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Keywords: Climate Change, Agriculture, Ricardian Analysis, Aggregation Bias, Semi-Parametric Models

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The impact of climate change on agriculture: nonlinear effects and aggregation bias in Ricardian models of farm land values

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Abstract

Ricardian (hedonic) analyses of the impact of climate change on farmland values typically assume additively separable effects of temperature and precipitation. Model estimation is implemented on data aggregated across counties or large regions. We investigate the potential bias induced by such approaches by using a large panel of farm-level data. Consistent with the literature on plant physiology, we observe significant non-linear interaction effects, with more abundant precipitation acting as a mitigating factor for increased heat stress. This interaction disappears when the same data is aggregated in the conventional manner, leading to predictions of climate change impacts which are significantly distorted.

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1. Introduction

There is a growing policy concern regarding the potential impact of climate change on agriculture as variation in temperature and precipitation significantly affect crop and livestock production (e.g. Intergovernmental Panel on Climate Change, IPCC, 2007). Different approaches have been used to try to quantify this effect (see Mendelsohn and Dinar, 2009, chap. 3, for a review). Early works focus on biophysical crop models simulating the impact of changes in weather on plants growth and input requirements (e.g. Adams et al., 1990; Kaufmann and Snell, 1997). These techniques include only limited behavioral responses in farmers' adaptation to climate change and, therefore, may risk over-estimating negative impacts. More recent studies derive the effect of climate on crop yield (Schlenker and Roberts, 2009; Welch et al., 2010; Lobell, Schlenker and Costa-Roberts, 2011) or farm profits (e.g. Deschênes and Greenstone, 2007, 2012) by fitting statistical or econometric models to time series, cross-sectional, or panel data. There are strengths and weaknesses in each of these approaches: for example, while time series or panel models can include location-specific fixed effects to absorb possible time-invariant omitted variables, identification rests on random year-to-year weather shocks, which are different from permanent shifts in climate (Fisher et al., 2012).

Among the economic analyses, the *Ricardian* (or hedonic) *method*, introduced by Mendelsohn et al. (1994), has gained considerable prominence. In recent years, this approach has been applied to various countries across the globe, including the United States (US, e.g. Schlenker et al, 2005; 2006), Brazil (Timmins, 2006), Germany (Lang, 2007), Latin America (Seo and Mendelsohn, 2008) and Africa (Seo et al., 2009). The Ricardian method is based on the notion that, in a competitive market, the value of farmland reflects the discounted value of all the expected future profits that can be derived from it (Ricardo, 1817). Estimation is typically implemented using data aggregated over counties or large regions. By regressing land prices on climatic determinants and a set of exogenous control variables, this technique estimates the impact of climate on farmers' expected incomes by relying on the cross-sectional variation observed in the current climate. This model is most commonly estimated using cross-sectional data as climate has not changed enough over time to allow the identification of its effect in any given location.

The major advantage of the Ricardian approach is that it automatically captures adaptation, since farmers adjust inputs and outputs to match local conditions. Three major drawbacks are (a) the implicit assumption of fixed prices, (b) possible omitted variables (an issue that typically affects all cross-sectional analyses) and (c) potential aggregation bias. Of these issues, fixed prices, set at the global level, are a common assumption in most studies that use a partial-equilibrium setting. Similarly, omitted variables, while not amenable to direct testing, tend to be of a lesser concern given the robustness of the observed relationship across years and settings (e.g. Schlenker et al., 2006). In contrast, data aggregation may conceal non-linear effects and farm-level heterogeneity resulting in biased parameters and subsequent predictions (e.g. Theil, 1954). Maybe surprisingly, almost all prior studies have employed county- or regional-level data (e.g. Mendelsohn et al., 1994; Schlenker et al., 2005; 2006; Lang 2008; Seo and Mendelsohn, 2008; Mendelsohn and Reinsborough, 2009; Seo et al., 2009) but none has yet tested the effect of the aggregation process on the parameter estimates and on the resulting projections of climate change impacts.[4]

In light of these issues, this study makes three main contributions to the literature. First, we test for aggregation bias by comparing the estimates resulting from a unique panel of farm-level data with those obtained after aggregating the same data to the conventional county-level in order to replicate previous findings. This test reveals a strong aggregation bias in both the coefficient estimates and in the resulting projections of climate change impacts. Second, in line with the literature on plant physiology (e.g. Monteith, 1977; Morison, 1996), our farm-level analysis estimates a significant interaction effect between precipitation and temperature in determining land values. This effect, typically ignored in previous Ricardian studies, disappears when the same data is aggregated at the county level. Third, we test for functional form miss-specification by estimating the first semi-parametric Ricardian model on farm-level data.

Aggregation bias is a long-standing issue in econometrics, recognized since the seminal works by Theil (1954), Grunfeld and Griliches (1960), and Feige and Watts (1972). This bias is particularly severe for the estimation of non-linear relations, which are normally not robust to the aggregation process (Stocker, 1984, 1986; Lewbel 1991; Garderen, Lee and Pesaran, 2000; Imbs et al., 2005). Nevertheless, previous Ricardian analyses use aggregated information to report strong non-linear climatic effects. We compare farm-level and county-level approaches to assess the suitability of aggregate data by (*a*) evaluating the parameter estimates of the climatic variables and by (*b*) measuring the predicted impact of climate change on agriculture. Such comparison exposes a strong aggregation bias with severe implications for predictions: on average, climate change impacts estimated on aggregated data differ by a factor of three compared with those derived on farm-level information. Our results also indicate that this bias is most probably caused by the fact that aggregated data do not adequately represent the fine variation in local climate experienced by each farm within a county.

[4] To our knowledge, the only Ricardian model estimated on farm-level data so far is the one presented by Schlenker et al. (2007). Other papers used farm-level information on yield (e.g. Welch et al., 2010) or farm revenues (e.g. Mendelsohn and Dinar, 2009; Wang et al., 2009), but the standard Ricardian approach requires farmland value data (analyses of farm net-revenues are sometimes referred to as *semi-Ricardian* approaches, McKinsey and Evenson, 1998).

Since farmland values are the discounted sums of future profits, any factor that impacts crop productivity and yield should also affect farmland values. Crop research has shown that plant yield response to weather and climate is highly non-linear and includes significant interaction effects between temperature and precipitation (e.g. Hillel and Rosenzweig, 2010; Welch et al., 2010). Surprisingly, most Ricardian studies (e.g. Mendelsohn et al., 1994; Schlenker et al., 2005; 2006) do not document such an interaction but rather assume the impact of temperature and precipitation to be additively separable.[5] Additive effects are at odds with plant physiology, since increased heat generates higher demand for water in crop development (e.g. Monteith, 1977; Morison, 1996). Our farm-level analysis reconciles the Ricardian approach with the literature on plants and crops growth by confirming a significant interaction effect: precipitation is more valuable when temperatures are high. Similarly, temperature has a positive effect on land value only if there is enough precipitation to prevent possible droughts. We only observe the interaction effect in our farm-level data set, again highlighting the importance of using micro-level data. This result is robust in a variety of settings, including different datasets, climate definitions and estimation methods.

A related issue is that Ricardian analyses typically assume climatic effects to have simple quadratic forms (e.g. Mendelsohn et al., 1994; Schlenker et al., 2005; 2006). However, previous research has shown that in hedonic models restrictive parametric specification can be rarely justified *a priori* (e.g. Cropper et al., 1987; Ekeland et al., 2002, 2004), and that semi- and non-parametric alternatives can provide several advantages (Anglin and Gencay, 1996; Parmeter et al., 2007; Bontemps et al., 2008). In addition, findings reported by Deschênes and Greenstone's (2012) seems to indicate that the predicted impacts of climate change on farm profits are heavily dependent on the functional form assumed for the climatic and control variables. Therefore, we test for functional form miss-specification arising from omitted non-linear effects by estimating a semi-parametric farm-level Ricardian model. Compared with the parametric regression, this approach provides a superior fit and reveals an even stronger interaction between rainfall and temperature. However, climate change impact predictions are not significantly different from those obtained using the simpler specification.

Our empirical application covers farms located in Great Britain (GB). While GB is smaller than the spatial extent of other Ricardian analyses, its geographic position (surrounded to the south by the Gulf Stream and to the north by sub-Arctic waters) generates a diversity of micro-climates yielding a wide

[5] Mendelsohn and Reinsborough (2007) and Seo et al. (2009) do include interaction effects but represent climate using temperature and precipitation during the months of January, April, July and October, rather than degree days and precipitation in the growing season as recommended by Schlenker et al. (2006) and extensively applied thereafter (e.g. Lang, 2007; Schlenker et al., 2007; Deschênes and Greenstone 2007; 2012, Fisher et al. 2012). An issue with using monthly averages is that the high cross-sectional correlation which characterizes these variables significantly limits the interpretability of the resulting interaction terms (in our sample, for instance, the correlations between the average temperature in October with the one in January, April and July are, respectively, 0.93, 0.97 and 0.91).

range of variation in temperature and precipitation. Obviously, variation in climate is necessary to obtain precise estimates. Focusing on a narrow spatial scale that has significant variation in climate is even preferable as other, potentially confounding, variables are more homogenous. In the extreme, having two identical farms that only differ in climate would be the best-case scenario for identifying the effect of climate on land values. The limited spatial scale can therefore be considered as an advantage rather than a constraint on the analysis. However, the major benefit arising from focusing on GB is the availability of accurate local climate measurements derived by one of the most dense weather station networks in the world, comprising 540 temperature and 4400 rainfall stations (Perry and Hollis, 2005). Comparison with the PRISM data (Di Luzio et al., 2008) used in the most recent Ricardian analyses (Deschênes and Greenstone 2012, Fisher et al. 2012) reveals that the number of temperature stations per square mile is roughly twice that of the US and the number of precipitation-stations is more than 20 times higher. Given that precipitation and (to a lesser extent) temperature are notoriously highly variable over space (e.g. Baigorria et al., 2006; Mendelsohn et al. 2007), this substantial increase in accuracy is crucial to obtain precise estimates of the farm-level climatic conditions and to effectively test for aggregation bias. Conversely, a sparse network of weather stations would introduce significant measurement error in local climatic values, undermining the superiority of farm-level estimates over their county-level counterparts.

2. The data

This analysis employs a database covering the whole of Great Britain by integrating multiple sources of information expressed at different spatial resolutions. These are detailed throughout the remainder of this section.

