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Abstract

We estimate a Ricardian model of Western European agricultural land values using farm-level data. We model the effect of temperature on land values using a flexible specification of daily mean temperature to test if there are temperature threshold effects. Results indicate that there are no temperature thresholds beyond which agricultural land values suddenly drop. The results are robust to alternative model specifications. Adaptation explains why a smooth aggregate response function is compatible with sharply non-linear crop yield functions. With adaptation, the effect of warming on Western European agriculture is likely to be smooth.

JEL-Codes: Q120, Q210, Q510, Q540.

Keywords: agriculture, climate change, extreme temperature, Ricardian, threshold, Europe.

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1 Introduction

A large literature finds evidence of sharply non-linear effects of temperature on yields of major field crops. Yields are almost not affected by warming until temperature reaches about 30 °C, but after crossing this "threshold" yields collapse (e.g. Schlenker and Roberts, 2009, Gammans, Mérel and Ortiz-Bobea, 2017). These results reveal serious vulnerabilities of individual crops to warming, but they do not imply that total agricultural output or total welfare collapse after reaching a temperature threshold.

A first problem is that this literature assumes no adaptation (Massetti and Mendelsohn, 2018b).[1] Results indicate that in present-day production areas, with present-day methods, warming is potentially very harmful. However, farmers can change management practices, and most importantly, farmers can switch to more heat tolerant crops, and/or slowly moving production to cooler areas. Thus, these results do not imply that production of, for example, corn, cotton or soybeans will collapse. A second problem is that the literature studies only major field crops, mostly corn, cotton, soybeans and wheat. The literature does not study fruits, nuts, vegetables, dairy products and animal farms. Major field crops are important, but from 2012 to 2016, on average, they accounted for 30% of total added value in agriculture in the United States (USDA/ERS, 2018) and only for 24% in the European Union (Eurostat, 2018). It is thus impossible to guess from the crop yield studies alone the effect of temperature on total agricultural welfare.

Three studies have tested the existence of temperature thresholds on aggregate agriculture productivity using a Ricardian model of US agriculture, with different results discussed below (Schlenker, Hanemann and Fisher, 2006, Fezzi and Bateman, 2015, Massetti, Mendelsohn and Chonabayashi, 2016, Massetti and Mendelsohn, 2018b). This study contributes to this literature by estimating a Ricardian model of agriculture in Western Europe with a functional form that allows detecting abrupt declines of agricultural productivity due to warming.

Ricardian studies regress land values on a set of variables that determine farm productivity, including climate (Mendelsohn, Nordhaus and Shaw, 1994). The hedonic function that relates land values and

[1] Temperature effects are identified using local random temperature deviations from local average temperature, with no room for adaptation. As weather shocks are both unpredictable and transitory in nature, the literature rules out most of the adaptations, especially those that require long-term planning. In fact, absence of adaptation is a key identifying assumption of this literature because temperature shocks must only have a direct impact on yields. Any adaptation – i.e. any response of farmers to weather shocks – would be a potential source of inconsistency because it is correlated with both the weather shock and yields.

climate is used to estimate the welfare impact of climate change, assuming that land values are equal to the discounted sum of future expected agricultural rents (Ricardo, 1891). The underlying assumption in Ricardian studies is that profit-maximizing farmers have adapted to local conditions. This means that the hedonic function captures the relationship between land values and climate including all the efficient adaptations. The hedonic function is the outer envelope of a progression of net revenue functions under alternative management choices. This hedonic function is used to estimate the impact of climate change in a *ceteris paribus* exercise: the difference between land values predicted with future climate and with present climate measures the welfare effect of climate change.

In most Ricardian studies, climate variables enter the hedonic function with linear and quadratic terms to capture nonlinear effects of climate on land values (Mendelsohn, Nordhaus and Shaw, 1994, Schlenker, Hanemann and Fisher, 2005, Klein, et al., 2014, Massetti, Mendelsohn and Chonabayashi, 2016, Van Passel, Massetti and Mendelsohn, 2017). The squared terms on climate have generally been statistically significant and the quadratic specification of seasonal average temperature and precipitations is a shared feature of Ricardian studies (Mendelsohn and Massetti, 2017). Marginal temperature and precipitation effects change depending on the present level of temperature and precipitation and increasingly large deviations from average conditions lead to increasingly large marginal effects. The quadratic function thus captures non-linear effects of warming, but it may be too restrictive in imposing a smooth transition if the underlying response function is sharply non-linear. The use of average seasonal temperatures may also hide the harmful effect of short periods of exceptional heat.

Schlenker, Hanemann and Fisher (2006) (SHF) criticize the use of a quadratic functional form of average seasonal temperatures. Instead of the traditional four season quadratic specification, they use a quadratic specification of the total number of degree days between 8 and 32 °C from April to September, with a separate control for the number of degree days above 34 °C, to capture a temperature threshold effect.[2] Their results suggest that climate change will sharply reduce aggregate welfare and most of the loss will come from crossing the temperature threshold at 34 °C. This model specification imposes restrictions that are not in agreement with agronomic studies and results are not

[2] Degree days during a day are calculated by subtracting from the mean daily temperature the base temperature that in this case is equal to 8 °C for the 8 to 32°C degree days and 34°C for the extreme degree days. The authors assumes that days with temperature between 32 and 34 °C are irrelevant.

robust to alternative data and model specifications (Massetti, Mendelsohn and Chonabayashi, 2016).[3] However, Schlenker, Hanemann and Fisher (2006) raise an important question: is the quadratic functional form of seasonal average temperature able to identify sharply non-linear temperature effects as in the crop yields literature?

To answer this question Massetti and Mendelsohn (2018a) estimate a Ricardian model using county-level agricultural land values for the Eastern United States and use the same flexible functional form for temperature that Schlenker and Roberts (2009) have used to estimate the effect of temperature shocks on corn, soybeans and cotton yields. Massetti and Mendelsohn (2018a) divide the observed temperature range in narrow intervals and then count the number of days they observe temperature within these intervals during different seasons. These temperature bins are included in a standard Ricardian regression. This method allows estimating unrestricted temperature marginal effects. Strong non-linearities in the welfare impact of temperature would appear as large and significant variations in the marginal effect of temperature in two or more adjacent bins. Results indicate that there is no temperature threshold for aggregate agricultural productivity. Surprisingly, the impact of warming is more gradual than in a quadratic model. Models that use a quadratic specification of temperature predict larger losses than models that use daily temperature bins, although the difference is not significant.

Fezzi and Bateman (2015) estimate a Ricardian model of land values in the United Kingdom using farm data and high-resolution climate data. They find that high-resolution data reveals some effects of climate that do not appear when they aggregate data at county level, but they find that a flexible functional form of temperature capable of revealing threshold effects does not produce impact estimates that are significantly different from a quadratic model. This result is not at the core of the paper, but we interpret it as evidence that a temperature threshold effects does not exist in the United Kingdom. One explanation for this result may be that in the UK very harmful temperatures are almost never observed. Another explanation may be that the authors may not observe some extreme temperatures because they do not use high frequency temperature.

[3] Degree days and average temperature are perfectly correlated when short duration temperature measurements are lumped together in the 8 to 32 °C degree days variable, thus they are interchangeable; the threshold effect at 34 °C is arbitrary, neither supported by agronomic studies nor robust to alternative datasets and specifications; a four-season model has lower out-of-sample forecasting accuracy than a one-season model. There is also no indication in the agronomic literature that degree days are better than average temperature at predicting yields. Agronomists and farmers use degree days to predict the duration of different stages of growth not to predict yields.

In this paper, we follow Massetti and Mendelsohn (2018b) and we study if temperature thresholds threaten agriculture in a large number of states in Western Europe with very diverse climates. We use a dataset obtained by matching data on more than 37,000 farms from the Farm Accountancy Data Network (FADN) with high frequency temperature data from the ERA-INTERIM database. We do not find evidence of temperature thresholds after which agricultural land values collapse. Our result is robust to several alternative model specifications and suggests that welfare of Western European agriculture is resilient to the worst effects of warming, possibly due to adaptation.

The rest of this paper proceeds as follows. Section 2 illustrates the method used for the analysis and discusses weaknesses of the Ricardian method, in particular omitted variable bias. Section 3 describes the dataset used. Section 4 illustrates results and Section 5 presents robustness tests. Conclusions follow.

2 Methodology

In a Ricardian study land values are assumed to be equal to the discounted flow of future net revenues from farm operation and from potential non-farm uses (Mendelsohn, Nordhaus, and Shaw 1994). The reduced form equation of the Ricardian model specifies land values as a function of only exogenous variables. In this paper, we estimate the following reduced form cross-section model:

$$Y_{i,r} = \alpha + \sum_s \left(\sum_{j=1.}^{J_s} \beta_{j,s} x_{j,r,s} + \gamma_{1,s} P_{r,s} + \gamma_{2,s} P_{r,s}^2 \right) + \boldsymbol{\eta} X_{i,r} + \boldsymbol{\theta} Z_r + \psi_c + \epsilon_i. \quad (1)$$

$Y_{i,r}$ is the natural logarithm of value per hectare of farm *i* in region *r*. We use a log transformation because it fits agricultural land values more closely than a linear model (Schlenker, Hanemann and Fisher, 2005, Mendelsohn, Dinar and Williams, 2006, Massetti and Mendelsohn, 2011a, b, Van Passel, Massetti and Mendelsohn, 2017). We divide the range of observed temperatures in *J* equal intervals. $x_{j,r,s}$ is long-run average of the number of days with mean temperature within each corresponding temperature interval *j* in region *r*.

Note that in Equation (1) we use averages of temperature and precipitation variables over 30 years (i.e. the climatological mean). We assume that long-term averages explain average agricultural productivity better than short-term weather observations and that farmers use adaptive expectations in forecasting future climate. If climate is stationary over long periods adaptive expectations are equivalent to rational expectations. However, if climate changes and farmers forecast future agricultural rents using climate change scenarios, not including controls for expected temperature and precipitation changes may lead to omitted variable bias. The literature has typically assumed that farmers have adaptive expectations but Severen, Costello and Deschenes (2018) introduce expected future climate from two general circulation models and find that US agricultural land markets capitalize expectations about future climate. This leads to an over-estimation of climate change impacts because present land values have already discounted a fraction of future impacts from climate change. Future research should assess if this result holds in Europe with farm level data, instead of county level data, and using all the available future scenarios. However, if a bias exists, it likely leads to an overestimation of the harmful effect of extreme temperature bins, which does not substantially change our main results.

We omit one of the temperature bins in each season to avoid perfect multicollinearity. The remaining $J-1$ temperature coefficients measure the percentage change of land value per hectare relative to the omitted bin. We use temperature bins that are 3 °C because smaller intervals lead to loss of precision, but for completeness, we estimate a model with 2 °C wide temperature bins as a robustness test.

The extreme temperature bins, especially on the right tail of the distribution, are typically different from zero only for few regions. These bins often capture very rare events, such as a heat wave that occurred only once in the previous 30 years. The coefficients of these extreme temperature bins are typically very large, non-significant and non-robust. These extreme temperature bins, on both the cold and the warm side of the temperature distribution, are similar to dummy variables for a small set of observations (Massetti, Mendelsohn and Chonabayashi, 2016). To avoid these problems, we lump together temperature observations at the extremes of the distribution so that temperatures in the first and in the last bins represent at least 1% of the total distribution of observed daily temperatures. The exact temperature cut-off point varies depending on the season and on the regions over which we estimate the model.

