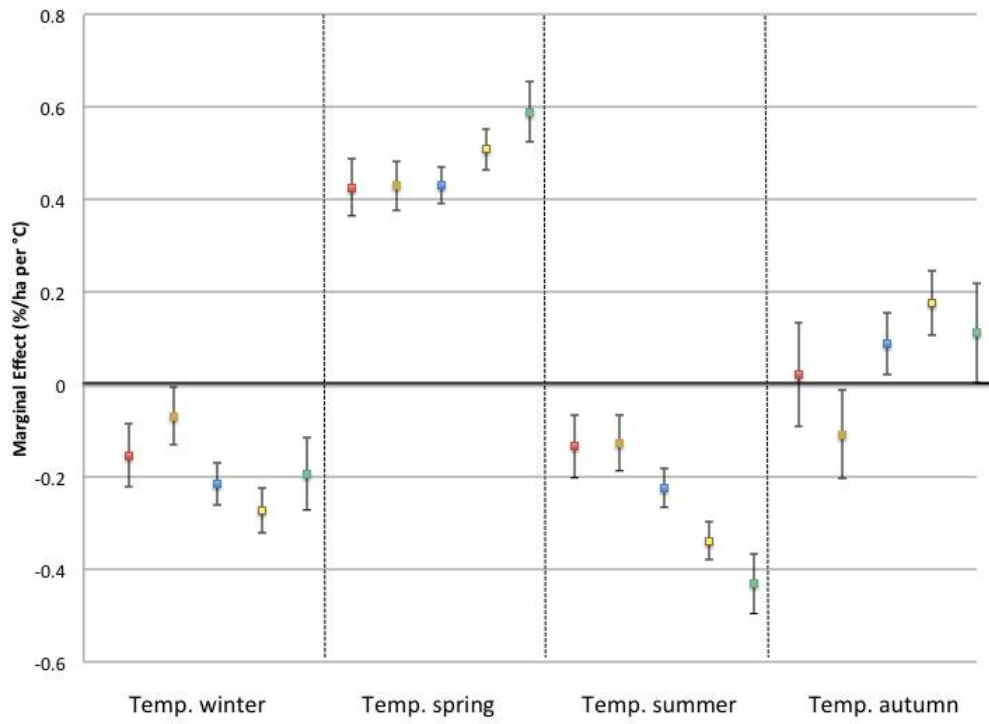


637
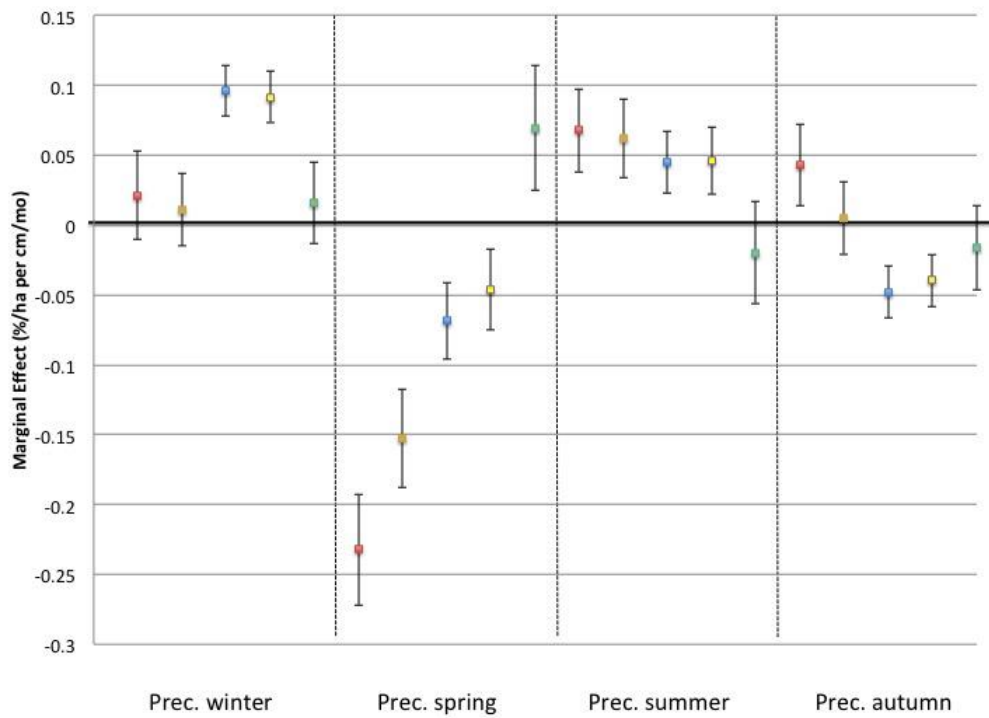


638

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

640

**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)**