Land value data. Data on land value are derived from the Farm Business Survey and the Scottish Farm Accounts Survey panels which, sampled annually, include information on the physical characteristics and economic performance of farm businesses throughout Great Britain. Farms are retained in the sample for several years, with only 10% of them being replaced in each survey. The two Farm Surveys (FS) include a specific figure for land value, which excludes buildings and other improvements used for agriculture (it includes, however, the value of buildings and dwellings older than 30 years) and reflects the expected sale value assessed by professional farmland sales agents. Since these estimates are not revised each year, we discard from the analysis all the records in which the farmland value stays constant from one year to the next, as this indicates that the value has not been updated in that year.[6] The database also contains the location of the farm on a 10x10 km grid square basis, which we use to link farm value to environmental and climatic characteristics. In this analysis we consider 10 years of FS data, from 1999 to 2008, consisting of approximately 2500 farm records each year. Farms included in the panel comprise a variety of land uses including arable crops, livestock pasture and forestry. Eliminating farms with less than 30ha of owned land and farms for which the land value or the location are missing, leaves about 9500 observations for the analysis.[7]

Climatic variables. Temperature and precipitation are represented by the 5x5 km grid cell data available from the UK Meteorological Office archive (Met Office, http://www.metoffice.gov.uk/). As previously mentioned, this data is derived from one of the most dense network of weather stations in the world which include, on average, one temperature station every 20x20 km (540 stations) and one rainfall station every 7x7 km (4400 stations). The process used to derive the 5x5 km grid climate data published by UK Met Office is based on multiple regressions with inverse distance-weighted interpolation and take into account geographic and topographic factors, validated by randomly excluding 10% of the stations and predicting for their values (Perry and Hollis, 2005). This approach yields an out-of-sample Root Mean Square Error (RMSE) of 0.36°C for the monthly mean temperature (3.5% of the mean value) and of 16mm (3.6%) for the total monthly precipitation. This strong predictive performance reassures us of the ability of the 5x5 km climatic data to accurately represent the local conditions faced by the individual farmers within our sample. This feature is essential to effectively test for aggregation bias. Data collected on a sparser network of weather stations, in fact, would introduce significant measurement error in local temperature and precipitation values, undermining the superiority of farm-level estimates over their county-level counterparts.

As Deschênes and Greenstone (2012) and Fisher et al. (2012), for each observation we calculate climatic variables as averages over the 30 years period 1971-2000. Temperature has been included in Ricardian models as monthly or seasonal averages (Mendelsohn et al., 1994; Seo et al., 2009 consider average temperature in the month of January, April, July and October) or as the number of degree days in the growing season (Schlenker et al., 2005; Deschênes and Greenstone 2009; 2012; Fisher et al. 2012). Degree days are defined as the sum of degrees between two temperature thresholds. This concept is derived from the agronomic literature and reflects the fact that plant growth is linear in

[6] As an example, consider a farm which is surveyed in the years 2000-2005. The farmland value is estimated to be £1000 per hectare in year 2000, £1500 in 2001, 2002 and 2003 and £1800 in 2004 and 2005. In this case we include in the analysis only the records relative to years 2000, 2001 and 2004. However, as a robustness test we also estimate the model including the years in which the farmland value remains constant showing that the results remain essentially unchanged.

[7] In farms with only a small amount of owned land, farmland price per hectare can be significantly inflated when the property contains buildings or houses older than 30 years, since their value is included in the farmland price. To reduce this source of noise in the data we eliminate all farms in which the owned land is smaller than 30 hectares. In the robustness tests Appendix III, however, we also report the estimates obtained by including all farms and show that our findings remain consistent.

temperature only within a certain range, with temperatures below this interval being irrelevant for crops development, while temperatures above that threshold being potentially harmful.[8] Schlenker et al. (2006) show how this strategy is superior to including monthly averages, mainly because temperatures in different months can be highly correlated with each other (for example, in our climatic data the correlation of the average temperature in October with the one in January, April and July are, respectively, 0.93, 0.97 and 0.91). As in previous contributions, we consider only the degree days during the main growing season, defined for GB as the months from April to September. To derive degree days, we use the common assumption that, during the day, temperature (*temp*) follows a sinusoidal function (Schlenker and Roberts, 2006):

$$temp = 0.5[temp_{\max} - temp_{\min}]\sin(\chi) + temp_{\min} + 0.5[temp_{\max} - temp_{\min}],$$

where χ is defined between -1/2π and 3/2π and $temp_{\min}$ ($temp_{\max}$) is the minimum (maximum) temperature within the day. Since data on the minimum and maximum temperature in each day of the year are not available, we use average monthly minimum and maximum temperature to compute the number of degree days.[9] Taking into account the characteristics of GB agriculture, we define the lower and upper threshold as 5.5°C and 32°C respectively. In our sample, the average monthly maximum temperature never surpasses 30°C (the highest average maximum temperature recorded in the sample is 28.24°C) and, therefore, this latter threshold is not relevant for our study. Considering rainfall, as in previous studies we include the total precipitation in the growing season. Finally, as the 5x5 km grid of climatic data and the 10x10 km grid of farm location data share the same origin, we aggregate degree days and precipitation from 5x5km to 10x10km grid squares to match the resolution of the farm location data by using arithmetic averages.

Environmental and other control variables. Besides climate, several other determinants can significantly influence farmland values. Considering soil characteristics, we include soil texture as the share of fine (clay share between 35% and 60%), medium fine (clay < 35% and sand < 15%), medium (clay between 18% and 35% and sand >15% or clay between 18% and 35% and sand < 65%), coarse (clay < 18% and sand > 65%) and peaty soils, and the depth to rock. These are derived from the 1km grid square data in the European Soil Database (ESDB) maintained by the European soil data centre (http://eusoils.jrc.ec.europa.eu/). We also include average slope (derived from the Ordnance Survey,

[8] This is, not surprisingly, just an approximation. Recent literature (e.g. Schlenker and Roberts, 2006) shows how the effect of temperature on yield can present non-linearities even within the two thresholds. However, since the objective of a Ricardian analysis is not to analyze crop growth but to understand the effect of climate on land value, the linearity assumption to compute degree days still constitutes a reasonable approximation.

[9] We do not use approach developed by Thom (1966), commonly implemented on US data, because his formula is based on the average monthly temperature and its standard deviation, while we have information on the average monthly minimum temperature and the average monthly maximum temperature. This information provide a better representation of the GB climate (Hitchin, 1983).

Digital Terrain Model, available at: http://www.ordnancesurvey.co.uk/oswebsite/), representing the suitability of land for machinery operations, and population density (computed from 1990 and 2000 census data, http://casweb.mimas.ac.uk/), to capture the opportunity value of converting land to residential use, distance to markets and the availability of amenities or off-farm work for the members of the farmer's family. Finally, to capture the impact of location-specific policies we include the share of each 10km grid square classified as National Park, Nitrate Vulnerable Zone (NVZ) or Environmentally Sensitive Areas (ESA) in each year. NVZs, established in 1996 and extended in 2003 and 2008 to cover more than 70% of English farmland, are designed to reduce surface and groundwater nitrate contamination, and impose some restrictions on the agricultural activities of the farms within their boundaries (e.g. limiting the amount of fertilizer to be used on fields, regulating the storage of organic manure, etc.). ESAs, introduced in 1987 and extended in subsequent years, are intended to safeguard and enhance areas of high landscape, wildlife or historic value. Unlike NVZs, participation in ESA schemes is voluntary and farmers receive monetary compensation for engaging in environmentally friendly farming practices, such as converting arable land to permanent grassland, establishing hedgerows, etc.

[TABLE 1 about here]

Farm-level data descriptive statistics

Descriptive statistics for these variables are reported in Table 1. The distribution of farmland values appears to be highly skewed with a long right tail, which could support a log-normal distribution as, for example, implemented by Schlenker et al. (2006). Considering rainfall levels, although GB covers a relatively modest area compared to those analyzed in other Ricardian studies (e.g. US, Brazil), its location between the warm waters of the Gulf Stream to the West and the cold climates of Scandinavia to the East means that it exhibits a wide range of precipitations across the growing season (from 244 to 1434 mm), this range actually exceeding that reported for the rainfed US counties (from 332 to 982mm) analyzed by Schlenker et al. (2006). Indeed, accounting for irrigation (Schlenker et al., 2005) is not necessary in the UK, since most farmland is rainfed (less than 1% of the farms in our sample use irrigation at all). Furthermore, temperatures rarely reach particularly high values (total degree days ranges between 654^{o}C and 1639^{o}C), with the maximum number of degree days in the growing season being well below 2400, which coincidentally is the optimal value for crop growth identified by Schlenker et al. (2006). Therefore, accounting for high temperatures which are potentially damaging crop development is also not an issue in our study.

Aggregation. In order to obtain units of aggregation comparable with those examined in previous Ricardian studies, we aggregate our farm-level values using the official 'third level' Nomenclature of Territorial Units for Statistics (NUTS), as defined by the European Union, which roughly correspond to GB counties. Their size varies considerably, ranging from about 40 km^2 to more than 10000 km^2, with an average of 1814 km^2 (for comparison, the average area of US counties is about 3000 km^2). We assign each farm to a county based on its spatial location and compute the aggregated land values as farmland-area weighted averages. Similarly, we aggregate climatic and control variables using as weights the amount of agricultural land within each 10 km grid square included in a county. This leads to over 30 farms records for each county (with an average of 11 farms in each year) and a total of 848 aggregated observations.

[TABLE 2 about here]

Descriptive statistics of the climatic variables aggregation

The statistics reported in Table 2 measure the impact of the aggregation process on the accuracy of the climatic variables. The between-county statistics, reported in the top half of the table, represent the variation in climate retained in the aggregated data. Considering degree days, the range of values is between 756^{o}C and 1611^{o}C (with a mean of 1290 ^{o}C), which is very similar to that observed for farm-level data. However, precipitation during the growing season presents a minimum value of 275 mm and a maximum of 811 mm, which is considerably lower than the highest value observed on the farm-level data (1420 mm). This can be explained by the high spatial variability of rainfall, which causes some of the extreme values observed in farm-level data to be lost in county-level statistics. The bottom-half of Table 2 reports within-county statistics, representing the heterogeneity in climate which is concealed by the aggregation. Within the average county, degree days and precipitation vary by about 230^{o}C and 150mm respectively. This loss of climatic information is not negligible, since it corresponds, in turn, to about 22% and 15% of the range of values observed across the entirety of GB. In addition, there is also considerable variation around this mean, with some counties presenting a relatively homogenous climate while others exhibiting strong heterogeneity. The county of Hertfordshire (1700km^2), for instance, located in the South-East of the country, is characterized by both low variation of temperature (*dd* between 1380 ^{o}C and 1520 ^{o}C) and precipitation (*prec* around 300-320 mm). On the other hand, South-West Derbyshire, a county of similar size (2000 km^2) located towards the middle of the country, has degree days varying from 950 ^{o}C to 1410 ^{o}C and precipitation ranging from 310mm to 650mm. This large variation, lost with the aggregation, corresponds to respectively 45% and 35% of the range of degree days and rainfall observed in the entire GB sample. Therefore, farms located within the same county can face significantly different climatic conditions. In the next Sections we test whether using aggregated data and assuming climatic-homogenous counties has any implication for Ricardian regression estimates.