While the traditional Ricardian models use a quadratic specification of climate variables in the four seasons, many studies follow Schlenker, Hanemann and Fisher (2006) and use one season only, from April to September. Studies that use only one season assume that temperature and precipitation have the same effect during spring and summer. They also assume that temperature and precipitation in autumn and winter are not relevant. However, many Ricardian studies find that seasonal effects are important in the US (Mendelsohn, Nordhaus and Shaw, 1994), in Europe (Bozzola, et al., 2017, Van Passel, Massetti and Mendelsohn, 2017) and in other continents (Mendelsohn, Dinar and Williams, 2006), even when using degree days (Massetti, Mendelsohn and Chonabayashi, 2016) or temperature bins models as in this paper (Massetti and Mendelsohn, 2018a). A four season model performs better than a one season model (Massetti, Mendelsohn and Chonabayashi, 2016) and there is compelling evidence in favor of even more granular separation of temperature effects over time (Ortiz-Bobea, 2013). Agronomic evidence also suggests that temperature has different effects on crop growth at different times of the growing season (e.g. Basra, 2000). Considering only one season is particularly problematic for Europe because climate of late autumn, winter and early spring affects perennials and winter crops, both widely diffused in Western Europe. For these reasons, temperature and precipitation variables enter our reduced form equation using the standard four climatological seasons (December-February, March-May, June-August, and September-November). For completeness, we also test a model with one season from April to September as in Schlenker, Hanemann and Fisher (2006), and a model with two seasons (April to June and July to September).

The unit of observation in our study is the farm. Unfortunately, the exact location of each farm is not available for confidentiality reasons but we know the NUTS 3 region of the farm. NUTS 3 regions are administrative areas between regions and cities, such as the Italian provinces, the French departments and the Swedish counties.[4] NUTS 3 regions are similar in size to counties in the United States. Thus, we use the average of all non-farm control variables (climate, geography, socio-economic characteristics) at NUTS 3 for all farms in the same region. To account for correlation of variables of farms in the same NUTS 3 region we cluster standard errors at NUTS 3 level and we control for a generic form of heteroscedasticity. In robustness tests we cluster at the level of the larger NUTS 2 regions and we run an additional test using a more flexible form of spatial correlation that can capture relations across administrative boundaries (Conley, 1999). Clustering and correction for a generic form of heteroscedasticity lead to efficiency losses. To minimize these losses, we run robustness tests using two alternative strategies. First, we estimate a clustered weighted least squares regression, with weights inversely proportional to the number of hectares in each farm, assuming that larger farms have error terms with smaller variance. Second, we estimate a random effects model with robust standard errors in which clustering is over NUTS 3 regions instead of being over time.

In Ricardian models, the standard identification assumption is that the error term is not correlated with climate and other control variables. This is a strong assumption that has been criticized. In an influential paper Deschenes and Greenstone (2007) argue that Ricardian estimates of climate impacts in the US are strongly biased because repeated cross-section estimates display a sharp time trend, from positive to

[4] NUTS 0 regions are countries; NUTS 1 are groups of regions, such as Wales or Southern Italy; NUTS 2 are regions such as Alsace, Andalusia and Tuscany.

strongly negative impacts. Massetti and Mendelsohn (2011a) have shown that in this specific case a pooled panel model with a control for time trends and other time varying variables is sufficient to stabilize impacts estimates. Fisher, et al. (2012) also find robust results in repeated cross- sections. However, as in all cross-section studies, concerns about omitted variable bias cannot be easily dismissed. Unfortunately, there is not an easy solution to this problem. Part of the literature has embraced the use of random weather variations to identify climate effects (e.g. Deschênes and Greenstone, 2007). As weather, shocks are both unpredictable and transitory in nature, the literature rules out most of the adaptations, especially those that require long-term planning. In fact, absence of adaptation is a key identifying assumption of this literature because temperature shocks must have only a direct impact on yields. Any adaptation – i.e. any response of farmers to weather shocks – would be a potential source of inconsistency because it is likely correlated with both the weather shock and yield. While this is a sensible strategy to estimate the impact of random weather variations, this method does not allow studying the effect of slow-moving climate change. Using the elasticity to weather shocks to project climate change impacts in the late future, although increasingly popular (Deschênes and Greenstone, 2007, Schlenker and Roberts, 2009, Carleton and Hsiang, 2016), is neither conceptually nor empirically justifiable. These panel weather studies consistently estimate weather effects, but inconsistently estimate climate change impacts due to model misspecification (Massetti and Mendelsohn, 2018b, Tol, 2018).

In this paper, we make the effort of controlling for many possible confounders. First, we use country dummy variables to control for unobserved variation at country level. Second, we use several geographic and socio-economic variables that the literature has repeatedly shown to affect land values. Third, we run several tests introducing and omitting some possible sources of omitted variable bias to check if our results are robust, including regional dummy variables. Finally, we estimate the model for different sub-regions to test if there are some region-specific omitted variables that change the results.

We prefer using a cross-section method because it includes long-term adaptation. If farmers will not adapt to future climate change a panel model with fixed effects would instead be preferable. Without adaptation, climate change is like a random weather shock. Will farmers adapt to future climate change as they have done to present climate so to justify the use of cross-section methods? Unfortunately, it is still not possible to find a robust empirical answer to this question (Massetti and Mendelsohn, 2018b).[5]

[5] Burke and Emerick (2016) suggest that farmers in the Eastern United States are not adapting to climate change. Their study finds that crop heat tolerance in areas that have experienced a period of warming is not significantly

First, one needs very long time series to identify robust patterns of climate change.[6] Second, even if data of sufficiently good quality are available, separating climate change from many other correlated trends is a formidable challenge. Absent any clear empirical evidence that adaptation to future climate change is not possible, we rely on theory and on a growing literature that shows how farmers' choices are affected by climate (e.g. Seo, et al., 2008, Seo and Mendelsohn, 2008b, a, Seo, 2010, Kurukulasuriya, Kala and Mendelsohn, 2011, Massetti and Mendelsohn, 2018b) to argue that farmers will likely adapt to long-term climate change.

3 Data and Variables Description

We use data from a sample of farms in the EU-15 from the 2007 European Union census of agriculture. The sample is representative of commercial agricultural holdings. Data collection and classification follows the Farm Accountancy Data Network (FADN) rules. The FADN is a harmonized dataset used by the EU to manage farm policy. The EU-15 comprises the following 15 countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, and United Kingdom. We omit Denmark, Finland and Sweden due to data problems and we refer to the remaining countries as Western Europe.

Table 1 displays descriptive statistics for the variables and the farms that we use in our main specification. We do not include farms with land either under glass or plastic greenhouses because they are little sensitive to climate. We drop all farms for which the ratio of net earnings in 2007 to land value in 2007 is greater than one in absolute value because we suspect either measurement error or constraints that do not allow land values to reflect the true economic profitability of the farm. We drop some farms due to lack of data for all the control variables. In total, we use 37,891 commercial farms and we cover 2.9 million hectare of farmland in 910 NUTS 3 regions.[7] Our dataset covers by stratification 68% of all agricultural land in the countries in our sample.

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different from heat tolerance in areas with stable or declining temperature. The authors use random deviations in temperature trends to identify their model, which implies that temperature trends must be unpredictable and transient, and thus unlikely to change expectations and trigger adaptation (Massetti and Mendelsohn, 2018b). In fact, any adaptation response would void their identification strategy due to possible omitted variable bias.

[6] Ideally, one needs 60 years or more to compare two 30-year periods.

[7] There are 5,662,480 farms in the EU-15 (census 2007 data), with a total utilized agricultural area of about 120 million hectares.

The dependent variable is the logarithm of the value per hectare of owned agricultural land in the farm, excluding the value of buildings. Land values are estimated using market prices for land of similar quality (net of transaction costs) in regional agricultural land markets. All countries follow FADN guidelines to estimate land values.

About 60 percent of all farms in our sample use at least some rented land. The share of rented land over total farmland may affect agricultural productivity, and thus land values, in two opposite ways. If farmers invest the capital that is not tied to the land in machinery and other land improvements, productivity of farms that rent land is higher than productivity of farms that only use owned land. If landowners are instead reluctant to invest in productivity improvements when the share of rented land is high, the productivity of both own and rented land suffers and land values are lower. The relative share of rented to owned land has thus an ambiguous effect on land values. Country dummies capture the effect of different national regulatory regimes on land ownership but we use the percentage of rented land over total farmland as a control variable because some sub-national patterns may be confounded with climate variables.

We control for farm size as farm size may affect agricultural rents in many different ways and farm size is likely correlated with climate variables because of geographic influences or regional regulations. We use the logarithm of hectares of land in the farm because this specification gives the best fit.

About 18 percent of farms have most of their land under a conservation program.[8] We expect that conservation programs impose some costly adaptations and reduce the market value of agricultural land. As conservation areas may have a different climate than the sample average, we introduce a dummy variable to identify farms with land under conservation.

Farms are in 910 NUTS 3 regions that range in size between 37 and 108,488 km^2, with an average size equal to 3,434 km^2. The number of farms in each region ranges from 1 to 442, with 42 farms in each region on average. We control for socio-economic, geographic and soil characteristics at NUTS 3 level because we do not know the exact farm location inside each region. We use population density, the growth rate of population and GDP per capita to control for the opportunity cost of agricultural land. We expect that regions with higher population density, faster population growth, and higher GDP per capita have higher value of farmland, ceteris paribus. Geographic variables control for other drivers of

[8] We consider land under the EU 'Natura 2000' conservation program and/or affected by Directive 2000/60/EC for the protection of freshwater quality. Most of Natura 2000 areas are privately owned. Land owners/managers must respect any legally binding provision adopted to safeguard the conservation effort.

agricultural rents. Latitude at the centroid of the NUTS 3 region proxies for effects of solar radiation other than temperature. Mean elevation affects agricultural productivity by changing the diurnal cycle of temperature (at higher elevations the diurnal range of temperature increases). High elevations may also increase transportation costs by making access more difficult. Distance of the region centroid from major cities (those with more than 500,000 inhabitants) and medium and large ports increases the cost of having access to transportation hubs and we expect it reduces land values.

Soil characteristics change agricultural productivity and may be correlated with climate variables. In our main specification, we control for gravel, sand and silt content and for the pH level. Soil data are from the Harmonized World Soil Database, a partnership between the Food and Agriculture Organization (FAO) and the European Soil Bureau Network (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2008).

Temperature and precipitations data is from the ERA-interim database of the European Centre for Medium-Range Weather Forecasts (ECMWF). This dataset provides 6-hour temperature and precipitation reanalysis data over a 0.125x0.125 degrees grid (Dee, et al., 2011, Jones, et al., 2012). At the European latitudes grid cells are approximately 14 x 10 km. For each grid cell, we calculate the mean daily temperature over all days in the climatological period 1981-2010 by averaging the four infra-daily measurements. Then, for each grid cell, we calculate how many times, on average, we observe a day within each 3 °C interval from 1981 to 2100, separately for each season. Finally, we estimate NUTS 3 level temperature bins by taking the average of each bin across all grid cells that fall in the region. The number of grid cells that fall in each region ranges from 1 to 1,393. For precipitation data, we calculate the average of total rainfall over 1981-2010, during each season, at each grid cell, and then we average over all grid cells that fall in the region.

Table 1 presents summary statistics of seasonal precipitations. Mean seasonal precipitations average 5-6 cm/month over the entire year, with large regional variation. Summers are very dry in Greece, Italy, Portugal and Spain, while they tend to be wet in the other countries. Mountain regions receive the largest amount of rainfall during summer. Overall, there is a great amount of rainfall variation across space, especially during summer. Figure 1 displays the distribution of mean daily temperature over the four seasons. We show the frequency of each temperature over the entire sample of observations, using farms as observation units. Table A - 1 in the Appendix provides minimum, mean, maximum and standard deviation of each temperature bin. As explained in the methodological section, bins with very low frequency collect temperatures observed in one or two NUTS 3 regions that have peculiar climate. If included in the regression the extreme temperature bins are equivalent to dummy variables for these regions and capture all other local characteristics. The coefficients of these extreme bins are also not robust. To avoid these problems, we merge adjacent temperature bins so that each temperature bin has at least 1% of total seasonal daily mean temperature observations. For example, during summer 3.1 % of observations have a mean temperature between 27 and 30 °C, 0.3 % between 30 and 33 °C, 0.008% between 33 and 36 °C and 0.00001% at or above 36 °C. Only two of the regions in our sample have ever observed a day with temperature greater than 36 °C from 1981 to 2010. Our rule dictates that the last temperature bin collects all daily mean temperatures at or above 30 °C. The threshold beyond which we merge temperature bins varies with the seasons. As a robustness test, we estimate a model in which we estimate the coefficients of the extreme temperature bins.