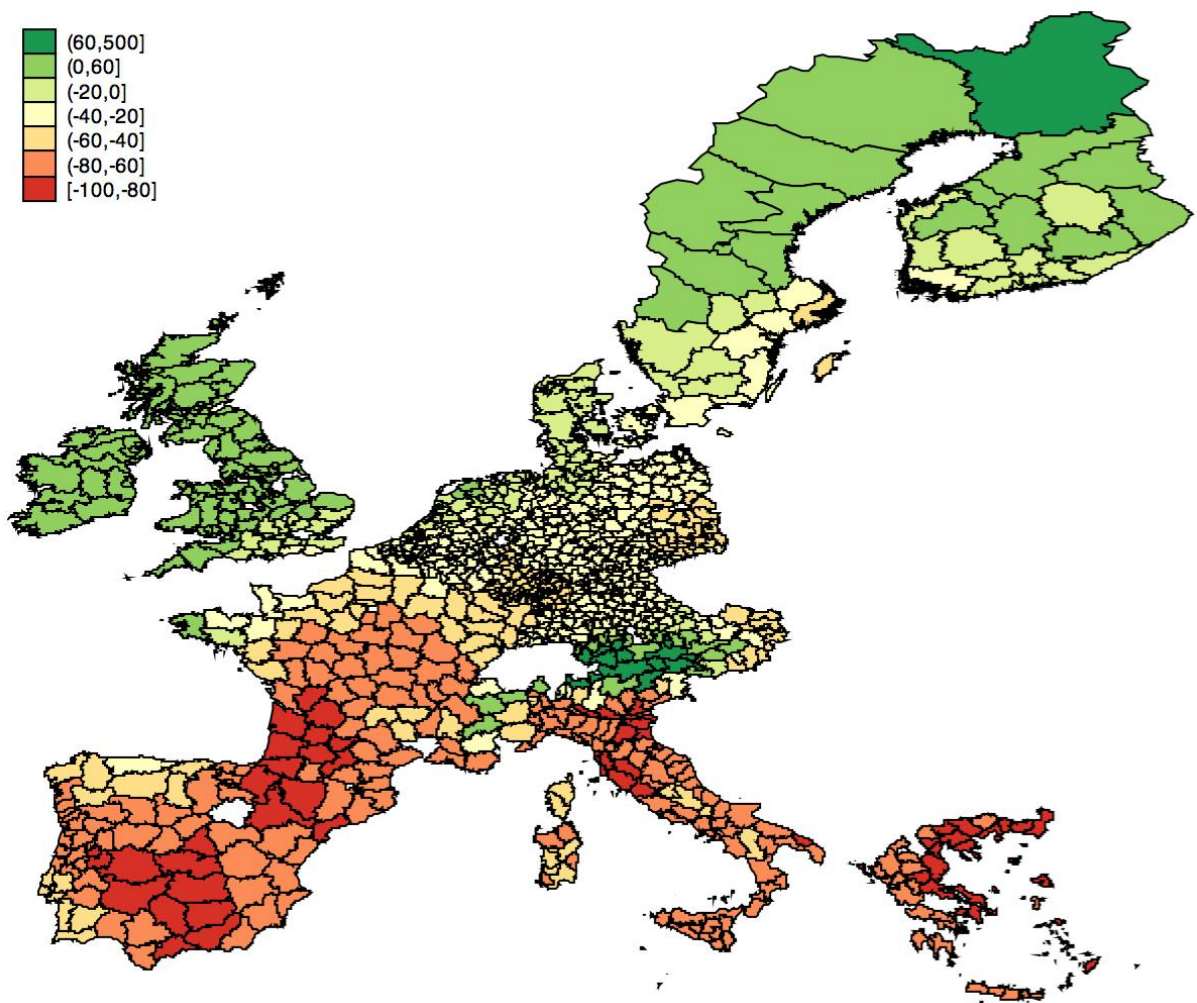


color coding: red (all farms), orange (rainfed farms), blue (irrigated farms), yellow (crop farms) and green (grazing farms)