3. Methodology

3.1 The Ricardian model

The Ricardian approach assumes that each farmer allocates land among different activities in order to maximize net revenues. Consequently, in a competitive market, farmland price equals to the expected present value of the future stream of income derived from land. We assume that farms are atomistic, and input demand is small enough to not influence input prices. By the same token, idiosyncratic weather shocks do not influence the exogenous output prices since the quantity produced in the UK is not large enough to affect the global market. The Ricardian approach does not model farmers' land allocations, input and output choices explicitly, but rather estimates the overall value of each land characteristic by specifying the hedonic, reduced form model:

(1) $V_t = f(\mathbf{p}, \mathbf{r}, \mathbf{z}, \mathbf{g})$,

where *f*(.) is a functional form unknown *a priori*. As in most hedonic models, economic theory provides little guidance on the shape of this relation, which, while arguably non-linear, remains an open empirical question.

3.2 Testing for aggregation bias and omitted non-linearities

Virtually all Ricardian analyses have translated equation (1) into an empirically tractable model by assuming a linear or semi-log specification with a quadratic formulation for the climatic variables (here degree days, *dd*, and precipitation, *prec*) and a linear function for all other determinants. Findings reported by Schlenker et al. (2006) suggest that a log-transformation of the dependent variable outperforms a linear specification, since the distribution of land values is non-negative and typically highly skewed. Estimation is normally implemented on data aggregated over counties or larger regions. As a starting point, we open our analysis by replicating such a model, which has implemented in the majority of Ricardian studies so far. This hedonic equation (*Model A*) is specified as:

(2) $\ln V_{c,t} = \beta_0 + \beta_1 prec_c + \beta_2 dd_c + \beta_3 dd_c^2 + \beta_4 prec_c^2 + \boldsymbol{\gamma}'\mathbf{g}_{c,t} + u_{c,t}$,

where *c* indicates the county, *t* indicates the time at which expectations are taken, β_0, ... , β_4 and $\boldsymbol{\gamma}$ are the county-level parameters to be estimated and $u_{c,t}$ is a residual component which we define as being the sum of a county-specific random effect and a residual, both normally distributed and uncorrelated

($u_{c,t} = \alpha_c + \varepsilon_{c,t}$). The vector $\mathbf{g}_{c,t}$ includes population density (*dpop* and $dpop^2$, see SFH), depth to rock (*dtr*), slope, soil texture shares, National Park (s_{park}), ESA (s_{esa}) and NVZ (s_{nvz}) shares, regional fixed effects (for England, Wales and Scotland) and yearly fixed effects.

This quadratic approximation with additively separable climatic effect (on the logarithmic scale) has been implemented in most applications (see Mendelsohn and Dinar, 2009, for a review) because it allows the identification of "optimal" crop growing conditions while maintaining simplicity in estimation. In this specification, climatic effects are multiplicative. For example, the marginal effect of precipitation is:

$$(3)\quad \frac{\partial V_c}{\partial prec_c} = V_c(\beta_2 + 2\beta_4 prec_c)\,.$$

This effect, therefore, depends on all the variables which determine the land value V_c. However, this formulation does not encompass all interactions among climatic variables. In fact, the sign of the marginal effect (3) depends solely on the term $\beta_2 + 2\beta_4\, prec_c$, which contains only the parameters of precipitation itself, and none of those relating to other variables. This means that the optimal amount of rainfall will not depend on the level of temperature, and *vice versa*. This constraint might not necessarily be valid. For instance, agronomic experiments have shown that warmer conditions typically lead to an increase in crop requirements for water (e.g. Morison, 1996).

The simplest approach to relax the assumption of additively separable climatic effects is to include an interaction term to equation (2) to allow the effect of precipitation and temperature to be mutually dependent. Therefore, we estimate our second specification (*Model B*) as:

$$(4)\quad \ln V_{c,t} = \beta_0 + \beta_1 prec_c + \beta_2 dd_c + \beta_3 prec_c^2 + \beta_4 dd_c^2 + \beta_5 prec_c dd_c + \boldsymbol{\gamma}'\mathbf{g}_{c,t} + u_{c,t}\,,$$

There are good theoretical reasons to believe that even simple non-linear relations, such as those represented by equations (2) and (4), are not robust to the aggregation process. Stocker (1984, 1986), for instance, shows that even the parameters of the simple quadratic or logarithmic models, when estimated on aggregated data, will be a non-linear combination of the micro-level coefficients and of the parameters of the distributions of the exogenous variables. Therefore, even under very stringent conditions, recovering the farm-level parameters using a county-level regression would require the inclusion of squares and cross-products of the explanatory variables and very complex functional forms (Van Garderen, Lee and Pesaran, 2000, provide a few examples). Given that most Ricardian analysis have been implemented on aggregated data, it is important to investigate the size of any bias inherent in such approaches and its implications climate change impacts predictions.

The simplest strategy to test for aggregation bias it to re-estimate model (4) using the same data, but disaggregated at the farm-level, testing whether parameters and climate change impacts predictions are significantly different from those obtained with county-level data. The resulting specification (*Model C*) can be written as:

(5) $\ln V_{i,j,t} = \alpha_0 + \alpha_1 prec_{i,j} + \alpha_2 dd_{i,j} + \alpha_3 prec_{i,j}^2 + \alpha_4 dd_{i,j}^2 + \alpha_5 prec_{i,j} dd_{i,j} + \boldsymbol{\xi}'\mathbf{g}_{i,j,t} + u_{i,j,t}$,

where i indicates the farm, j the 10km grid square, $\alpha_0, \ldots, \alpha_5$ and $\boldsymbol{\xi}$ are the farm-level parameters to be estimated and all other symbols are defined as previously. We specify the residual component to include both a farm- and a 10x10km cell-specific random effect ($u_{i,j,t} = w_j + \alpha_{i,j} + \varepsilon_{i,j,t}$), to take into account that farms located within the same area may share common un-modelled factors which may significantly affect their land value. This is also a simple approach to account for spatial auto-correlation by allowing the residuals of the farms located within the same cell to be correlated with each other.[10]

A drawback of this last approach (and of any other strict parameterization) is that it constrains the effects to assume very specific functional forms. In such model, climatic impacts are forced to be quadratic and their interaction is assumed to be linear. While these could be reasonable approximations, there is no theoretical justification underpinning such a rigid structure, which is mainly adopted for ease of estimation. Therefore, it is worth investigating possible functional form miss-specification by using a more flexible model. Here we represent the relationships of interest via smooth functions, deriving an Additive Mixed Model (AMM) which is our most general and last specification (*Model D*):

(6) $\ln V_{i,t} = f(z_{1,t}, z_{2,t}) + s_1(g_{1i,t}) + \ldots + s_h(g_{hi,t}) + u_{i,t}$.

[10] This is similar to using cluster robust standard errors, as implemented, among others by Fisher at al. (2012) and Deschênes and Greenstone (2012). Including a more general form of residual spatial autocorrelation (e.g. $\varepsilon_{i,t} = \rho W_\varepsilon + \varepsilon_{i,t}$, with ρ = spatial correlation parameter, W_ε = spatial weight matrix, $\varepsilon_{i,t}$ = i.i.d. error term, see Schlenker et al., 2006, and Maddison, 2009) does not change significantly the parameter estimates of Model C. However, the size of our dataset makes this approach computationally too demanding for the estimation of the semi-parametric specification (Model D). Therefore, for ease of comparison we present the simplest specification with farm- and cell-specific random effects for both models. In the robustness test Appendix III we also test the impact of allowing a stronger spatial autocorrelation by adding an additional random effect term grouping together clusters of 9 cells, showing that the results do not change significantly.

In this model the joint effects of temperature and precipitation are encompassed by a multidimensional smooth function *f(.)*, which allows the estimation of flexible non-linear relationships and interaction effects. The control variables are also included via smooth functions, $s_1(.)$,..., $s_h(.)$, to capture possible non-linear relations. However, to maintain simplicity in the interpretation and avoid the well-known curse of dimensionality, their effects are assumed to be additively separable. The marginal effects of rainfall can be derived as:

$$(7)\ \frac{\partial V_i}{\partial prec_i} = V_i \frac{\partial f(prec_i, dd_i)}{\partial prec_i}.$$

Note that the sign of this marginal effect is a function of both precipitation and temperature. As a result, the model encompasses, in a flexible form, the interaction effects amongst all climatic factors. This is a very general specification and encompasses Model C as a special case. Comparing the estimates from the two models allow us to test for omitted non-linear relations.

4. Empirical application

4.1 Estimation results

We estimate models (2), (4), (5) and (6) via Restricted Maximum Likelihood (REML) using the *R* software (R development core team, 2008). Model A, B and C are standard linear regression with random effects, and are estimated via the package *nlme* (Pinheiro and Bates, 2000). Model D is implemented by representing the smooth functions as natural cubic splines, which fit third degree polynomial functions between a set of knots located between the range of values of each explanatory variable. The number and the location of the knots effectively determine the flexibility of each smooth function. We estimate the optimal number of knots (i.e. the optimal amount of smoothing) directly from the data by following the approach illustrated by Ruppert, Wand and Carroll (2003), who suggest representing the smoothing splines as random effects (details are in the Appendix). This model is estimated via REML by using the package *mgcv* (Wood, 2006b). This approach automatically reduces the smooth functions of the variables for which the optimal fit does not include any non-linearity to standard linear forms. In the extreme, a model in which none of the non-linear relationships are supported by the data will be reduced directly to a standard linear regression during estimation. The optimal level of non-linearity of each smooth function is indicated by the 'Effective Degrees of Freedom' (EDF). The higher the EDF, the more non-linear is the estimated function. An EDF equal to 1 suggests that the best smooth function representation is linear.

The parameter estimates and diagnostics of the four models are presented in Table 3. The first column reports the coefficients of Model A: the standard Ricardian regression based on county-averaged data. The estimated effect of degree days is always positive (with the quadratic effect being non-significant) and the effect of precipitation is negative with a quadratic shape. This is not entirely surprising, given the relatively wet and cold conditions which characterize GB. The coefficients of the control variables have intuitive signs. Better physical environments (lower slope and deeper soils) translate into higher land values. Finally, while not reported in the table to preserve space, the yearly fixed effects are also significant, highlighting the presence of important differences among the (deflated) land values among different years, probably reflecting evolutions in market conditions, policy and technology. Also the regional fixed effects are significant.