Variable	Measurement Unit	Unit	Mean	Std. Dev	Min	Max
Value of land	EUR / ha	Farm	16,584	26,057	27	498,991
Farm variables						
Farm size	ha	Farm	77.5	184.4	1.0	7845.3
Rented land	percentage	Farm	32.9%	33.5%	0.00%	100%
Conservation program	dummy (1 yes)	Farm	0.185	0.388	0.000	1.000
Socio-economic variables						
Population density	'000 people per km^2	NUTS 3	0.16	0.22	0.00	3.05
GDP per capita	'000 EUR	NUTS 3	24.019	8.344	8.868	74.582
Population growth rate	percentage	NUTS 3	2.60%	4.07%	-10.0%	24.0%
Geographic variables						
Latitude	Degrees north	NUTS 3	46.29	6.15	35.14	67.71
Mean elevation	km	NUTS 3	0.367	0.321	0.000	2.092
Distance from cities	km	NUTS 3	0.115	0.081	0.001	0.843
Distance from ports	km	NUTS 3	0.159	0.110	0.001	0.537
Soil variables						
Topsoil gravel content	%vol	NUTS 3	9.15%	2.75%	2.44%	18.3%
Topsoil sand fraction	%vol	NUTS 3	46.3%	9.85%	28.2%	83.0%
Topsoil silt fraction	%vol	NUTS 3	31.4%	6.04%	10.8%	46.0%
Topsoil ph	-log(H+)	NUTS 3	6.30%	0.70%	4.18%	7.88%
Precipitation variables						
Winter	cm/month	NUTS 3	5.3	1.4	2.3	11.3
Spring	cm/month	NUTS 3	6.2	1.7	1.8	11.6
Summer	cm/month	NUTS 3	5.5	3.2	0.1	19.5
Autumn	cm/month	NUTS 3	6.9	1.7	2.6	13.9

Summary statistics over 37,891 farms for both variables measured at farm and at NUTS 3 level.

Table 1. Descriptive statistics.

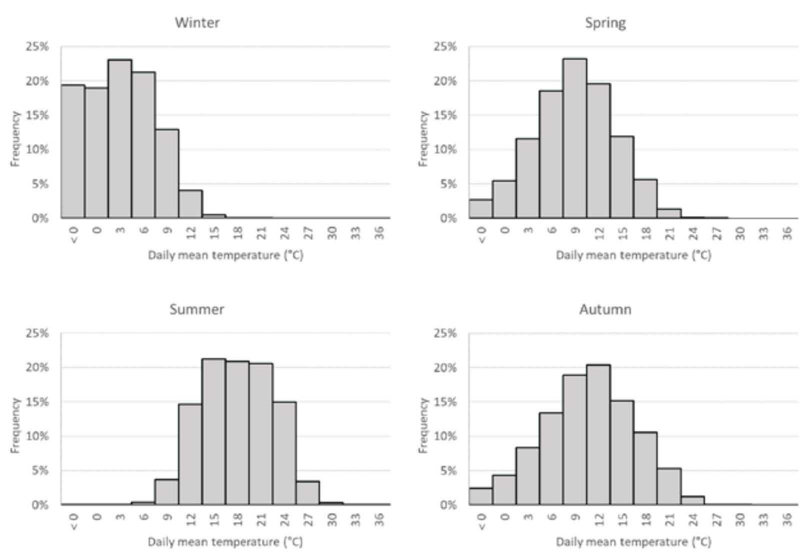


Figure 1. Distribution of daily mean temperature.

4 Results and Discussion

We present results of our preferred model and then we test alternative methods to measure temperature, different models of correlation of residuals across farms, alternative control variables and model specifications. We graphically display the temperature coefficients of the main specification and for the most important robustness tests in the paper while we leave in the Appendix the full set of results. There is not a shared definition of temperature threshold in the literature, but we are looking for a sharp, statistically significant drop of land values as we move from average temperatures to the highest temperature bins.

Figure 2 displays results for our main specification. We use the four climatological seasons: winter (Dec-Feb), spring (Mar-May), summer (Jun-Aug) and autumn (Sep-Nov). We use dummies at national level (NUTS 0), controls for population density, population growth rate, GPD per capita, the logarithm of total land in farm, the share of rented to total land, latitude, mean elevation, distance from cities with more than 500,000 inhabitants and from medium and large seaports, a dummy for whether the majority of land in farm is located in a Natura 2000 area (environmental constraints) and controls for soil qualities (percentage of gravel, sand, silt and pH level). We cluster standard errors within each of the NUTS 3 regions.

For each bin, the figures display the frequency of days with mean temperature that falls in the corresponding 3 °C wide interval. We merge bins with less than 1% of total daily temperature observations so that all bins have a sufficient number of observations. The figures show the percentage impact of changing one day at the reference temperature level (winter: 6-9 °C, spring 9-12 °C, summer 18-21 °C, autumn 12-15 °C) with one day in the other temperature bins. The dotted lines mark the 95% confidence intervals built using clustered standard errors. For example, substituting one day with mean temperature equal to 10 °C in spring with a day with temperature equal to 13 °C significantly increases land values by about 11%. Replacing a spring day with mean temperature equal to 10 °C with a day with mean temperature equal to 7 °C has a non-significant negative impact equal to approximately 1.5%.

The results suggest that winter temperature effects are not statistically significant, warming in spring generally has a positive effect on land values (the coefficients increase from negative to positive) while warming in summer reduces land values (the coefficients decline from positive to negative). Temperature effects during autumn are not statistically different from zero.

There is no evidence of a temperature threshold effect. Warming in summer is harmful, but the effect is gradual, with a peak of land values between 15 and 18 °C (about 11-14 °C at night and 19-22 °C during the day). Interestingly, we do not find a temperature threshold in summer, the season during which we observe the highest temperatures. This result does not mean that temperature threshold effects found by the crop yields literature are not real. We find instead evidence of adaptation: farmers avoid temperature thresholds by changing management practices, by selecting crops or by raising animals instead of growing crops. Adaptation however cannot totally offset the negative effect of higher temperatures in summer, a result in line with all the Ricardian literature.

The coefficients of the control variables are reported in Table A - 2. Precipitation linear and squared coefficients are not significant. The coefficients of population density and population growth rate are positive and significant. GDP per capita in the NUTS 3 regions does not significantly affect land values. The share of rented to total farm land positively and significantly affects land values while the logarithm of farm size negatively and significantly affect land values per hectare. A high percentage of gravel in soil negatively and significantly affects land values while the effect of higher pH level is positive and significant. Other soil characteristics do not significantly affect land values. Having a high share of land under a conservation program significantly reduces land values. Latitude, elevation and distance from cities with more than 500,000 inhabitants do not significantly affect land values while increased distance from medium and large ports significantly reduces land values, an unexpected result.

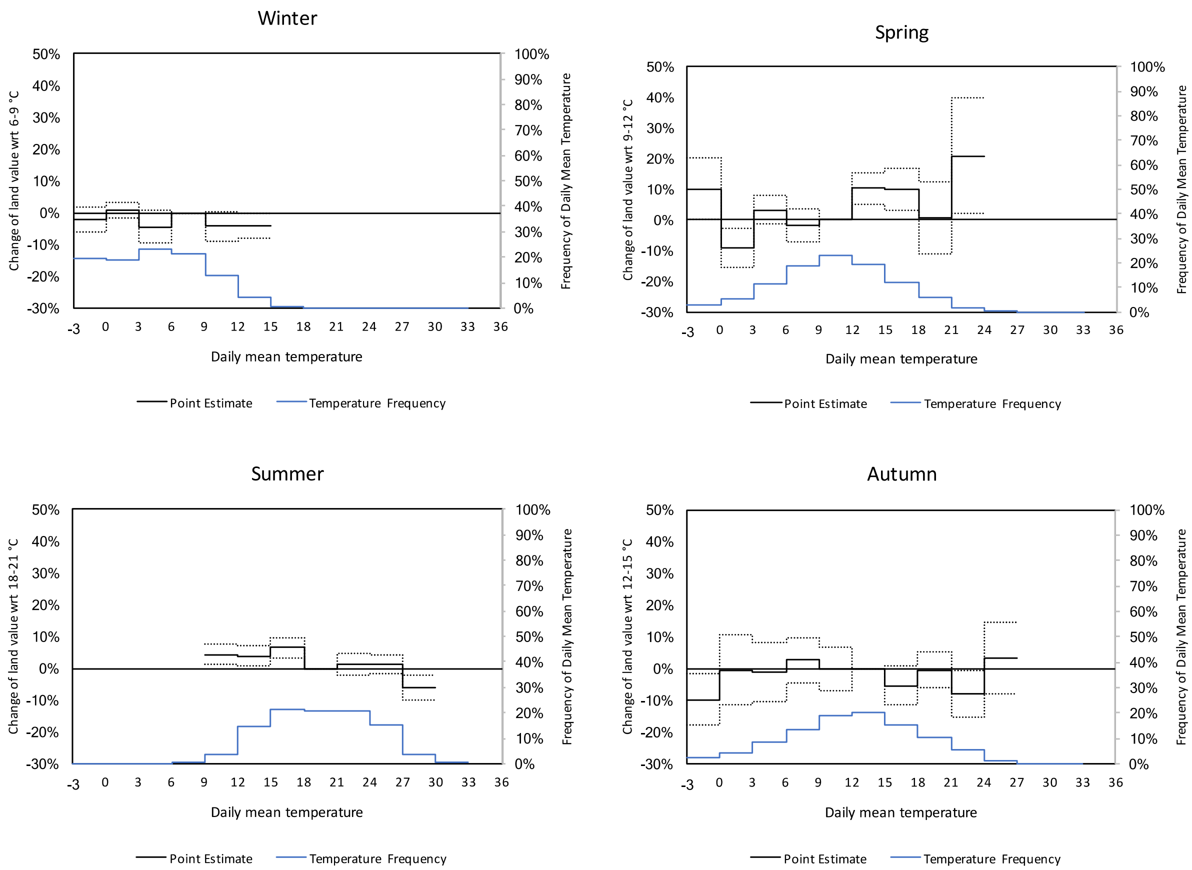


Figure 2. Main specification.

5 Robustness Tests

The temperature coefficients are robust to alternative sets of control variables and model specifications as shown in the following robustness tests.

5.1 Seasons

In temperate countries, the Ricardian literature has traditionally measured separately the effect of temperature and precipitation in the four seasons. However, for completeness, we test a model that uses only spring and summer (Figure 3) and a model that aggregates climate data from April to September (Figure 4). Spring coefficients in the two-season model are not significantly different from each other. Summer coefficients in the two-season model show a hill-shaped relationship with a maximum between 15 and 18 °C. A similar pattern emerges in the one-season model. In any case, we do not find evidence of a temperature threshold.

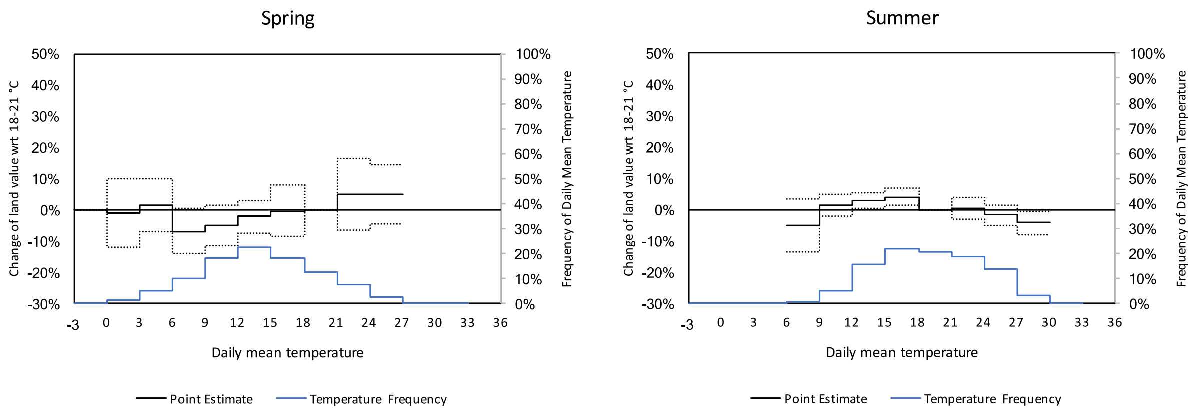


Figure 3. Two season model.