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



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650

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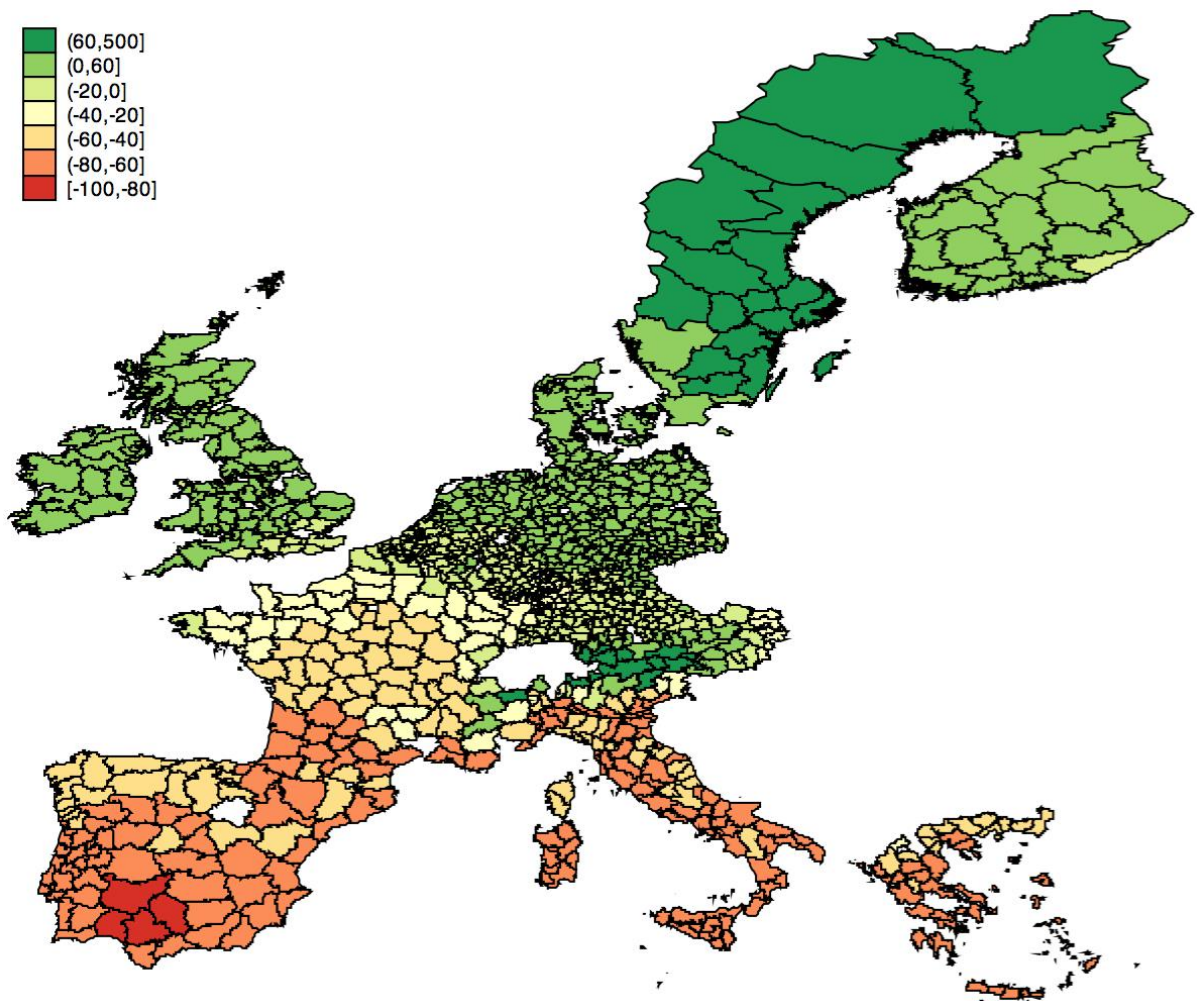