Model B, presented in the second column, also employs aggregated county-level data to test whether the interaction effect between degree days and precipitation is significant. The approximate t-test is -1.73, with approximate p-value of 0.08, which does not reject the null hypothesis of no interaction at the standard 5% level. In addition, the negative sign of the corresponding coefficient is counter-intuitive. Previous crop studies (e.g. Monteith, 1977; Morison, 1996) demonstrated that the amount of water required for plant development increases with temperature, implying a positive rather than a negative interaction. Altogether, we conclude that county-level estimates indicate predominantly additive climatic effect without a strong interaction between precipitation and temperature. Overall, taking into account the wet and cold British climate, these conclusions are in line with those reported by previous Ricardian analyses (see Mendelsohn and Dinar, 2009, chap. 7, for a useful review).

[TABLE 3 about here]

Parameter estimates and diagnostics

These results obtained on aggregated data are, however, overturned when individual farm records are analyzed. As the estimates of Model C (third column) shown, rainfall and degree days present strong non-linear effects, with both the quadratic terms and the interaction being highly statistically significant. This interaction is positive: consistent with the agronomic literature, the optimal amount of rainfall increases with temperature. The estimates of the semi-parametric Model D, reported in last column of Table 3, confirm these results. The 'Effective Degrees of Freedom' of the bivariate smooth function of temperature and precipitation is equal to 8.61, indicating strong non-linear effects and interactions. For comparison, the bivariate smooth function corresponding to the climatic effects estimated in Model C (i.e. two quadratic effects with a linear interaction term) would have an EDF equal to 5.[11]

Figure 1 provides a graphical representation of the estimates produced by the semi-parametric model. The right-hand panel represents with iso-value lines the joint effects of the climatic variables on land price. We only draw such contours for values of degree days and temperature observed within the estimation sample, as represented in the scatter plot in the left-hand panel. For example, in GB there are no areas with both relatively high temperature and high precipitations and, therefore, the top-right corner of the right-hand plot is blank. Furthermore, the distribution of the climatic variables appear to be highly skewed, with most farms located in areas characterized by relatively high temperatures (*dd* > 1300) and low precipitations (*prec* < 500). Therefore, the upper-left parts of the contour graphs are the most relevant for climate change predictions in GB.[12] The contour-plot shows a clear interaction effect. In the colder areas (*dd* < 1200), abundant precipitation reduces agricultural values, since the excess of moisture within the soil can considerably delay machinery operations until late in the growing season. On the other hand, in warmer areas (*dd* > 1400) the crop requirement for water increases and the effect of rainfall becomes positive. Therefore, beyond a certain level, higher temperatures increase land values only if there is enough precipitation to prevent the risk of drought. This means that there is not a generalized, ideal level of temperature which defines the best crop growing conditions (as assumed in previous Ricardian studies) but, rather, that the optimal level of temperature depends on the amount of precipitation. Vice versa, the profit maximizing level of precipitation depends on the level of temperature.

[Figure 1 about here]

This interaction effect is analyzed in greater detail through the next two figures. Figure 2 represents the estimated impact of precipitation on land value for two levels of temperature. When temperature is low (*dd* = 1100 ^{o}C, right hand panel), we observe a strong negative effect which can be attributed to soil waterlogging, delayed ploughing and sowing, and to the negative effect that excess soil moisture can have on plant growth (e.g. IPCC, 2007). However, as temperature increases, the relationship becomes more moderate and in the warmest areas (*dd* = 1650, left-hand panel) rainfall has a positive effect within the entire range of observed data. Moving to consider the effect of temperature, Figure 3

[11] We cannot compare Model C and D via a likelihood ratio test, since the two models are not nested. However, the log-likelihoods, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), reported at the end of Table 3, all support the semi-parametric specification. Ignoring this non-linearity also comes at the cost of increasing the un-modelled spatial autocorrelation, which is reflected in the higher value of the cell-specific random component of Model C compared to that of Model D. This is consistent with Kostov's (2009) findings, which shows that flexible functional forms can significantly reduce residual spatial auto-correlation in farmland price modelling.

[12] The next section shows how our sample of farm is representative of the overall conditions in the country.

represents the impact of degree days for two different levels of precipitation. In areas where rainfall is relatively low (300mm, left hand panel) the positive effect of warmer temperatures on plant growth are offset by the increase in drought risk such that the resulting net effect on land value is not significant. However, in areas of higher precipitation (500mm, right hand panel) increased water availability protects plants from heat stress allowing temperature to have a strong and positive effect on land value.

[Figure 2 about here]

[Figure 3 about here]

Overall, the interaction effect between temperature and rainfall, which is positive and significant in the farm-level analyses, completely disappears (or even becomes negative) in county-level estimates. The main reason for this attenuation bias is that county-level data ignore the heterogeneity in climate faced by the individual farms within a county. Since both temperature and rainfall patterns are expected to alter as a result of climate change, this bias may have significant implications for climate change predictions. Such a hypothesis is tested in next section which compares the projected climate change impacts according to our four Ricardian regressions. However, we first report a series of checks to test whether our farm-level results are stable and robust to possible omitted-variable bias and to examine whether our aggregation bias evidence is consistent across specifications, data and climate definitions.

4.2 Robustness tests

We open this sub-section by undertaking some robustness analyses on our farm-level estimates, testing for omitted variable bias and parameter stability. We then move to consider alternative Ricardian models to show that our aggregation bias findings are robust in to diversity of specifications and data definitions.

Concerns about potential omitted cross-sectional variables in Ricardian analyses have been pointed out by Deschênes and Greenstone (2007, 2012), among others. A panel fixed-effect estimator provides little help in addressing this issue, since it would eliminate not only the potential bias but also all the cross-sectional variation on which the parameters of the Ricardian model hinge upon. In Ricardian models, in fact, in order to represent climate (as opposed to weather), temperature and rainfall are constructed as long-term averages and, even in long panels, present a time-variability which is almost negligible compared to the cross-sectional (spatial) variability. This means that fixed-effect estimators, intended to eliminate potential time-invariant omitted variables, cannot be implemented in this context, because they would also remove the crucial spatial variation of climate. A second, related, issue, concerns the distortions in the land market which various agricultural policies tend to create (e.g. Barnard et al., 1997). For instance, crop and environmental payments could be capitalized in the land price and, if correlated with climatic variables, introduce a bias in their coefficient estimates.

We address both issues by testing whether the parameters of degree days and precipitation are stable over time. If omitted variable bias is a concern, in fact, these coefficients should exhibit significant temporal variation, reflecting changes in agricultural prices and policies. Our sample provides a particularly hard benchmark for this test, since during the 10 years covered by our data, agricultural policies in GB have changed markedly, following various reforms of the EU Common Agricultural Policy. These policy developments culminated with the introduction of decoupled single farm payments in 2005, replacing the system of area-based crop-specific subsidies in place since 1992. Input and output prices have also changed dramatically during this period, with, for instance, cereal prices more than doubling during the period from 2007 to 2008. This variation is reflected in the yearly fixed-effects, which are strongly significant in all specifications. If there are omitted variables correlated with climate, therefore, one would expect the smooth functions of temperature and precipitation to present significant variation over time in such unstable market conditions. To investigate this hypothesis, we choose the first year in our sample (1999) as the baseline and test for parameter stability comparing one year at a time via pairwise F-tests (Pinheiro and Bates, 2000). We test our final and more flexible specification, Model D, and in order to use the standard inference for random-effect models, we define the spline bases of the model *a priori* and implement un-penalized estimation via ML. To attain a level of flexibility comparable to the optimal one selected by the penalized likelihood, we choose natural cubic splines with 4 knots for population density and 16 knots for the joint function of precipitation and rainfall, while all other variables are modelled as linear terms. Table 4 reports the results: none of the pairwise instability tests is significant at the 5% level, and only one is significant at the 10%. This is consistent with the null hypothesis of parameter invariance which, therefore, we find no evidence to reject. Overall, these results reassure us about the robustness of our climate impact estimates to omitted variable bias such as changes in prices and agro-environmental policies.

[TABLE 4 about here]

Pairwise stability tests

We now test whether the evidence of aggregation bias is consistent across different data, models and aggregation methods. For each alternative specification, Table 5 reports the climate coefficients of the parametric models with interactions estimated on county-level (Model B) and farm-level data (Model

C). Since the two models have the same structure and variables, any difference in the parameter estimates can be attributed to the aggregation process. For comparison, the first row reports the coefficients of the original specification. In the second row we test the effect of using a different aggregation method. Rather than taking area-weighted averages of the land value of all farms located in each county, we use simple, un-weighted averages. As can be seen, the aggregation bias becomes even larger, with the interaction effect remaining negative but now growing stronger and significant. This is not unexpected, given that not taking into account the relative size of the properties can produce aggregated data which are less representative of the original population.

[TABLE 5 about here]

Parameter estimates according to alternative specifications

The third row of Table 5 reports the results obtained using a different climate specification. Rather than calculating climate as the average weather between the years 1971-2000, we follow Schlenker et al. (2006) and define climate as the average weather in the 30 years preceding each observations (e.g. for 2005 data the climate is defined as the average between the years 1975-2004). This means that we introduce some temporal variation which allows climate to change somewhat from year to year in each cell or county. The resulting coefficients are very similar to those in the baseline approach, suggesting that our conclusions are robust to different definitions of climate.

In the fourth row we re-estimate the models including also all observations in which the farmland value is not updated in that year. In fact, replicated entries might reflect periods over which owners do not perceive significant changes in their property value. While the magnitude of some of the climate coefficients appears to slightly increase, the results are consistent with the baseline specification in that we observe a strong, positive and significant interaction effect on farm-level observations and no interaction on county-level data.

Rows five and six report the results obtained by broadening the farm sample to include very small farms. Recalling section 2, the rationale behind limiting our analysis to properties larger than 30ha is that our definition of farmland value includes the value of buildings and houses older than 30 years. While this is not a problem for large farms, very small properties with old household buildings can present a significantly inflated farmland values per hectare. However, as shown in the fifth row, including all farms larger than 5ha (3801 farms) does not significantly impact the estimated climatic coefficients. The sixth row shows that even encompassing all properties in the FS sample (4044 farms), including those smaller than 1ha, does not change the sign and the magnitude of the coefficients, although the interaction effect becomes not significant because the additional noise introduced the data.

Row seven we allow for a stronger spatial autocorrelation in the farm-level model, including an additional random effect term grouping together clusters of nine 10x10 cells, for a total of 900km^2. While the magnitude of some of the coefficients slightly decreases, the interaction effect is still positive and significant at the 5% level.