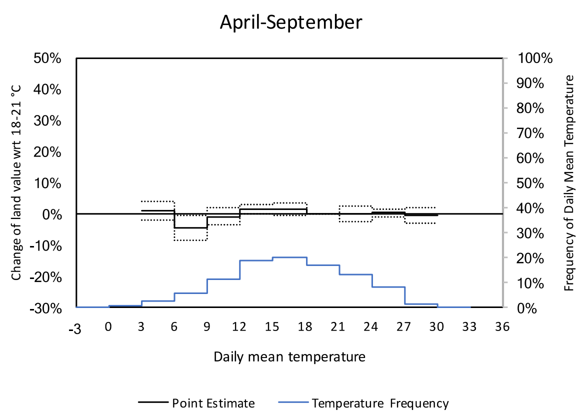


Figure 4. One season model.

5.2 Duration of temperature measurements

In our preferred model specification, we use bins of daily mean temperatures. The literature has used temperature measurements over hours but shorter than daily temperature observations do not reveal any significant effect of temperature on land values. They are very noisy and with large confidence intervals (Mendelsohn and Massetti, 2017). Longer duration temperature bins are instead more robust and significant. In Figure 5 we display coefficients of temperature bins of average monthly temperatures. Note the change of the scale of the vertical axis. For winter, spring and summer we find very similar results to the daily temperature bins model. For autumn, monthly temperatures reveal significant gradual harmful effects of warming that did not appear when using daily mean temperatures. We prefer using daily temperatures in the main specification because monthly bins control average conditions better than daily temperature bins but may not reveal the effect of short-term spikes in temperature.

In the main specification and in robustness tests temperature bins cannot have less than 1% of total temperature observations. As a robustness test, we estimate a model in which we use all temperature bins. Figure 6 displays summer temperature effects up to 36 °C because the bin with temperature above 36 °C is not significant and totally out-of-scale (-5,179% [-21,561% ; 11,203%]). It does not appear that farms with extreme daily temperatures are significantly affected. This is not evidence that extreme heat is not harmful. It is possible that single isolated episodes of extreme daily temperatures have a non-significant effect but prolonged periods of extreme heat (i.e. heat waves) may be harmful.

We group observations of daily temperatures in 3 °C wide intervals because narrower intervals induce high multicollinearity. When we use 2 °C wide temperature intervals, we find more variance in the estimated temperature effects but we confirm all our results (Figure A - 1 in the Appendix).

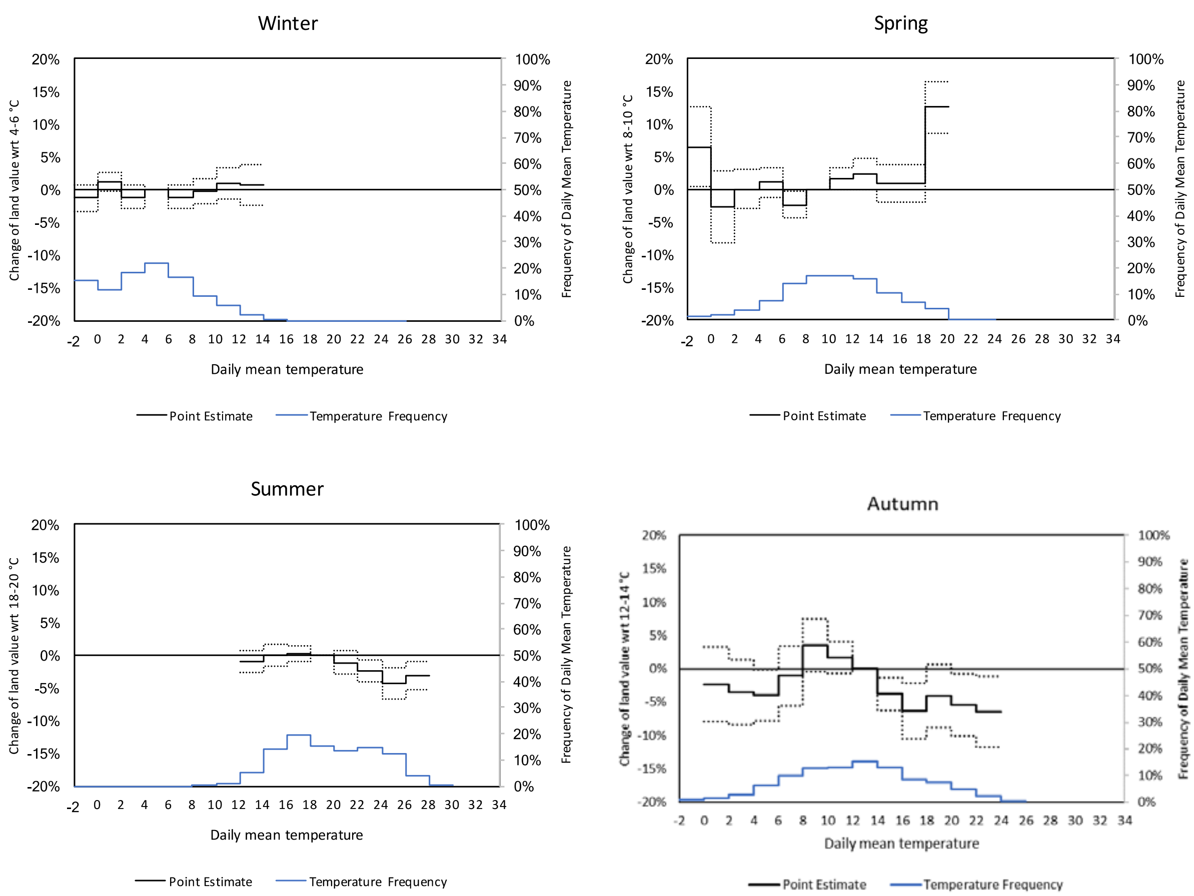


Figure 5. Monthly temperature bins.

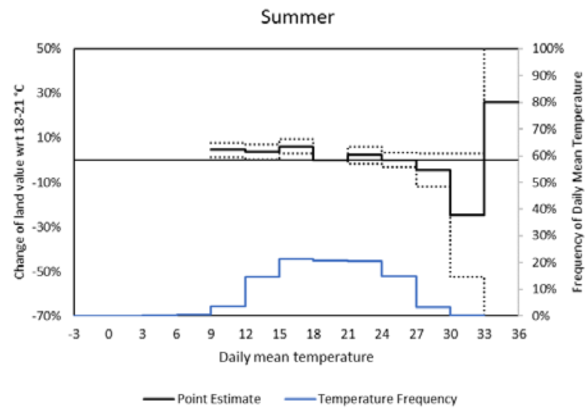


Figure 6. Extremely hot days.

5.3 Alternative assumptions on correlation between observations

We estimate all confidence intervals in previous models using standard errors clustered at NUTS 3 level. We estimate the main model by clustering at the wider NUTS 2 level and we do not find any substantial change to the significance of the temperature effects (Figure A - 2 in the Appendix). Clustering assumes that no correlation exists between observations in two different clusters. In many cases, this assumption is justified because political and geographic boundaries overlap in many regions of Europe. However, it is possible that correlation between farms stretches across clusters. We repeat estimates of the main specification using a model of spatial correlation. The unobservable component is assumed to be correlated over space, but correlation declines until a certain maximum distance, after which there is no correlation (Conley, 1999). We use two cut-off points for correlation, at 100 km and 50 km. The robustness test confirms our main results (Figure A - 3 and Figure A - 4 in the Appendix).

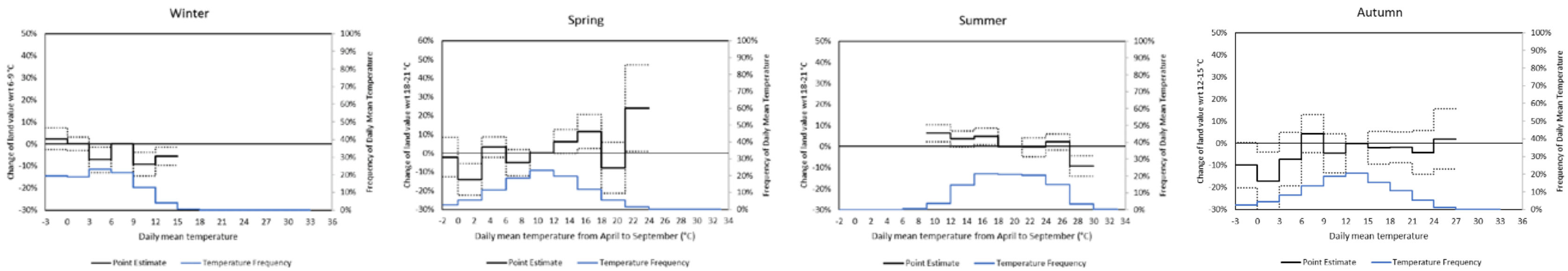
We also test weighted least squares and a random effects model in which we cluster at NUTS 3 level. We report the results in Figure A - 5 and Figure A - 6 in the Appendix. Coefficients are robust to the two alternative model specifications. There is no sudden decline of land values at the high temperatures in any season.

5.4 Alternative control variables, regional aggregation and sensitivity to outliers

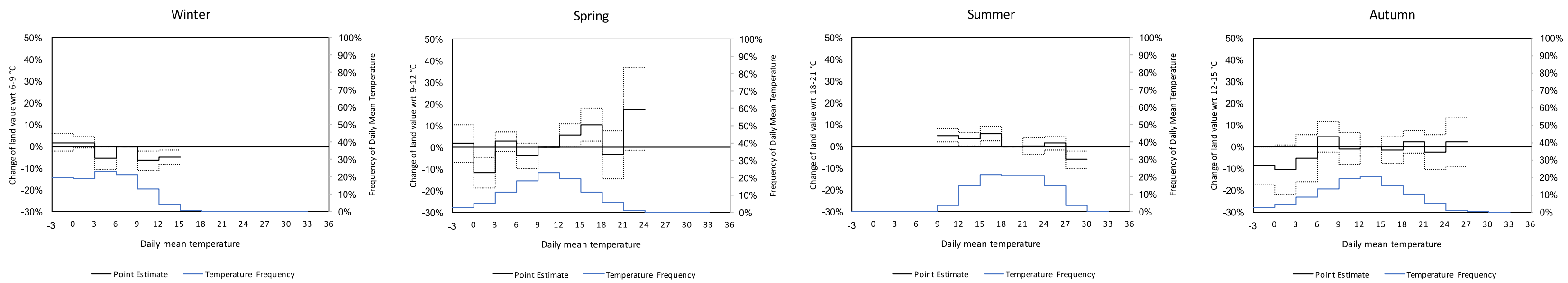
Ricardian studies identify the effect of climate on land values under the assumption that the error component in equation (1) is random. Omitted variables correlated with both the regressors and the dependent variable lead to inconsistency. This is the main concern of Ricardian studies. Although it is impossible to completely rule out the possibility of omitted variable bias, we perform a series of robustness tests to verify the sensitivity of estimated temperature parameters to alternative sets of variables. We start with a simple model in which we only use climate variables and country (NUTS 0) dummies (panel a in Figure 7) and then we add in sequence farm control variables (panel b in Figure 7), county socio-economic variables (panel c in Figure 7) geographic variables (panel d in Figure 7), soil variables (panel e in Figure 7, our main specification) and an extended set of soil variables with linear and quadratic terms for all soil variables (panel f in Figure 7). The results are remarkably robust. Only winter temperature effects tend to become flatter and loose significance when we add control variables. All other estimates are virtually unchanged. Under no specification we observe temperature thresholds. The weighted least squares and the random effects estimates are also very robust, suggesting consistency of temperature coefficients. For all models, we report the adjusted R-squared. Our main specification has an adjusted R-squared value of 0.618. For comparison, a model with only country dummies (NUTS 0) has an adjusted R-squared equal to 0.412.