653

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



Legend:
- (60,500]
- (0,60]
- (-20,0]
- (-40,-20]
- (-60,-40]
- (-80,-60]
- [-100,-80]

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657

658
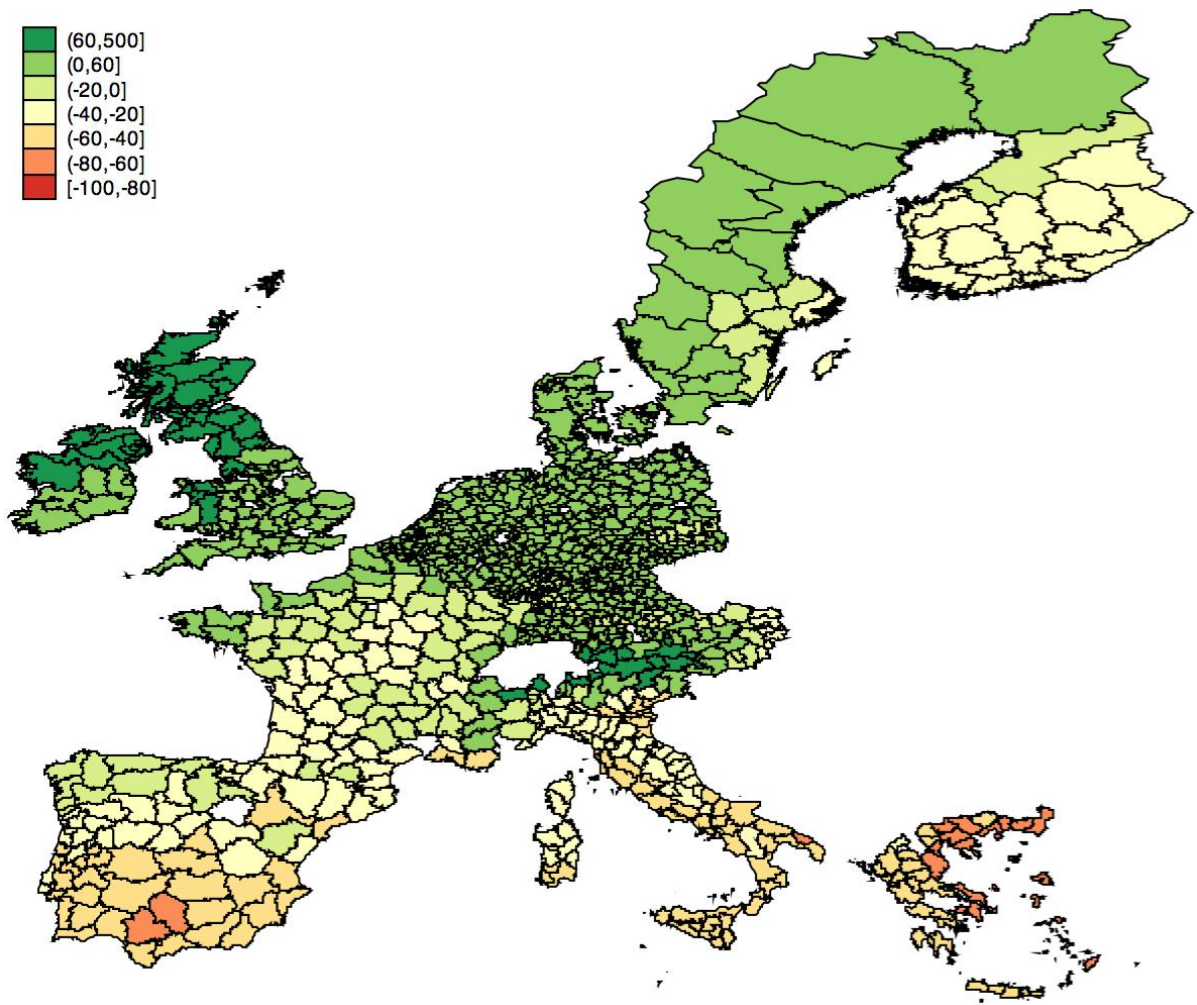
**Supplementary Materials:**

**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)**

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