All these robustness tests confirm the presence of strong aggregation bias. Is this bias caused by grouping together properties with different land values, or by the cruder representation of climate in county-level information? In order to answer this question, in the eighth row we report the estimates of a farm-level model which represents climate using the values of rainfall and precipitations calculated for the aggregated data, i.e. county-level weighted averages. The resulting coefficients are indeed biased and similar to those estimated on aggregated data, with the interaction effect, in particular, being non-significant. This shows that not taking into account the important within-county variation in climate (previously illustrated in Table 2) may well be the main cause of the bias we detect on the models estimated on aggregated data.

5. Climate change impact predictions

We combine the estimates presented in the previous section with the recently released UK Climatic Projections 2009 (UKCIP09, source: ukclimateprojections.defra.gov.uk) to project the impact of climate change on agriculture in Great Britain and to test whether aggregation bias has any implication for predictions. Specifically, we use the UKCIP09 projected changes in monthly average minimum temperature, maximum temperature and precipitation in the medium level emission scenario for years 2020-2049 (corresponding to the SRES A1B in the IPCC Special Report on Emissions Scenarios, Nakicenovic et al., 2000). This data is available on 25x25 km grid squares covering the entire UK. We derive the corresponding values of degree days and precipitation in the growing season by applying these changes to the 10x10 km Met Office historical averages for the years 1960-1990, which are the baseline climatic conditions indentified by the UKCIP09. We also take this climate as our baseline.

To derive the impact of climate change, we predict log-agricultural land price under both the baseline and the climate change scenario. The only difference between the two scenarios is climate: all other determinants (soil, population density, etc.) are kept constant at their 2008 values, the last year of our farm data. Consequently, we do not consider other factors that are likely to change in the future, such as technology, prices, land use and population. Therefore, our results are intended to estimate how climate will affect agriculture *ceteris paribus*, and should not be interpreted as predictions of the future. Table 6 reports descriptive statistics for the climatic and environmental determinants in the baseline and climate change scenarios. The ranges of the exogenous variables are similar to those of the data used for estimation (see Table 1), indicating that our FS sample is representative of the overall environmental conditions in Great Britain.

[TABLE 6 about here]

Descriptive statistics of the climatic and environmental variables

Compared to the baseline, the UKCIP 2020-2049 medium emission climate change scenario is characterized by both higher temperatures and lower precipitation during the growing season. The highest value of degree days is 1948, still considerably below 2400: the threshold identified by SHF as the level at which temperature begins to have a negative effect on land values. Therefore, we can extrapolate our model estimates with sufficient confidence. However, to test the robustness to these out-of-sample projections, we also compute climate change impacts using a "limited" scenario, in which all combinations of rainfall and temperature are restricted to be within the range used for estimation. For example, in this "limited" scenario we set to 1700 the maximum value for degree days and to 240 mm the minimum quantity of precipitation. While we calculate predictions from the parametric specifications (Models A, B and C) using both the "original" and "limited" climate change scenarios, we only use the latter for the semi-parametric regression (Model D) since the bi-dimensional smooth function of degree days and precipitation tends to be very erratic outside the range of values used for estimation, generating unreliable results when used out-of-sample.

The predicted impacts of climate change on farmland values derived from our four models are reported in Table 7. To provide a meaningful summary of grid squares or counties with different agricultural areas and land values, the percentage changes are weighted by the baseline total agricultural land value in each cell or county.[13] The county-level regression with no interaction terms (Model A) predicts strong and positive impacts on the rural sector, with an overall increase of 30% in GB farm values compared to baseline levels. By applying a 5% discount rate (as per Mendelsohn et al., 1994), this translates into an increase in total GB farm net revenues of £1.5 billion per annum. Furthermore, according to Model A, the 1st decile of the predicted changes corresponds to an increase

[13] We compute the total agricultural area within each square or county using 1 km grid data from the Land Cover Map 2000 (LCM2000, http://www.ceh.ac.uk/LandCoverMap2000.html), produced by the Centre for Ecology and Hydrology. LCM2000 is a parcel-based classification of satellite image data showing land cover for the entire United Kingdom. We include in agriculture the land classified as: (a) arable and horticultural, (b) improved grassland, (c) semi-natural, rough grass and bracken and (d) mountain, heat and bog. This definition slightly overestimates the amount of agriculture in GB, resulting in a total of about 19 million hectares rather than the 17 million presented in the official statistics (e.g. http://www.defra.gov.uk/statistics/). Therefore, we rescaled the agricultural area in each cell or county by multiplying it by a factor of 0.9 to match with the official GB total.

of around 25%, indicating that almost all counties will be significantly better-off as a result of projected climate change. Model B presents a slightly different and more heterogeneous picture, with the first decile being a loss of 15% and gains rising to about 70% for the last decile. Overall, this translates in an overall 20% increase in average farm values (£1 billion per annum).

[TABLE 7 about here]

Climate change impact on agriculture in the 2020-2049 UKCIP medium emission scenario

However, the estimates provided by our farm-level models (Model C and D) are considerably less optimistic. Model C predicts a mean increase in farm value ranging between 6% and 8% (which is lower than the first decile predicted by Model A) with large areas experiencing losses and the a first decile now indicating a loss of some 20%. These results are not significantly different to those obtained using our most flexible regression, Model D, which suggest that climate change will induce a diverse set of impacts on agricultural land values ranging from (again) a lower decile loss of 20% to an upper decile increase of more than 40% with a mean value around +7%, comparable to an annual rise in net revenues of about £400 million.

Not surprisingly, the motivation for this difference in predictions between farm-level and county-level models can be found in the interaction effect between temperature and rainfall. Recalling Figure 2 and 3, precipitation in farm-level models can either have a negative or positive effect on land values depending on the level of temperature. While the warmer growing season projected in this climate change scenario can boost yields, it can also increase crop water demand and reduce drought-tolerance. Climate change is also expected to decrease precipitations which, in the driest areas of GB, can lead to water deficiency and less favourable farming conditions, ultimately lowering land values. In contrast, county-level models do not capture the interaction effect between temperature and precipitation and erroneously project lower rainfall and higher temperatures to have positive impacts on land values. This bias is particularly severe for Model A, which does not account for interaction effects and in fact predicts an increase in land values throughout the country. However, it is also present in Model B, which significantly over-estimates the average impact of climate change.

Finally, in Figure 4 we present box-plots of the distribution of the change in total GB farm net revenues according to different models, computed via 5000 bootstrap repetitions. Results compare county level against farm level estimates using eight among the specifications reported in Table 5, including four county-level and four farm-level models. Specifically, we plot the results using the baseline model (row 1 in Table 5), using a different aggregation method (row 2), using a different climate definition (row 3), including the observations for which the value of the farm value has not been updated (row 4) and including a larger spatial-autocorrelation (row 5). For each specification we plot results using both the original UKCIP temperature and precipitation values ("original" climate scenario) and by restricting the climate change conditions within the boundaries of the estimation sample ("limited" climate scenario). The bias introduced by aggregation is evident, with the county-level model projections, represented in the first eight plots, being significantly different from the farm-level results, shown in the last eight plots. None of the mean impacts predicted by the county-level models fall within the 95% confidence intervals of the impacts predicted by the farm-level models. In comparison, restricting the climate change conditions within the boundaries of the estimation sample ("limited" climate scenario) as opposed to using the original UKCIP temperature and precipitation values ("original" climate scenario) has a small effect on the results. These results show that the aggregation has not only affected the parameter estimates, as shown in the previous section, but has also led to climate change impact projections which are significantly distorted .

6. Concluding remarks

Both Fisher, Hanemann, Roberts and Schlenker (2012) and Deschênes and Greenstone (2012) conclude their analyses by pointing out that, despite the growing literature, a consensus on the potential economic impact of climate change on agriculture remains still far from being achieved. This paper contributes the debate by highlighting two significant issues which has been previously overlooked: aggregation bias and interactions between temperature and precipitation. We present a Ricardian land value regression using a unique, 10 year panel of more than 3000 farms located in GB, which is characterized by one of the most dense weather station network in the world. This allows us to accurately represent the local climatic conditions affecting each farm in our sample. We compare this analysis with the standard models estimated on data averaged across counties, demonstrating that a significant bias afflicts climatic coefficients based on aggregated data. While county-level regressions confirm the assumption of additive climatic effects implemented in previous Ricardian studies, our farm-level analysis reveals important interactions between precipitation and temperature in determining land values. Consistent with the literature on plant physiology, which shows that the crop requirement for water increases with temperature, we find that higher precipitation is more valuable when temperatures are high. Accordingly, higher temperatures increase land values only if there is enough precipitation to prevent the risk of drought. This interaction effect becomes statistically insignificant when we analyze the same data aggregated over counties. These findings are consistent across different data, models and aggregation methods. Ignoring this interaction has significant implication for climate change impact projections which result in being severely distorted.

We also test for functional form miss-specification by estimating a semi-parametric model based on penalized splines. The results do not appear to be significantly different from those obtained using the simpler, quadratic regression. Although farmland values have changed considerably in the 10 years included in the analysis, our estimates remain remarkably robust. As Schlenker, Hanemann and Fisher (2006) and Fisher, Hanemann, Roberts and Schlenker (2012), we find that the fundamental dependence of agricultural incomes on climatic conditions is independent of government policies and crop prices.

One possible explanation for the aggregation bias is measurement error. As shown in this paper, aggregate data fail to account for the fine-scale variations in the local climate affecting single farms and erroneously assumes counties to be climatic-homogenous units. On this point, using county-level climate averages with farm-level land value data still produces biases coefficients. Unfortunately, in most countries weather stations are not dense enough to provide the accurate local climate measures (in particular regarding precipitation) required for extensive farm-level analyses. Our findings are consistent with previous research (e.g. Sinclair, 2011) in showing that local patterns of precipitation play a fundamental role in understanding the impact of climate change on agriculture. They also highlight the importance of collecting weather data accurate enough to truthfully represent local climatic conditions.

While aggregation bias could be less significant in countries where climate presents less local variation, the fact that previous county-level analyses ignored the interaction effect between precipitation and temperature casts some doubt on the validity of their conclusions. This is an empirical question which could be worth investigating in the future by, for example, analyzing farm-level statistics for enterprises located close to weather stations, in order to have precise information on the their climate. Obviously, the usual caveats of Ricardian analyses apply also here. Prices, population and other drivers are assumed to remain constant between the scenarios. Possible beneficial effects of increased CO_2 fertilization on crop growth are also not taken into account, though some recent research suggests that those may be much smaller than previously believed (Long et al., 2006).

7. References

Adams R.M., Rosenzweig C., Pear R.M., Ritchie J.T., McCarl B.A., Glyer J.D., Curry R.B., Jones J.W., Boote K.J, Hartwell A.L. (1990) Global climate change and US agriculture, *Nature*, vol. 344, pp. 219 – 224.