We separate Greece, Italy, Spain and Portugal from the remaining Wester European countries to test if temperature effects are significantly different across macro-regions. Figure 8 illustrates the results. There are only minor differences between the temperature effects in the two macro-regions, mostly non-significant.

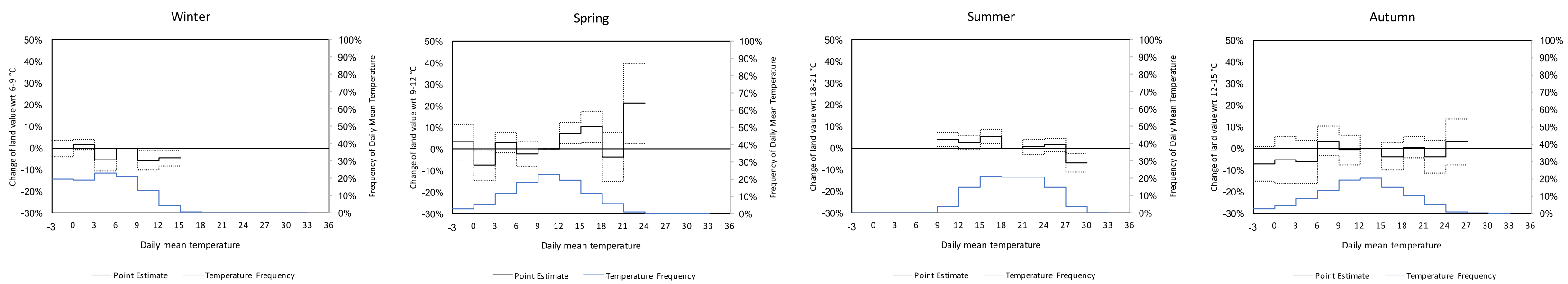
Finally, we test whether the results are sensitive to outliers by estimating two median regression models, one with four seasons (Figure A - 7) and the other with spring and summer only (Figure A - 8). The temperature effects are very robust and we do not find evidence of a sudden decline of land values at the high temperatures.



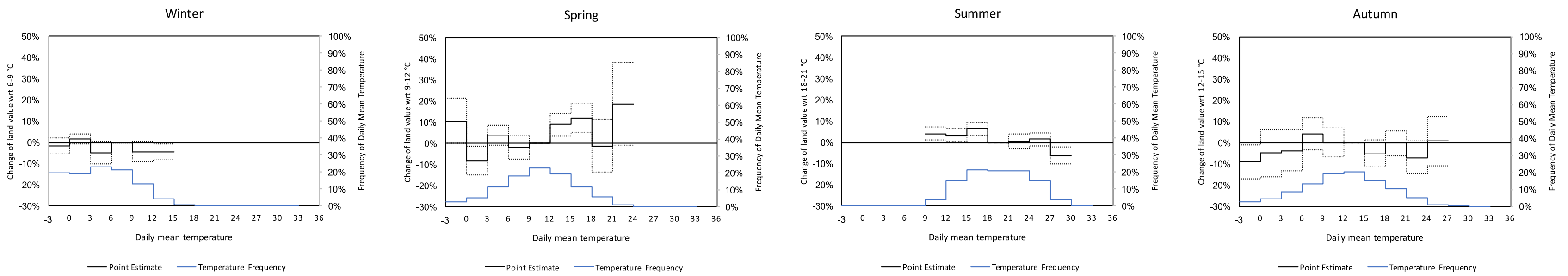
(a) climate variables and NUTS 0 dummies (Adjusted R-squared: 0.530)



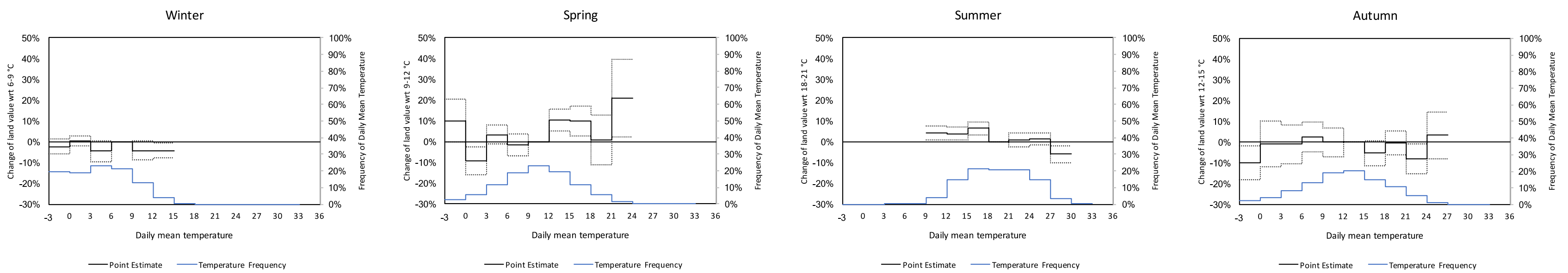
(b) Climate variables, NUTS 0 dummies, farm variables (Adjusted R-squared: 0.598)



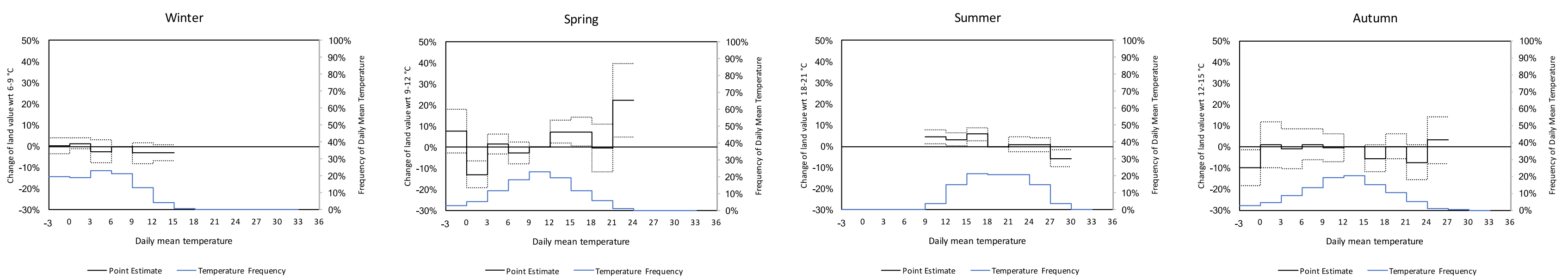
(c) Climate variables, NUTS 0 dummies, farm variables, county socio-economic variables (Adjusted R-squared: 0.612)



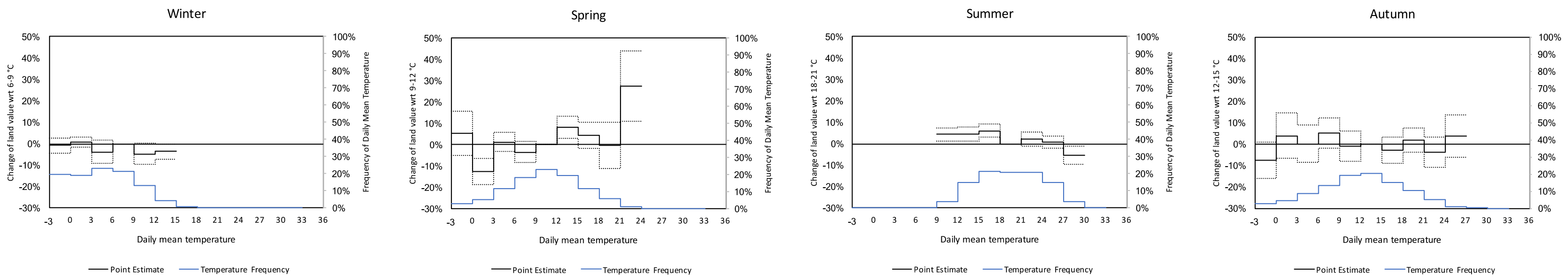
(d) climate variables, NUTS 0 dummies, farm variables, county socio-economic variables, geographic variables (Adjusted R-squared: 0.614)



(e) Climate variables, NUTS 0 dummies, farm variables, county socio-economic variables, geographic variables, soil variables (Main specification, Adjusted R-squared: 0.618)

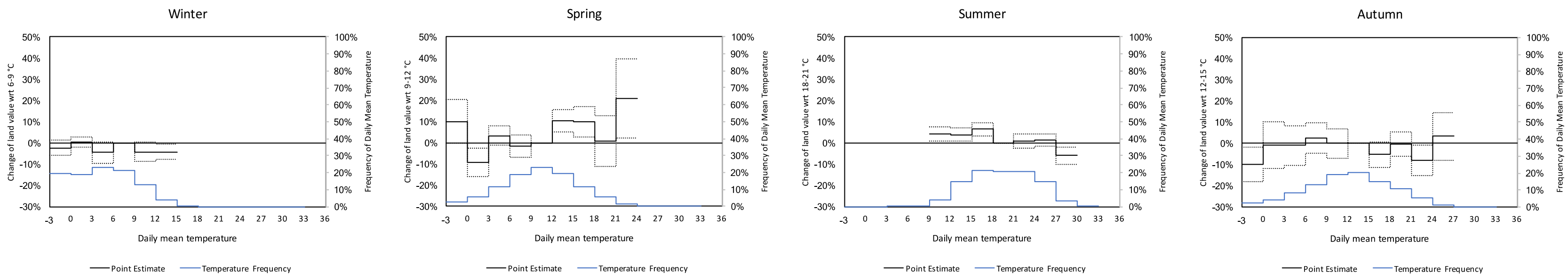


(f) Climate variables, NUTS 0 dummies, farm variables, county socio-economic variables, extended geographic variables (Adjusted R-squared: 0.623)

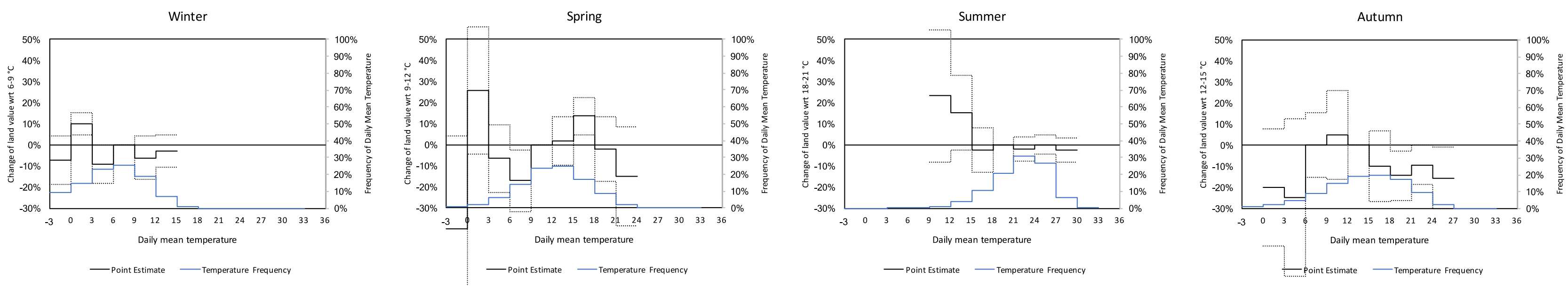


(g) Climate variables, NUTS0 dummies, farm variables, county socio-economic variables, extended geographic and soil variables (Adjusted R-squared: 0.634)

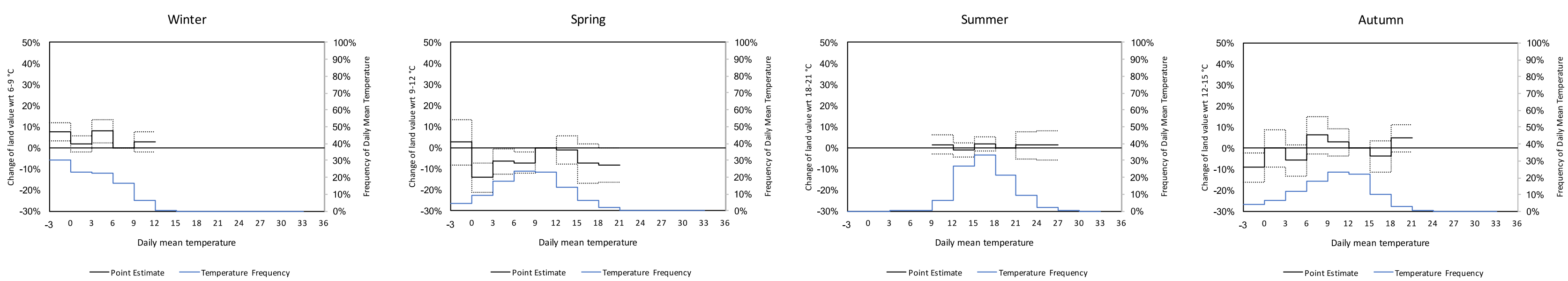
Figure 7. Robustness to alternative sets of control variables.