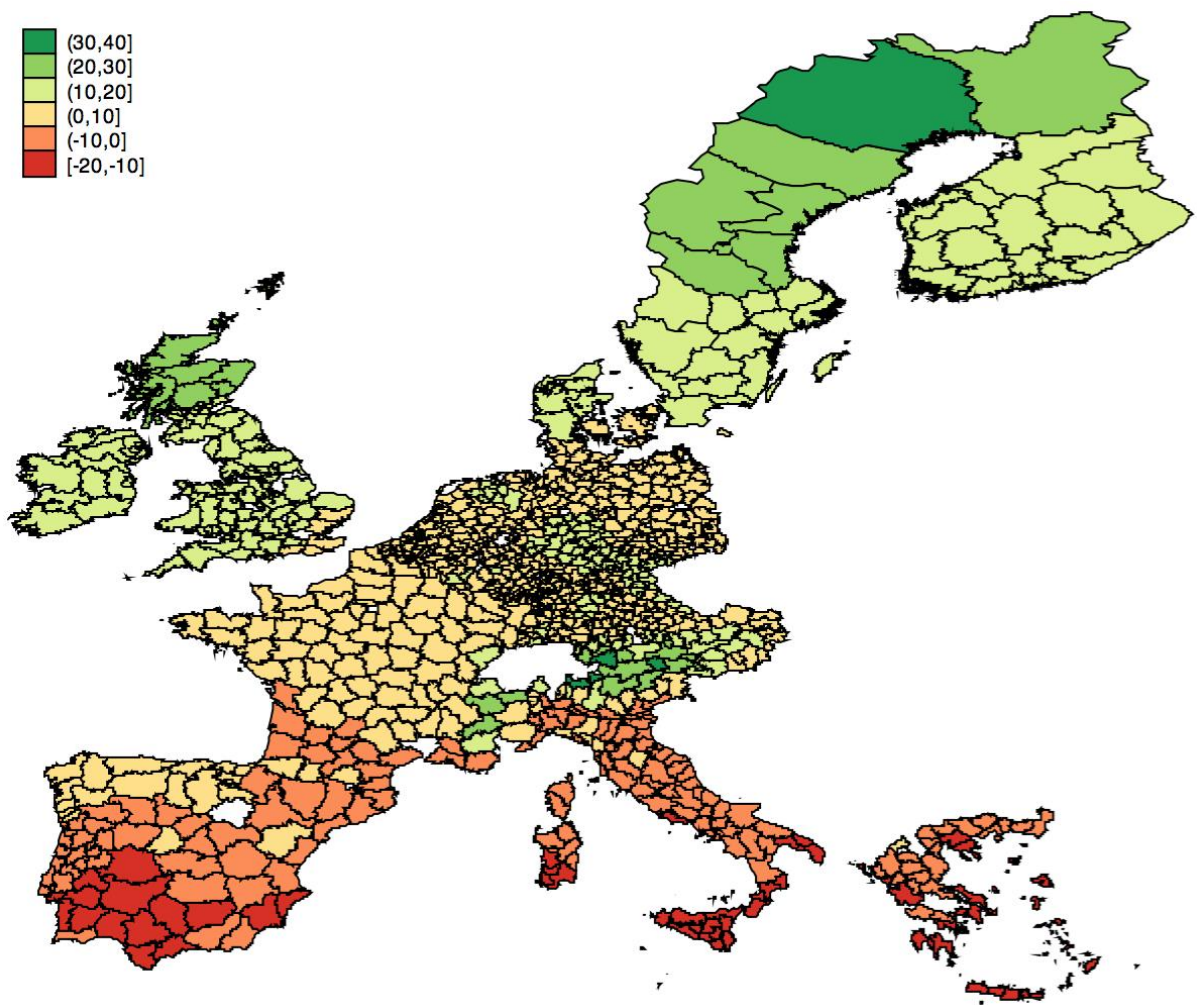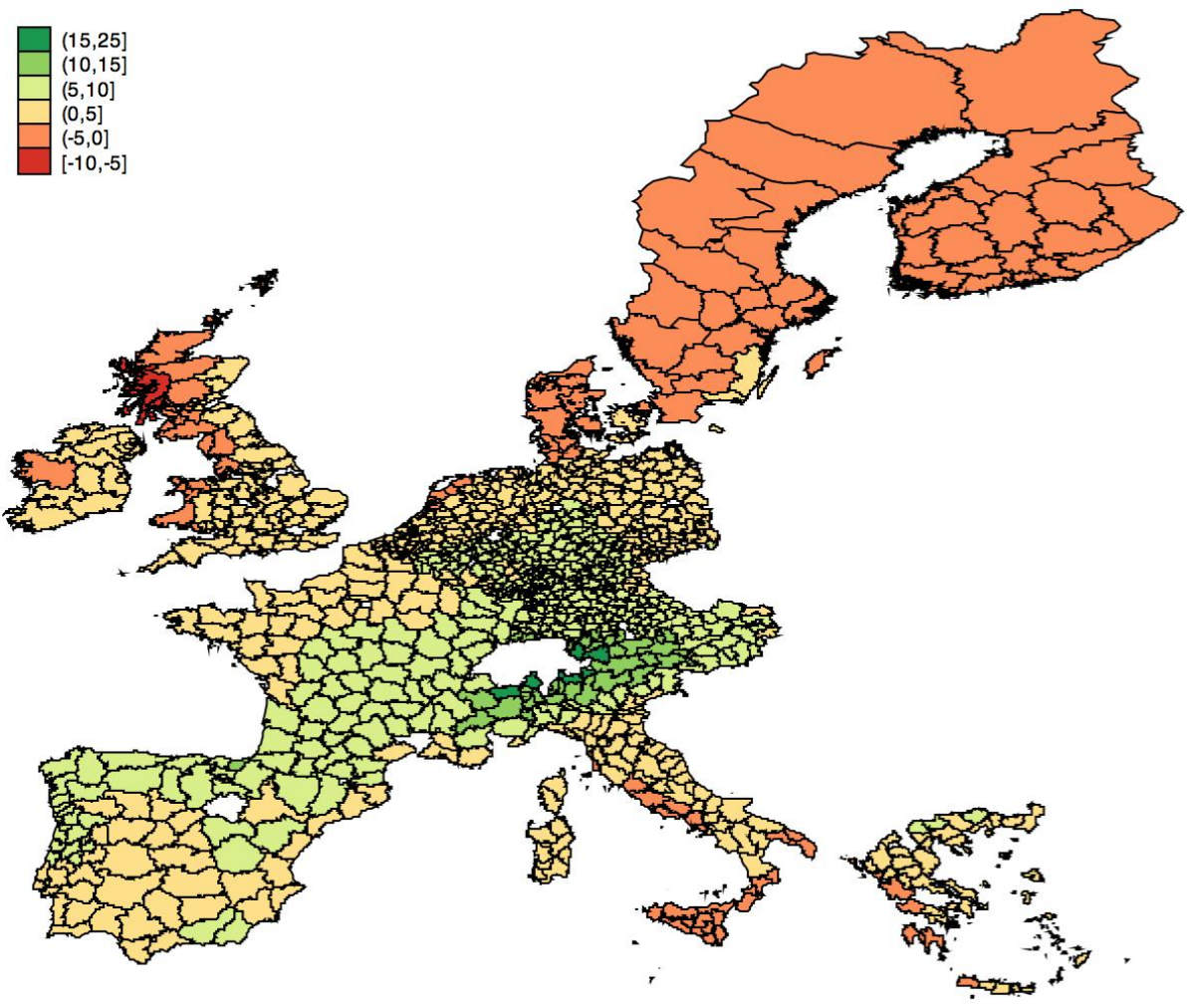| | Temp. annual | | Prec. annual | | Temp. winter | | Temp. spring | | Temp. summer | | Temp. autumn | | Prec. winter | | Prec. spring | | Prec. summer | | Prec. autumn | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Austria | 0.094 | *** | 0.065 | *** | -0.252 | *** | 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 | *** |

667

668 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
669 farms represented by each farm. Significant different from 0 (no impact): *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

670

671

672 **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 | *** |

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674 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
675 each farm. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

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