Anglin P., Gencay R. (1996) Semiparametric estimation of a hedonic price function, *Journal of Applied Econometrics*, vol. 11, pp. 633-648.

Baigorria G.A., Jones J.W., O'Brien J.J. (2006) Understanding rainfall spatial variability in southeast USA at different timescales, *International Journal of Climatology*, vol. 27, pp. 749-760.

Barnard C.H., Whittaker G., Westenbarger D., Ahearn M. (1997) Evidence of capitalization of direct government payments into U.S. cropland values, *American Journal of Agricultural Economics*, vol. 79, pp. 1642-1650.

Bontemps C., Simioni M., Surry Y. (2008) Semiparametric hedonic price models: assessing the effects of agricultural nonpoint source pollution, *Journal of Applied Econometrics*, vol. 23, pp. 825-842.

Cropper M.L, Deck L.B, McConnell K.E. (1988) On the choice of functional form for hedonic price functions, *The Review of Economics and Statistics*, vol. 70, pp. 668-675.

Davidson R., MacKinnon J.G. (1981) Several tests for model specification in the presence of alternative hypotheses, *Econometrica*, vol. 49, pp. 781-793.

Davidson R., MacKinnon J.G. (2002) Bootstrap J tests for nonnested linear regression models, *Journal of Econometrics*, vol. 109, pp. 167-193.

Deschênes O., Greenstone M. (2007) The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather, *American Economic Review*, vol. 97, pp. 354-385.

Deschênes O., Greenstone M. (2012) The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather: reply, *American Economic Review*, vol. 102, pp 3761-73.

Di Luzio M., Johnson G.L., Daly C., Eisheid J.K., Arnold J.G. (2008) Constructing retrospective griddedd daily precipitation and temperature datasets for the conterminous United States, *Journal of Applied Meteorology and Climatology*, vol. 47, pp. 475-497.

Ekeland I., Heckman J., Nesheim L. (2002) Identifying hedonic models, *American Economic Review*, vol. 92, pp. 304-309.

Ekeland I., Heckman J., Nesheim L. (2004) Identification and estimation of hedonic models, *Journal of Political Economy*, vol. 112, pp. S60-S109.

Feige E., Watts H. (1972) An investigation of the consequences of partial aggregation of micro-economic data, *Econometrica*, vol. 40, pp. 343-360.

Fisher A., Hanemann M., Roberts M., Schlenker, W. (2012) The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather: comment, *American Economic Review*, vol. 102, pp. 3749-3760.

Grunfeld Y., Griliches Z. (1960) Is aggregation necessarily bad? *Review of Economics and Statistics*, vol. 42, pp. 1-13.

Hillel D., Rosenzweig C. (2010) *Handbook of climate change and agroecosystems: impacts, adaptation and mitigation*, Imperial College Press, London.

Hitchin E R (1983) Estimating monthly degree-days, *Building Service Engineering Research and Technology*, vol. 4, pp. 159-162.

Imbs J., Mumtaz H., Ravn M.O., Rey H. (2005) PPP strikes back: aggregation and the real exchange rate, *Quarterly Journal of Economics*, vol. 120, pp. 1-43.

Intergovernmental Panel on Climate Change (2007) *Climate change 2007: synthesis report*, (Eds: A.

Allali, R. Bojariu, S. Diaz, I. Elgizouli, D. Griggs, D. Hawkins, O. Hohmeyer, B.P. Jallow, L. Kajfez-Bogataj, N. Leary, H. Lee, D. Wratt), published by the Intergovernmental Panel on Climate Change, Geneva.

Kaufmann R.K., Snell S.E. (1997) A biophysical model of corn yield: integrating climatic and social determinants, *American Journal of Agricultural Economics*, vol. 79, pp. 178-190

Keele L. (2009) *Semiparametric regression for the social sciences*, Wiley and Sons, Chichester.

Kostov P. (2009) Spatial dependence in agricultural land prices: does it exist?, *Agricultural Economics*, vol. 40, pp. 347-353.

Laird N.M., Ware J.H. (1982) Random-effects models for longitudinal data, *Biometrics*, vol. 38, pp. 963-974.

Lang G. (2007) Where are Germany's gains from Kyoto? Estimating the effects of global warming on agriculture, *Climatic Change*, vol. 84, pp. 423–439

Lewbel A. (1991) Aggregation with log-linear models, *Review of Economic Studies*, vol. 59, pp. 635-642.

Lobell D.B, Schlenker W., Costa-Roberts J. (2011) Climate trends and global crop production since 1980, *Science*, vol. 333, pp. 616-620.

Long S. P., Ainsworth E.A, Leakey A.D.B., Nosberger J., Ort D.R. (2006) Food for thought: lower-than-expected crop yield stimulation with rising CO2 concentrations, *Science*, vol. 312, pp. 1918–1921.

Maddison D. (2009) A spatio-temporal model of farmland values, *Journal of Agricultural Economics*, vol. 60, pp. 171-189.

Mendelsohn R., Dinar A., (2009) *Climate change and agriculture: an economic analysis of global impacts, adaptation and distributional effects*, Northampton, Edward Elgar.

McKinsey J., Evenson R. (1998) Technology-climate interactions: was the green revolution climate friendly? In: *Measuring the Impact of Climate Change on Indian Agriculture*, chapter 6, pp. 185-204, World Bank Technical Paper n. 402.

Mendelsohn R., Nordhaus W.D., Shaw D. (1994) The impact of global warming on agriculture: a Ricardian analysis, *American Economic Review*, vol. 84, pp.753-771.

Mendelsohn R., Kurukulasuriya P., Basist A., Kogan F., Williams C. (2007) Climate analysis with satellite versus weather station data, *Climatic Change*, vol. 81, pp. 71-83.

Mendelsohn R., Reinsborough M. (2007) A Ricardian analysis of US and Canadian farmland, *Climatic Change*, vol. 81, pp. 9-17.

Morison J.I.L. (1996) Climate change and crop growth, *Environmental Management and Health*, vol. 7, pp. 24-27.

Monteith, J.L. (1977) Climate and the efficiency of crop production in Britain, *Philosophical Transactions of the Royal Society B: Biological Sciences*, vol. 281, pp. 277-294.

Parmeter C.F., Henderson D.J., Kumbhakar S.C. (2007) Nonparametric estimation of a hedonic price function, *Journal of Applied Econometrics*, vol. 22, pp. 695-699.

Perry, M., Hollis D. (2005) The generation of monthly gridded datasets for a range of climatic variables over the UK, *The International Journal of Climatology*, vol. 25, pp. 1041-1054.

Pinheiro J.C., Bates D.M. (2000) *Mixed effects models in S and S-plus*, Springer, New York.

R Development Core Team (2008) *R: a language and environment for statistical computing*, R Foundation for Statistical Computing, Vienna, Austria, http://www.r-project.org.

Ricardo D. (1817) *On the principles of political economy and taxation*, London, John Murray.

Ruppert D., Wand M.P., Carroll R.J. (2003) *Semiparametric regression*, Cambridge University Press, New York.

Schlenker W., Hanemann M., Fisher A.C. (2005) Will U.S. agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach, *American Economic Review*, vol. 95, pp. 395-406.

Schlenker W., Hanemann M., Fisher A.C. (2006) The impact of global warming on U.S. agriculture: an econometric analysis of optimal growing conditions, *Review of Economics and Statistics*, vol. 88, pp. 113-125.

Schlenker W., Hanemann M., Fisher A.C. (2007) Water availability, degree days and the potential impact of climate change on irrigated agriculture in California, *Climatic Change*, vol. 81, pp. 19-38.

Schlenker W., Roberts M. (2006) Nonlinear effects of weather on corn yields, *Review of Agricultural Economics*, vol. 28, pp. 391-398.

Schlenker W., Roberts M. (2009) Nonlinear Temperature Effects indicate Severe Damages to U.S. Crop Yields under Climate Change, *Proceedings of the National Academy of Sciences*, vol. 106, 2009, p. 15594-15598.

Seo S., Mendelsohn R. (2008) A Ricardian analysis of the impact of climate change on Latin American farms, *Chilean Journal of Agricultural Research*, vol. 68, pp. 69-79.

Seo S., Mendelsohn R., Dinar A., Hassan R., Kurukulasuriya P. (2009) A Ricardian analysis of the distribution of climate change impacts on agriculture across agro-ecological zones in Africa, *Environmental and Resource Economics*, vol. 43, pp. 313-332.

Sinclair T. (2011) Precipitation: the thousand-pound gorilla in crop response to climate change, in (Eds: Hillel D. and Rosenzweig C.), *Handbook of Climate Change and Agroecosystems - Vol. I*, Imperial College Press, pp. 179-190.

Speed T.P. (1991) Comment on: that BLUP is a good thing: the estimation of random effects (by G.K. Robinson), *Statistical Science*, vol. 6, pp. 42-44.

Stocker T. (1984) Completeness, distribution restriction and the form of aggregate functions, *Econometrica*, vol. 52, pp. 887-907.

Stocker T. (1986) Simple tests of distributional effects on macroeconomic equations, *Journal of Political Economy*, vol. 94, pp. 763-795.

Stram D. O., Lee, J. W. (1994) Variance components testing in the longitudinal mixed-effects models, *Biometrics*, vol. 50, pp. 1171–1177.

Theil H. (1954) *Linear Aggregation of Economic Relations*, Amsterdam, North-Holland.

Thom H.C.S. (1966) Normal degree days above any base by the universal truncation coefficient, *Monthly Weather Review*, vol. 94, pp. 461-465.

Timmins, C. (2006) Endogenous land use and the Ricardian valuation of climate change, *Environmental and Resource Economics*, vol. 33, pp 119-142.

UK Climate Impacts Programme (UKCIP, 2009) *UK climate projection: briefing report*, Met Office Hadley Centre, Exeter, UK.

Van Garderen K.J, Lee K., Pesaran M.H. (2000) Cross-sectional aggregation of non-linear models, *Journal of Econometrics*, vol. 95, pp. 285-331.

Wang, J., Mendelsohn R., Dinar A., Huang J., Rozelle S., Zhang L. (2009) The impact of climate change on China's agriculture, *Agricultural Economics*, vol. 40, pp. 323-337.

Welch J.R., Vincent J.R., Auffhammer M., Moya P.F., Dobermann A., Dawe D. (2010) Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maxim temperatures, *Proceedings of the National Academy of Science*, vol. 107, pp. 14562-14567.

Welham S.J., Cullis B.R., Kenward M.G., Thompson R. (2007) A comparison of mixed model splines for curve fitting, *Australian and New Zealand Journal of Statistics*, vol. 49, pp. 1-23.