(a) All countries (main specification)



(b) Southern countries: Greece, Italy, Portugal and Spain



(c) Remaining EU-15 countries

Figure 8. Regional differences.

Conclusions

We estimate a Ricardian model with a flexible specification of temperature to detect abrupt negative effects of temperature on land values. We use farm-level data from more than 37,000 farms in Western Europe and a rich weather dataset with high-resolution daily temperature data from 1981 to 2010. Our study is inspired by the work of Schlenker and Roberts (2009) who find abrupt declines of crop yields at about 30 °C in the Eastern United States. Similar effects of temperature on crop yields are found in Europe by Gammans, Mérel and Ortiz-Bobea (2017). The main motivation of this study is to test if there is a temperature level that, if crossed, severely reduces welfare of agriculture in Western Europe. Previous Ricardian studies of European Agriculture used a quadratic specification of seasonal mean temperature (Van Passel, Massetti and Mendelsohn, 2017) that cannot reveal a temperature threshold because they impose a smooth relationship between temperature and land values and because they cannot detect sharp short-term deviations from mean seasonal temperature. To our knowledge, our study is the first to study temperature thresholds on aggregate agricultural productivity in Western Europe. Massetti and Mendelsohn (2018a) conduct a similar analysis for the Eastern United States.

We do not find evidence of sudden drops of agricultural productivity at the high temperatures. In summer, when one would expect to find the largest negative impacts from high temperatures, warming reduces agricultural land values, but the decline is gradual. These results are robust to a large number of alternative model specifications. Also Massetti and Mendelsohn (2018a) do not find evidence of temperature thresholds in the Eastern United States. These results do not contradict the literature that finds sharp negative effects of temperature on crop yields. Temperature thresholds for individual crops are consistent with a smooth aggregate response of agricultural productivity to temperature, as captured by farmland values. All these results suggest that farmers have adapted to the historical climate and have reduced the probability of observing large losses by changing management practices, crops, and farm type. This suggests that if farmers will use the present-day range of adaptations to adapt to future climate change, crop switching and other management adaptations will greatly limit the large losses from unexpected weather shocks.

The main limitation of our study is that it cannot have a causal interpretation because of its non-experimental nature. Unfortunately, it is impossible to generate a truly random change of climate. Natural experiments are also not viable because either they capture short-term random weather effects or, if they capture climate change, they suffer from omitted variable bias because differences of climate change trends across space are not random.

We have limited our analysis to short-duration effects of temperature. Future studies should test the effect of observing many consecutive days of extreme heat. The study of the effect of heat waves, droughts and other extreme events on agricultural rents is a promising area of research.

References

Basra, A. (2000). *Crop Responses and Adaptations to Temperature Stress: New Insights and Approaches*. CRC Press.

Bozzola, M., Massetti, E., Mendelsohn, R., Capitanio, F. (2017). A Ricardian Analysis of the Impact of Climate Change on Italian Agriculture. *European Review of Agricultural Economics* 45: 57-79.

Burke, M. and Emerick, K. (2016). Adaptation to Climate Change: Evidence from Us Agriculture. *American Economic Journal: Economic Policy* 8: 106-140.

Carleton, T. A. and Hsiang, S. M. (2016). Social and Economic Impacts of Climate. *Science* 353: aad9837.

Conley, T. G. (1999). Gmm Estimation with Cross Sectional Dependence. *Journal of econometrics* 92: 1-45.

Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M. A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A. C. M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A. J., Haimberger, L., Healy, S. B., Hersbach, H., Hólm, E. V., Isaksen, L., Kållberg, P., Köhler, M., Matricardi, M., McNally, A. P., Monge-Sanz, B. M., Morcrette, J. J., Park, B. K., Peubey, C., de Rosnay, P., Tavolato, C., Thépaut, J. N., Vitart, F. (2011). The Era-Interim Reanalysis: Configuration and Performance of the Data Assimilation System. *Quarterly Journal of the Royal Meteorological Society* 137: 553-597.

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

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

Eurostat (2018). Economic Accounts for Agriculture.

FAO/IIASA/ISRIC/ISS-CAS/JRC (2008). Harmonized World Soil Database (Version 1.0). Rome, Italy and Laxenburg, Austria: FAO and IIASA.

Fezzi, C. and Bateman, I. (2015). The Impact of Climate Change on Agriculture: Nonlinear Effects and Aggregation Bias in Ricardian Models of Farmland Values. *Journal of the Association of Environmental and Resource Economists* 2: 57-92.

Fisher, A. C., Hanemann, W. M., Roberts, M. J., Schlenker, W. (2012). The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Comment. *The American Economic Review*: 3749-3760.

Gammans, M., Mérel, P., Ortiz-Bobea, A. (2017). Negative Impacts of Climate Change on Cereal Yields: Statistical Evidence from France. *Environmental Research Letters* 12: 054007.

Jones, P. D., Lister, D. H., Osborn, T. J., Harpham, C., Salmon, M., Morice, C. P. (2012). Hemispheric and Large-Scale Land-Surface Air Temperature Variations: An Extensive Revision and an Update to 2010. *Journal of Geophysical Research: Atmospheres* 117.

Klein, R. J. T., Midgley, G. F., Preston, B. L., Alam, M., Berkhout, F. G. H., Dow, K., Shaw, M. R. (2014). Adaptation Opportunities, Constraints, and Limits. *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects.* Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press, 899-943.

Kurukulasuriya, P., Kala, N., Mendelsohn, R. (2011). Adaptation and Climate Change Impacts: A Structural Ricardian Model of Irrigation and Farm Income in Africa. *Climate Change Economics* 2: 149-174.

Massetti, E. and Mendelsohn, R. (2011a). Estimating Ricardian Models with Panel Data. *Climate Change Economics* 2: 301-319.

Massetti, E. and Mendelsohn, R. (2011b). The Impact of Climate Change on Us Agriculture: A Repeated Cross Sectional Ricardian Analysis. In R. Mendelsohn and A. Dinar (eds), *Handbook on Climate Change and Agriculture*. Edward Elgar.

Massetti, E. and Mendelsohn, R. (2018a). Do Temperature Thresholds Threaten American Farmland? Georgia Institute of Technology and Yale University, mimeo.

Massetti, E. and Mendelsohn, R. (2018b). Measuring Climate Adaptation: Methods and Evidence. *Review of Environmental Economics and Policy* 12: 324-341.

Massetti, E., Mendelsohn, R., Chonabayashi, S. (2016). How Well Do Degree Days over the Growing Season Capture the Effect of Climate on Farmland Values? *Energy Economics* 60: 144-150.

Mendelsohn, R., Dinar, A., Williams, L. (2006). The Distributional Impact of Climate Change on Rich and Poor Countries. *Environment and Development Economics* 11: 159-178.

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

Mendelsohn, R. O. and Massetti, E. (2017). The Use of Cross-Sectional Analysis to Measure Climate Impacts on Agriculture: Theory and Evidence. *Review of Environmental Economics and Policy* 11: 280-298.

Ortiz-Bobea, A. (2013). Is Weather Really Additive in Agricultural Production? Implications for Climate Change Impacts.

Ricardo, D. (1891). *Principles of Political Economy and Taxation*. G. Bell.

Schlenker, W., Hanemann, W. M., Fisher, A. C. (2005). Will Us Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach. *American Economic Review*: 395-406.

Schlenker, W., Hanemann, W. M., Fisher, A. C. (2006). The Impact of Global Warming on Us Agriculture: An Econometric Analysis of Optimal Growing Conditions. *Review of Economics and Statistics* 88: 113-125.

Schlenker, W. and Roberts, M. J. (2009). Nonlinear Temperature Effects Indicate Severe Damages to Us Crop Yields under Climate Change. *Proceedings of the National Academy of sciences* 106: 15594-15598.

Seo, N., Mendelsohn, R., Kurukulasuriya, P., Dinar, A. (2008). An Analysis of Adaptation to Climate Change in African Livestock Management by Agro-Ecological Zones. *BE Journal of Economic Analysis & Policy*.

Seo, S. N. (2010). Is an Integrated Farm More Resilient against Climate Change? A Micro-Econometric Analysis of Portfolio Diversification in African Agriculture. *Food Policy* 35: 32-40.

Seo, S. N. and Mendelsohn, R. (2008a). An Analysis of Crop Choice: Adapting to Climate Change in South American Farms. *Ecological Economics* 67: 109-116.

Seo, S. N. and Mendelsohn, R. (2008b). Measuring Impacts and Adaptations to Climate Change: A Structural Ricardian Model of African Livestock Management. *Agricultural Economics* 38: 151-165.

Severen, C., Costello, C., Deschenes, O. (2018). A Forward-Looking Ricardian Approach: Do Land Markets Capitalize Climate Change Forecasts? *Journal of Environmental Economics and Management* 89: 235-254.

Tol, R. S. (2018). The Economic Impacts of Climate Change. *Review of Environmental Economics and Policy* 12: 4-25.

USDA/ERS (2018). Farm Income and Wealth Statistics.

Van Passel, S., Massetti, E., Mendelsohn, R. (2017). A Ricardian Analysis of the Impact of Climate Change on European Agriculture. *Environmental and Resource Economics* 67: 725-760.

Appendix

Winter

	Mean	Mean (% of total)	Std dev	Min	Max
< 0	17.49	19.38%	19.32	0.0	86.43
0 - 3	17.10	18.94%	9.194	0.0	36.06
3 - 6	20.82	23.07%	9.008	0.2	38.86
6 - 9	19.14	21.21%	10.37	0.0	38.34
9 - 12	11.62	12.87%	12.04	0.0	44.94
12 - 15	3.655	4.051%	7.638	0.0	45.04
15 - 18	0.418	0.463%	1.674	0.0	23.49
18 - 21	0.008	0.009%	0.052	0.0	1.019
21 - 24	0.000	0.000%	0.001	0.0	0.019
24 - 27	0.000	0.000%	0.000	0.0	0.000
27 - 30	0.000	0.000%	0.000	0.0	0.000
30 - 33	0.000	0.000%	0.000	0.0	0.000
33 - 36	0.000	0.000%	0.000	0.0	0.000
≥ 36	0.000	0.000%	0.000	0.0	0.000

Spring

	Mean	Mean (% of total)	Std dev	Min	Max
< 0	2.5	2.7%	5.4	0.0	48.02
0 - 3	5.0	5.4%	5.5	0.0	23.78
3 - 6	10.6	11.6%	7.1	0.0	29.28
6 - 9	17.1	18.5%	7.3	0.4	48.96
9 - 12	21.4	23.2%	5.8	2.9	42.62
12 - 15	18.0	19.5%	7.4	0.3	39.11
15 - 18	10.9	11.9%	7.1	0.0	38.38
18 - 21	5.2	5.6%	4.5	0.0	22.24
21 - 24	1.2	1.3%	1.5	0.0	9.116
24 - 27	0.1	0.1%	0.2	0.0	1.494
27 - 30	0.0	0.0%	0.0	0.0	0.288
30 - 33	0.0	0.0%	0.0	0.0	0.000
33 - 36	0.0	0.0%	0.0	0.0	0.000
≥ 36	0.0	0.0%	0.0	0.0	0.000

Summer

	Mean	Mean (% of total)	Std dev	Min	Max
< 0	0.000	0.000%	0.000	0.0	0.027
0 - 3	0.004	0.004%	0.035	0.0	0.826
3 - 6	0.042	0.046%	0.282	0.0	5.184
6 - 9	0.361	0.400%	1.200	0.0	15.61
9 - 12	3.370	3.734%	4.469	0.0	44.44
12 - 15	13.44	14.90%	13.56	0.0	50.96
15 - 18	19.51	21.62%	13.45	0.0	50.57
18 - 21	19.20	21.28%	8.433	0.0	45.38
21 - 24	18.90	20.94%	12.78	0.0	42.68
24 - 27	13.77	15.26%	15.31	0.0	57.83
27 - 30	3.121	3.458%	5.038	0.0	24.33
30 - 33	0.270	0.299%	0.799	0.0	5.197
33 - 36	0.008	0.008%	0.024	0.0	0.221
≥ 36	0.000	0.00001%	0.000	0.0	0.006

Autumn

	Mean	Mean (% of total)	Std dev	Min	Max
< 0	2.190	2.380%	4.3	0.0	40.84
0 - 3	3.939	4.281%	4.0	0.0	18.42
3 - 6	7.597	8.258%	5.0	0.0	17.68
6 - 9	12.17	13.23%	5.6	0.0	27.89
9 - 12	17.18	18.68%	6.0	0.5	42.08
12 - 15	18.53	20.14%	4.7	1.3	37.37
15 - 18	13.83	15.03%	6.3	0.1	32.12
18 - 21	9.600	10.43%	8.3	0.0	29.05
21 - 24	4.816	5.235%	6.9	0.0	32.59
24 - 27	1.066	1.158%	2.2	0.0	16.53
27 - 30	0.076	0.082%	0.3	0.0	2.212
30 - 33	0.003	0.004%	0.0	0.0	0.246
33 - 36	0.000	0.000%	0.0	0.0	0.000
≥ 36	0.000	0.000%	0.0	0.0	0.000

Table A - 1. Summary statistics of daily mean temperature bins.

Season	Variable	Coeff.	Cluster robust std. err.	Variable	Coeff.	Cluster robust std. err.
Winter	T < 0	-0.0223	0.0191	Rented land	0.2391	0.0456
	0 ≤ T < 3	0.0055	0.0125	Log of farm size	-0.2751	0.0181
	3 ≤ T < 6	-0.0448	0.0257	Conservation program	-0.0750	0.0300
	6 ≤ T < 9	-0.0426	0.0237	GDP per capita	0.0031	0.0041
	T ≥ 12	-0.0413	0.0193	Population density	0.2987	0.0698
	Precip.	-0.1269	0.1729	Population growth rate	3.1269	0.8120
	Precip. Sq.	0.0030	0.0135	Topsoil gravel content	-0.0311	0.0141
Spring	T < 0	0.1016	0.0520	Topsoil sand fraction	-0.0054	0.0052
	0 ≤ T < 3	-0.0919	0.0333	Topsoil silt fraction	-0.0113	0.0086
	3 ≤ T < 6	0.0334	0.0233	Topsoil pH	0.1939	0.0504
	6 ≤ T < 9	-0.0160	0.0275	Latitude	-0.0542	0.0413
	12 ≤ T < 15	0.1022	0.0271	Mean elevation	0.0674	0.2380
	15 ≤ T < 18	0.0994	0.0355	Distance from cities	-0.2789	0.3947
	18 ≤ T < 21	0.0073	0.0606	Distance from ports	0.6942	0.3019
	T ≥ 21	0.2091	0.0959	BE	1.7352	0.1566
	Precip.	0.0003	0.2078	DE	2.3694	0.1304
	Precip. Sq.	-0.0054	0.0123	DK	2.4482	0.2733
Summer	T < 9	0.0426	0.0163	ES	1.0134	0.2796
	9 ≤ T < 12	0.0387	0.0157	FI	1.9102	0.6310
	15 ≤ T < 18	0.0654	0.0162	FR	0.8336	0.1943
	21 ≤ T < 24	0.0108	0.0174	GR	2.3062	0.2570
	24 ≤ T < 27	0.0134	0.0154	IE	2.2477	0.3249
	T ≥ 27	-0.0602	0.0205	IT	2.7314	0.2182
	Precip.	-0.1064	0.0919	LU	1.4653	0.2447
	Precip. Sq.	0.0064	0.0045	NL	2.6780	0.1634
Autumn	T < 0	-0.0977	0.0414	PT	0.3579	0.3651
	0 ≤ T < 3	-0.0060	0.0561	SE	2.0995	0.3978
	3 ≤ T < 6	-0.0095	0.0472	UK	1.9814	0.2586
	6 ≤ T < 9	0.0255	0.0374	Constant	7.9603	2.9379
	9 ≤ T < 12	-0.0006	0.0345			
	15 ≤ T < 18	-0.0531	0.0314	Observations		37,891
	18 ≤ T < 21	-0.0047	0.0292	Adj R-squared		0.6179
	21 ≤ T < 24	-0.0798	0.0376			
	T ≥ 24	0.0334	0.0577			
	Precip.	0.1281	0.1928			
	Precip. Sq.	-0.0002	0.0128			

Notes: All coefficients for the main specification. Standard errors clustered at NUTS 3 level. Note that the dependent variable is log transformed. Omitted temperature bins not reported. Measurement units available in Table A - 1.

Table A - 2. Coefficients of the main specification.

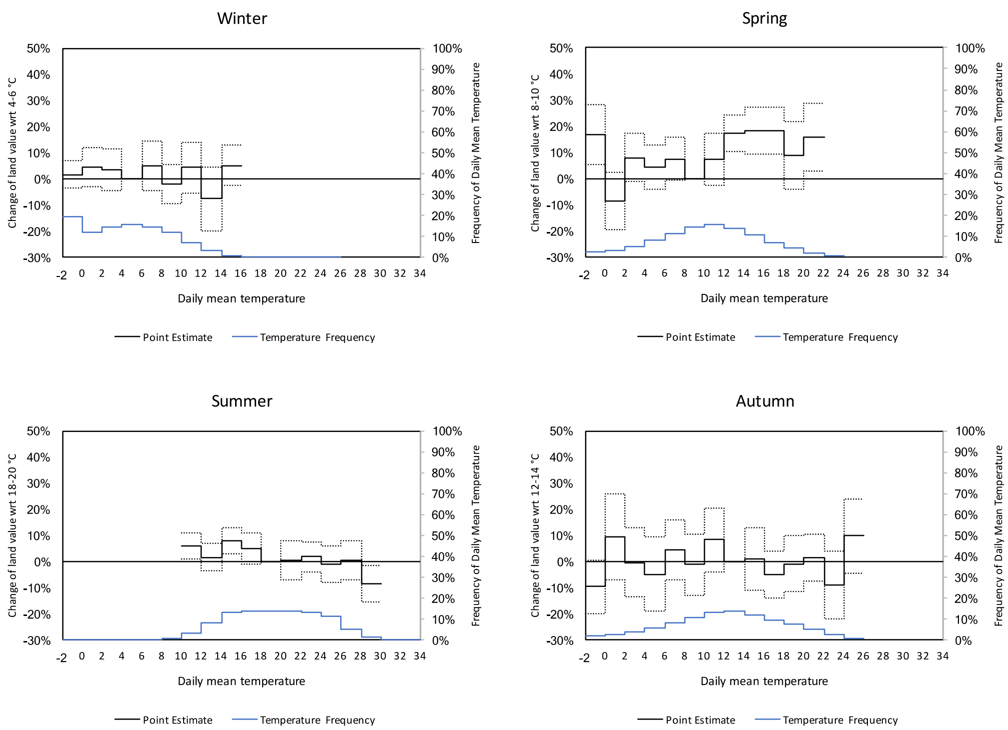


Figure A - 1. 2 °C wide temperature bins.

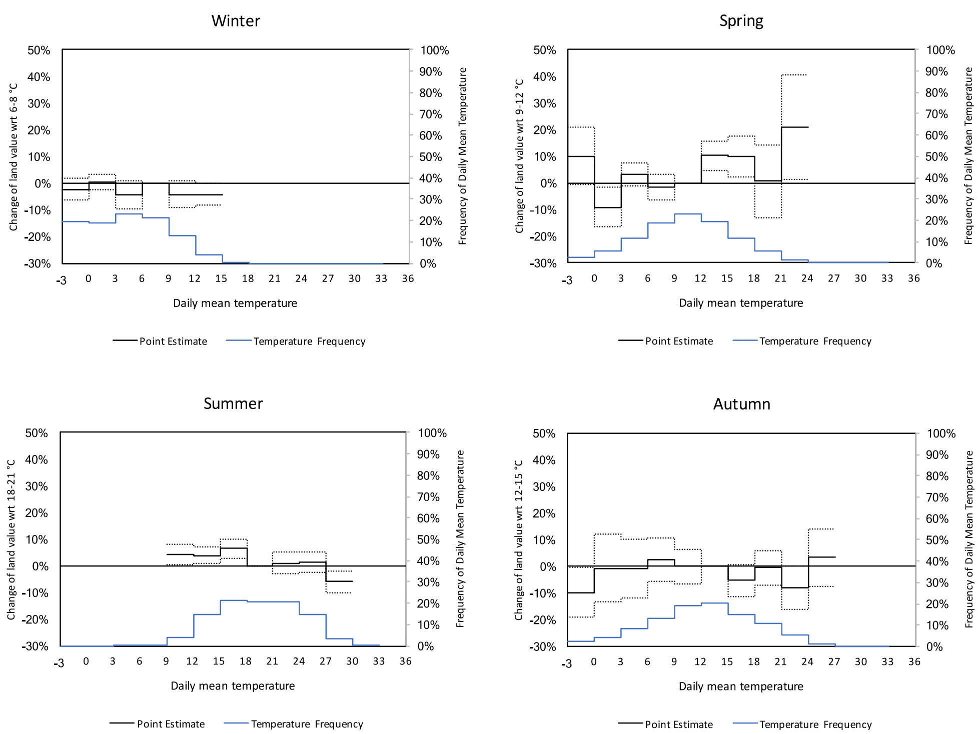


Figure A - 2. Main specification, with clustering at NUTS 2 level.

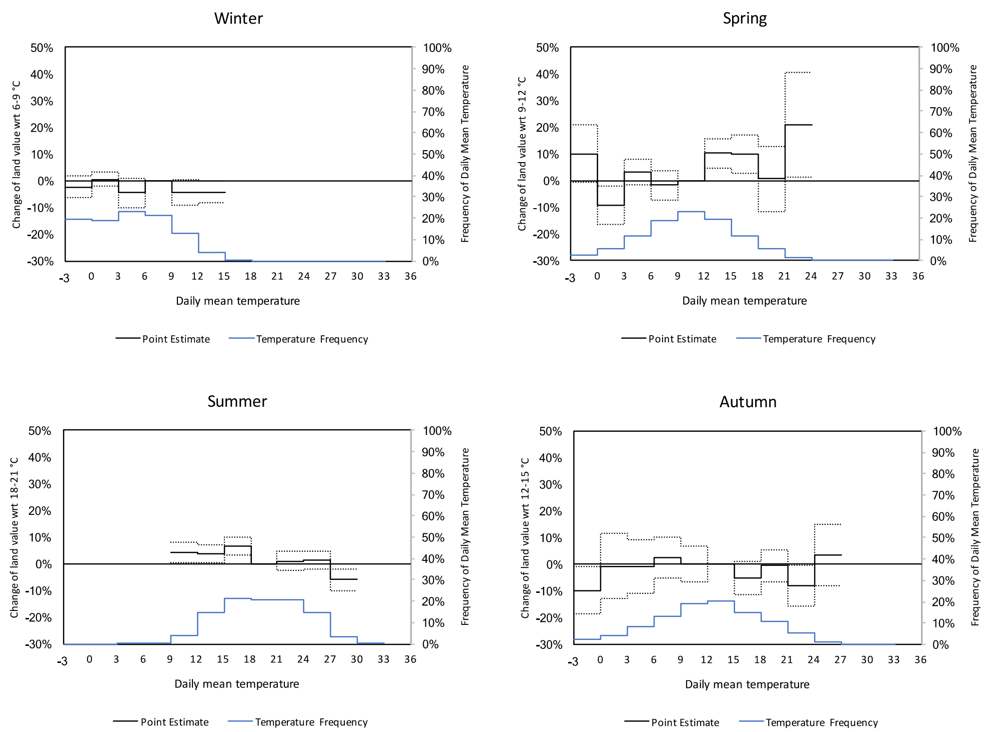


Figure A - 3. Base model with standard errors corrected for spatial correlation over a 100 km radius.