Wood, S.N. (2003) Thin plate regression splines, *Journal of the Royal Statistical Society, Series B*, vol. 65, pp. 95-114.

Wood, S.N. (2006a) Low rank scale invariant tensor product smooths for generalized additive mixed models, *Biometrics*, vol. 62, pp. 1025-1036.

Wood S.N. (2006b) *Generalized additive models: an introduction with R*, Chapman and Hall, New York.

Appendix: the semi-parametric AMM estimation

This Appendix provides the details regarding the estimation of the semi-parametric model. We represent the smooth functions in equation (6) as splines, i.e. linear combination of basis functions of the regressors (e.g. Ruppert, Wand and Carroll, 2003; Wood, 2006b; Keele, 2009). For example, considering one of the non-climatic factors g_x and indicating the basis functions with $b_{x,j}(g_x)$ (j=1,..,l_x), the corresponding smooth function can be written as:

$$\text{(A1)}\quad s_x(g_x) = \sum_{j=1}^{J_x} \delta_{x,j} b_{x,j}(s_x) = \boldsymbol{\delta}_x^{'} \mathbf{b}_x$$

where $\delta_{x,j}$ (j = 1,...,J_x) are the parameters to be estimated and J_x is the number of basis functions which determines the maximum possible flexibility of the relation between g_x and V (the higher the value, the more non-linear or 'wiggly' is the estimated effect). Among the simplest basis functions are those corresponding to linear regression splines, which fit a piecewise linear function between a set of knots located between the range of values of the regressor. The number of knots determines the flexibility of the splines and the number of parameters to be estimated. In the linear case with r knots (κ_{1x},..., κ_{rx}) and suppressing the subscript x for simplicity, equation (A1) becomes:

$$\text{(A2)}\quad s(g) = \delta_0 + \delta_1 g + \sum_{j=1}^{r} \delta_{j+1}(g - \kappa_j)_+ \ ,$$

where $(g - \kappa_j)_+ = \max(0, g - \kappa_j)$ (note that, if there are multiple smooth functions, the constant is only identifiable by imposing a sum-to-zero constraint). Whiles this type of spline is conceptually very intuitive, it can present sharp corners at the knots and, therefore, is too restrictive for many applications. In this paper we use natural cubic splines, which offer computational advantages when applied to large datasets (see Wood, 2006b). These splines fit third degree polynomial functions between each set of knot, with first and second derivatives constrained to be continuous in the entire range of *g(.)*. Furthermore, in order to avoid erratic behavior at the extremes, the fit before the first knot and after the last one is constrained to be linear (i.e. first and second derivatives are set to zero). This results in the number of basis functions J_x being equal to the number of knots r.[14]

[14] Several other types of bases have been proposed in the literature. Ruppert et al. (2003) and Wood (2006b) provide a comprehensive illustration. Welham et al. (2007) demonstrate the links existing among the most commonly used bases and undertake a simulation study from which no clear winner emerges.

The number of knots effectively determines the flexibility of the smooth function. Given a fixed number of knots, the model can be estimated as a standard regression, i.e. by Ordinary Least Squares (OLS) or Maximum Likelihood (ML). However, there is a trade-off between sufficient knots to accurately represent any unknown, non-linear relation and, at the same time, avoid the risk of overfitting. This is a common problem in semi-parametric approaches. A practical solution to this long-standing issue is penalized estimation (Ruppert, Wand and Carroll, 2003; Wood, 2006b). The idea here is to augment the likelihood by including a penalty for the excessive roughness (typically indicated with the term 'wiggliness') of the smooth functions, which can be expressed as a function of the integral of the square of its second derivative. The penalized likelihood corresponding to the smooth function in equation (A1) can then be written as:

(A3) $l_p(\boldsymbol{\delta}) = l(\boldsymbol{\delta}) + \lambda \int s''(g)^2 dg$,

where *l(.)* is the model likelihood, $l_p(.)$ is the model penalized likelihood, $\boldsymbol{\delta}$ is the vector of parameter to be estimated and λ is the smoothing parameter, which controls the weight given to the 'wiggliness' penalty. As λ increases so the function becomes smoother, with $\lambda \to \infty$ corresponding to a straight line fit. In this framework, therefore, the flexibility of the smooth function is regulated by the value of the smoothing parameter λ rather than by the number and placement of the knots, which actually make little difference (see Keele, 2009, for some examples). Ruppert, Wand and Carroll (2003), for example, show that the degrees of freedom of a smoothing spline are just a mathematical transformation of λ.

Various techniques have been proposed to estimate the optimal amount of smoothing (i.e. the parameter λ) directly from the data (see Wood, 2006b, and Keele, 2009). In this paper we use ML estimation techniques representing the smoothing splines as random effects (Ruppert, Wand and Carroll, 2003). The random effect representation of the natural cubic spline corresponding to equation (A1) can be written as:

(A4) $s(g) = \delta_0 + \delta_1 g + \sum_{j=1}^{r-2} \phi_j b_j(g)$,

where the $b_j(g)$ are non-linear basis functions (whose definition is somewhat lengthy and given, for example, in Welham et al., 2007), δ_0 and δ_1 are the fixed effect (un-penalized) parameters and the ϕ_j are elements of a vector of random effects drawn from a $N(0, \sigma_\phi^2 H)$, where H depends on the penalties (A3). This approach models non-linearity as a form of heterogeneity across groups. The data within each set of knots form each group. The intuition behind this representation is that a linear fit

($\phi_1 = \phi_2 = ... = \phi_{r-2} = 0$) would ignore these differences and capture the relationship with only two parameters, whereas an un-penalized likelihood (ϕ_1, ϕ_2, ..., ϕ_{r-2} estimated as fixed effect) would provide highly variable and "wiggly" estimates (in the extreme case, with a knot at each data point, it would perfectly interpolate the data). Between these two extremes, the random effect representation provides the optimal (i.e. best linear un-biased predictor, Speed, 1991) trade-off between excessive smoothing and overfitting of the non-linear function.

This specification can be estimated as a standard random effect model, i.e. by ML or Restricted Maximum Likelihood, (REML). By estimating each smoothing parameter λ as σ_u^2/σ_ϕ^2, these techniques resolve the subtle task of determining the model flexibility *a priori*, by incorporating this choice into the actual estimation process. Another important feature of this method is that, if a non-linear relationship is not supported by the data, the corresponding smoothing parameter will automatically be estimated to have a high value, the resulting random effect will be close to zero and the smooth function will reduce to a standard linear form. Moreover, this approach can also be extended to bivariate functions, in order to flexibly capture any joint non-linear effects of two explanatory variables. In this paper we model the impact of rainfall and temperature on land value by using tensor products (Wood, 2006a), which have the important properties of being invariant to changes in the scale of the regressors and can, therefore, be used to smooth variables expressed in different units. Finally, since this estimation technique expresses smoothing splines as random effect terms, inference can be implemented within the standard framework for this class of models (Pinheiro and Bates, 2000; Ruppert, Wand and Carroll, 2003). For instance, model reduction can be implemented with likelihood ratio tests for hypotheses on the random effects and with F-tests for hypotheses on the fixed effects. However, as in standard random effect models, testing for the random effects will be only approximate since it involves setting the variance of certain components of the random effects to zero, which is on the boundary of the parameter region (Stram and Lee, 1994).

Tables and Figures

TABLE 1

Farm level data descriptive statistics

	Symbol	Units	$\overline{x}$	$\hat{s}(x)$	Min	max
land value	*V*	1000£/ha	7.16	5.21	0.02	192.00
degree days	*Dd*	^{o}C	1314.00	185.21	654.70	1639.00
precipitation	*Prec*	Mm	384.70	101.60	245.20	1434.00
soil class						
-fine	s_f	%	14.96	28.03	0.00	100.00
-medium fine	s_{mf}	%	8.58	21.49	0.00	100.00
-medium	s_m	%	58.59	38.81	0.00	100.00
-coarse	s_c	%	12.13	21.42	0.00	100.00
-peat	s_p	%	5.74	16.72	0.00	100.00
depth to rock	*Dtr*	Dm	7.42	3.26	0.00	14.00
slope	*Slo*	^{o}	3.23	2.21	0.00	17.06
pop. density	*Popd*	pop/km^2	203.20	258.30	6.80	2896.0
park share	s_{park}	%	7.13	22.45	0.00	100.00
ESA share	s_{esa}	%	11.79	26.18	0.00	100.00
NVZ share	s_{nvz}	%	35.01	43.12	0.00	100.00

Notes: $\overline{x}$ indicates the sample mean, $\hat{s}(x)$ the sample standard deviation. Statistics refers to the observations in our FS sample, not to Great Britain as a whole. Land value and income deflated using the GDP deflator with 2008 as the baseline year (source: HM Treasury, http://www.hmtreasury.gov.uk/Economic_Data_and_Tools/GDP_Deflators/data_gdp_index.cfm, accessed on the 16th June 2010). The total number of observations is 9506 (3283 farms in located in 1361 different 10 km grid cells).

TABLE 2

Descriptive statistics of the climatic variables aggregation

	$\overline{x}$	$\hat{s}(x)$	min	max
Between-county statistics				
Precipitation (*mm*)	400.80	107.83	275.70	811.00
Degree days (^{o}C)	1290.00	197.37	756.90	1605.00
Within-county statistics				
Range of Precipitation (*mm*)	157.50	214.95	2.09	1075.00
Range of Degree days (^{o}C)	230.40	205.57	1.00	801.70

Notes: $\overline{x}$ indicates the sample mean, $\hat{s}(x)$ the sample standard deviation. Statistics refer to climatic conditions calculated as the weather average from year 1970 to year 2000. *Between-county statistics* denote the climatic conditions observed on aggregated county-level data, while the *within-county statistics* represent the loss of climatic variability due to the aggregation process.