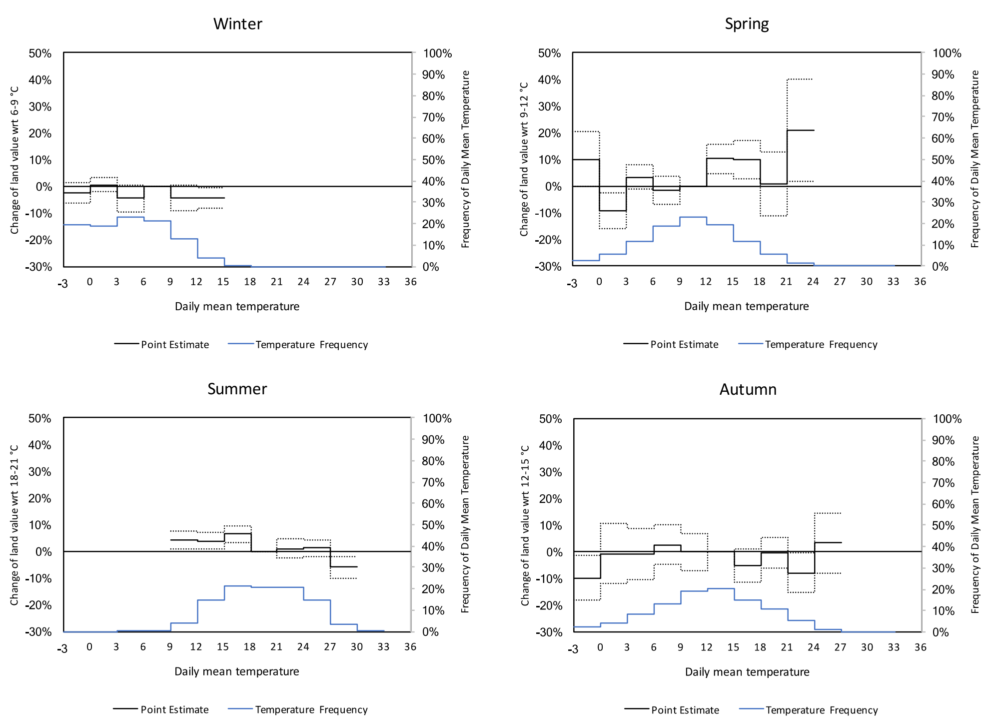


Figure A - 4. Base model with standard errors corrected for spatial correlation over a 50 km radius.

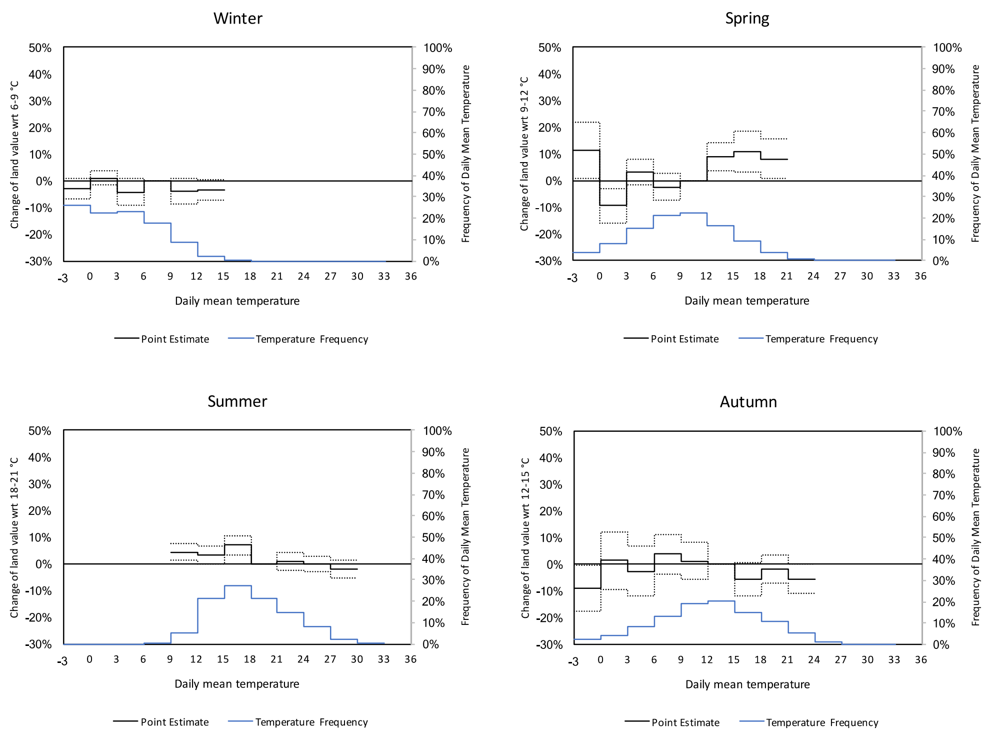


Figure A - 5. Weighted least squares.

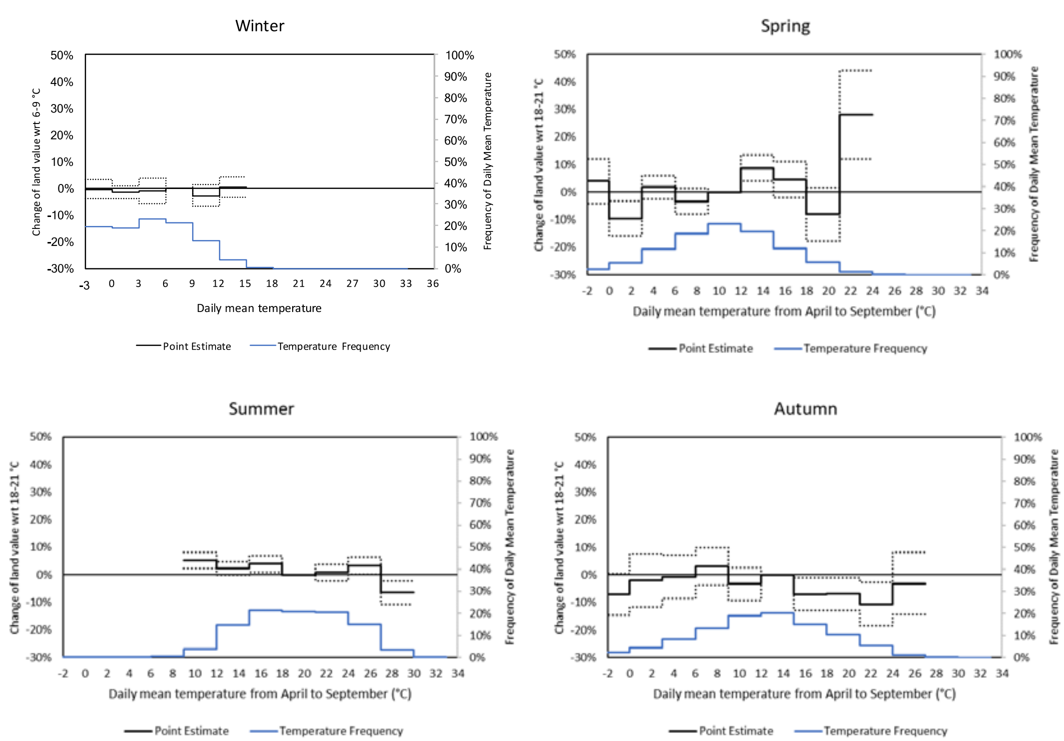


Figure A - 6. Random effects model.

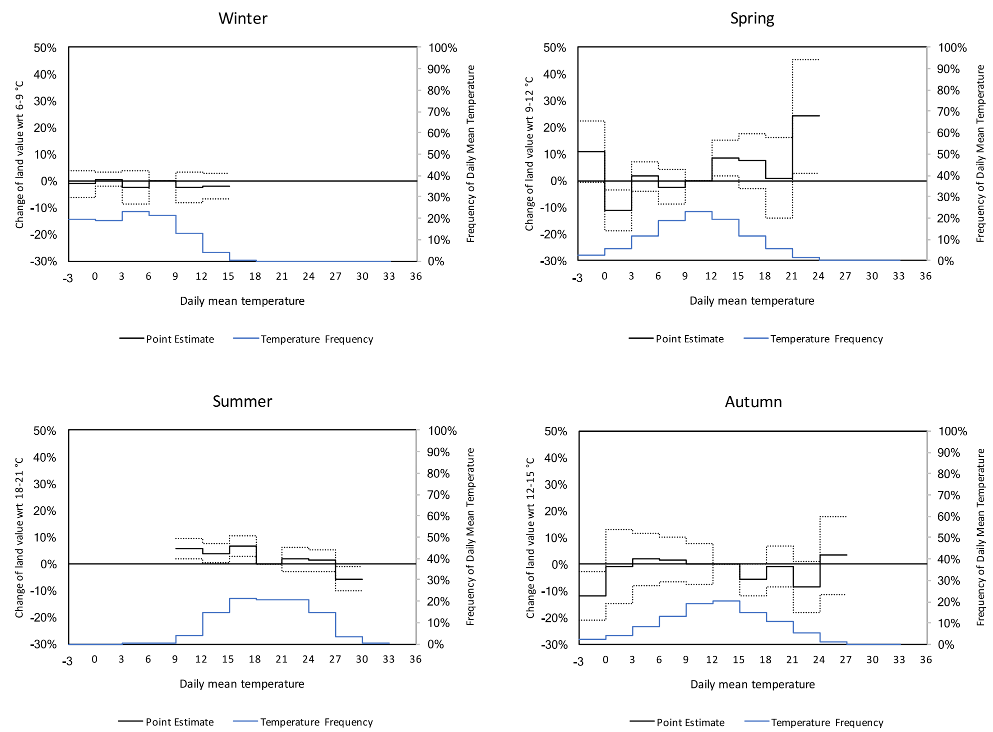


Figure A - 7. Median regression, four seasons.

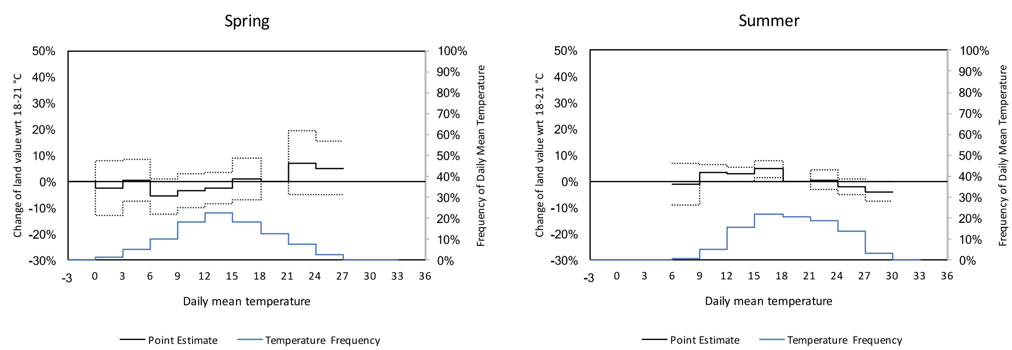


Figure A - 8. Median regression, two seasons.