TABLE 3

Parameter estimates and diagnostics

	Model A county-level, no climatic interaction	**Model B** county-level, climatic interaction	**Model C** farm-level, climatic interaction	**Model D** farm-level, semi-parametric
Climate variables				
precipitation (*prec*)	-3.165	-4.291	-5.284 *	--
	(2.152)	(2.219)	(2.252)	
$prec^2$	-3.848 ***	-5.109 ***	0.677	--
	(1.057)	(1.271)	(1.493)	
degree days (*dd*)	9.117 ***	8.148 ***	16.554 ***	--
	(2.298)	(2.332)	(2.031)	
dd^2	-1.479	-1.615	-5.729 ***	--
	(1.458)	(1.441)	(1.483)	
*dd * prec*	--	-98.962	495.636 **	8.606 ***
		(57.050)	(184.786)	
Control variables				
slope	-0.045	-0.057	-0.026 **	1.000 ***
	(0.031)	(0.031)	(0.008)	
depth to rock	-0.001	-0.001	-0.000	1.895
	(0.002)	(0.002)	(0.000)	
pop. density (*dpop*)	-0.167	-0.101	0.398 ***	3.751 ***
	(0.945)	(0.933)	(0.100)	
$dpop^2$	-0.528	-0.755	-0.201 ***	--
	(1.066)	(1.061)	(0.059)	
share park	0.747 **	0.710 **	0.175 **	0.191**
	(0.256)	(0.254)	(0.059)	(0.060)
share NVZ	0.011	0.011	-0.033 *	-0.031 *
	(0.049)	(0.049)	(0.013)	(0.013)
share ESA	-0.409 *	-0.403 *	0.027	0.011
	(0.174)	(0.171)	(0.045)	(0.045)
Fixed effects	**Yes *****	**Yes *****	**Yes *****	**Yes *****
Soils shares	**Yes**	**Yes**	**Yes *****	**Yes *****
Random effects				
County	0.234	0.230	--	--
Cell	--	--	0.279	0.271
Farm	--	--	0.403	0.402
Residuals	0.273	0.273	0.184	0.184
Model fit				
LogLik	-224.31	-219.00	-2032.97	-1966.49
AIC	506.6	498.01	4127.95	3998.97
BIC	643.2	639.28	4349.81	4235.24

Notes: Models A and B estimated on county averages, 848 observations for a total of 102 counties. Models C and D estimated on farm data, 9506 observations for a total of 3283 farms in 1361 cells of 10km. All models estimated with Restricted Maximum Likelihood. Yearly fixed effect and Scotland and Wales dummy variables strongly significant but not reported in the table to preserve space. In Models A, B and C the table reports the coefficient estimate (with standard error in parenthesis) and the significance calculated with an approximate t-value conditional on the random effects (details in Pinheiro and Bates, 2000). The asterisks are defined as: * = significant at the 0.05 level, ** = significant at the 0.01 level, *** = significant at the 0.001 level. In model D the table reports the "effective degree of freedom" and the significance calculated with an approximate F-test (details in Wood, 2006b). Asterisks are defined as for Models A, B and C. In models A, B and C precipitation, degree days and population density transformed into orthogonal polynomials to reduce multicollinearity. LogLik = (restricted) log-likelihood, AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion.

TABLE 4

Pairwise stability tests

years	*F-test*	*p-value*
1999 and 2000	0.58	0.932
1999 and 2001	1.76	0.156
1999 and 2002	1.19	0.366
1999 and 2003	1.75	0.116
1999 and 2004	1.12	0.294
1999 and 2005	1.64	0.084
1999 and 2006	1.96	0.138
1999 and 2007	1.23	0.212
1999 and 2008	1.14	0.344

Notes: test on Model D estimated only on the farms which are present in both years, with 4 knots for population density and 16 knots for the joint effect of rainfall and temperature. The F-statistics test the stability of the climate parameters from one year to the other and are conditional on the random-effect estimates, as suggested in Pinheiro and Bates (2000). Approximated p-values are calculated with 500 bootstrap repetitions.

TABLE 5

Parameter estimates according to alternative specifications

Specification	County level estimates (Model B)					Farm-level estimates (Model C)				
	prec	*prec*^{2}	*dd*	*dd*^{2}	*dd * prec*	*prec*	*prec*^{2}	*dd*	*dd*^{2}	*dd * prec*
Base specification (1)	-4.291	-5.109 ***	8.148 ***	-1.615	-98.962	-5.284 *	0.677	16.554 ***	-5.729 ***	495.636 **
(only farms bigger than 30ha, climate 1971-2000, area-weighted aggregation)	(2.219)	(1.271)	(2.332)	(1.441)	(57.050)	(2.252)	(1.493)	(2.031)	(1.483)	(184.786)
Different aggregation method (2)	-3.985	-5.503 ***	7.889 **	-1.947	-175.412 **	--	--	--	--	--
(aggregating data by using un-weighted arithmetic averages)	(2.311)	(1.326)	(2.427)	(1.499)	(59.614)					
Different climate specification (3)	-3.128	-3.290 **	7.613 **	0.644	-5.129	-4.697 *	0.967	15.577 ***	-2.574 *	721.851 ***
(climate calculated as the average weather of the 30 previous years)	(2.213)	(1.216)	(2.363)	(1.300)	(55.019)	(2.141)	(1.367)	(2.066)	(1.136)	(160.988)
Including not updated values (4)	-2.957	-4.103 **	9.305 ***	-1.173	-20.091	-8.731 **	0.596	24.189 ***	-7.263 ***	1047.749 **
(including observations in which the land value is not updated in that year)	(2.386)	(1.370)	(2.493)	(1.551)	(62.066)	(3.046)	(2.338)	(2.621)	(1.952)	(367.436)
Including also small farms (5)	-1.365	-5.694 ***	6.815 **	-1.185	-100.050	-3.384	-0.249	18.268 ***	-3.212 *	531.273 *
(including all farms bigger than 5ha)	(2.281)	(1.340)	(2.539)	(1.474)	(60.943)	(2.558)	(1.646)	(2.267)	(1.667)	(221.200)
Including all farms (6)	-2.882	-6.320 ***	11.130 ***	-4.614 *	-38.067	-4.173	-0.957	23.059 ***	-0.722	155.827
(including all farms, even farms smaller than 1ha)	(2.870)	(1.706)	(3.159)	(2.447)	(77.959)	(3.368)	(2.170)	(2.952)	(2.207)	(296.560)
Larger spatial autocorrelation (7)	--	--	--	--	--	-5.289	3.008 *	9.528 **	-3.055	464.509 *
(including an additional random effect term grouping nine 10km cells)						(3.099)	(1.611)	(3.058)	(1.911)	(229.254)
Using county-level climate (8)	--	--	--	--	--	0.979	-14.022 ***	23.683 ***	-5.298 ***	60.986
(using county-level climate data on farm land value data)						(2.157)	(1.774)	(2.165)	(1.585)	(214.444)

Notes: Coefficients estimated via Restricted Maximum Likelihood (REML) and defined as in Table 3. Standard errors conditional to the random-effects in parenthesis. Asterisks indicate significance, * = significant at the 0.05 level, ** = significant at the 0.01 level, *** = significant at the 0.001 level.

TABLE 6

Descriptive statistics of the climatic and environmental variables

	units	$\bar{x}$	$\hat{s}(x)$	min	max
Baseline (1960-1990)					
degree days	^{o}C	1164.0	251.8	367.4	1645.0
precipitation	mm	450.7	169.0	250.8	1504.0
Climate change projections (UKCIP 2020-2049)					
degree days	^{o}C	1424.0	276.1	571.6	1948.0
precipitation	mm	395.8	188.3	158.6	1444.0
Control variables					
depth to rock	dm	6.4	3.5	0.0	14.0
Slope	^{o}	4.4	3.6	0.0	24.7
pop. density	pop/Km^2	226.4	434.6	8.0	4924.0

Notes: $\bar{x}$ indicates the sample mean, $\hat{s}(x)$ the sample standard deviation. Data refer to Great Britain 10 km grid square cells, only including only cells in which there is some agricultural land. Control variables are assumed to remain constant between the two scenarios.

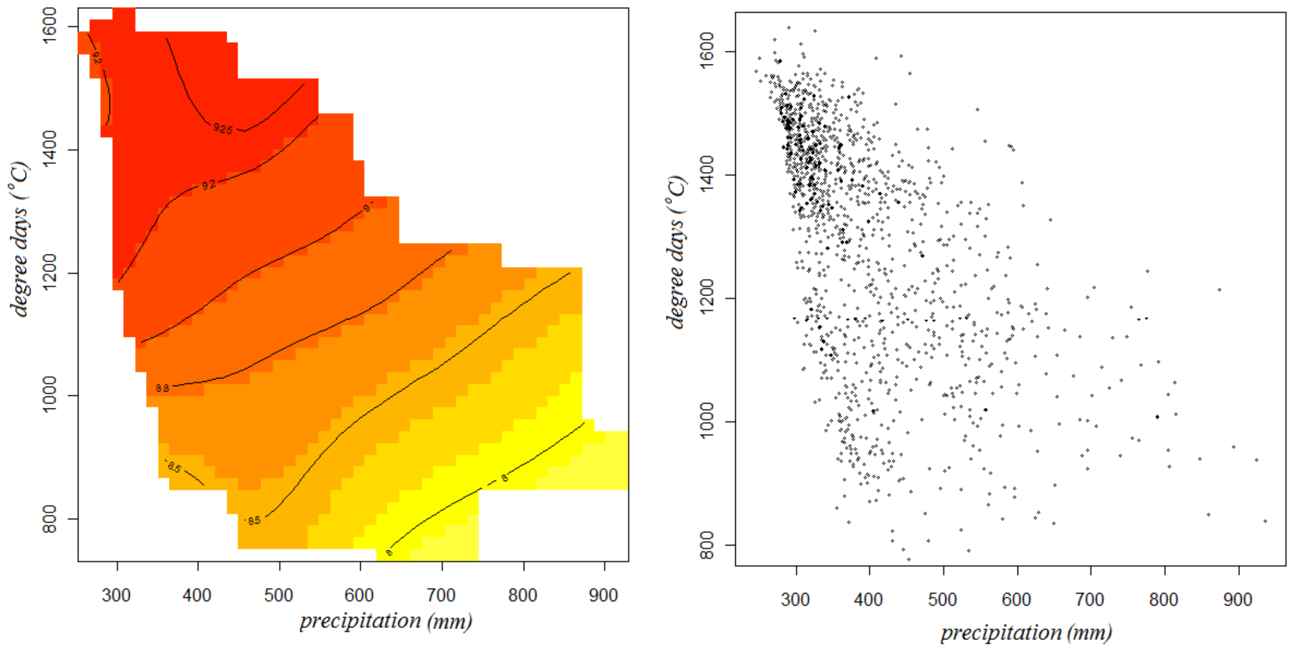
TABLE 7:

Climate change impact on agriculture in the 2020-2049 UKCIP medium emission scenario

Model	sample	mean (%)	Q 10 (%)	Q 90 (%)	Total (M£)	std.err (M£)
Model A (county, no climatic interactions)	original	33.31	27.40	39.45	1717	571
	limited	30.99	24.39	39.45	1597	517
Model B (county, climatic interactions)	original	18.53	-12.46	69.66	955	391
	limited	19.51	-18.99	69.93	1005	336
Model C (farm, climatic interactions)	original	5.82	-19.86	41.05	300	219
	limited	7.66	-12.58	40.33	394	243
Model D (farm, semi-parametric)	limited	7.75	-4.78	37.01	400	409

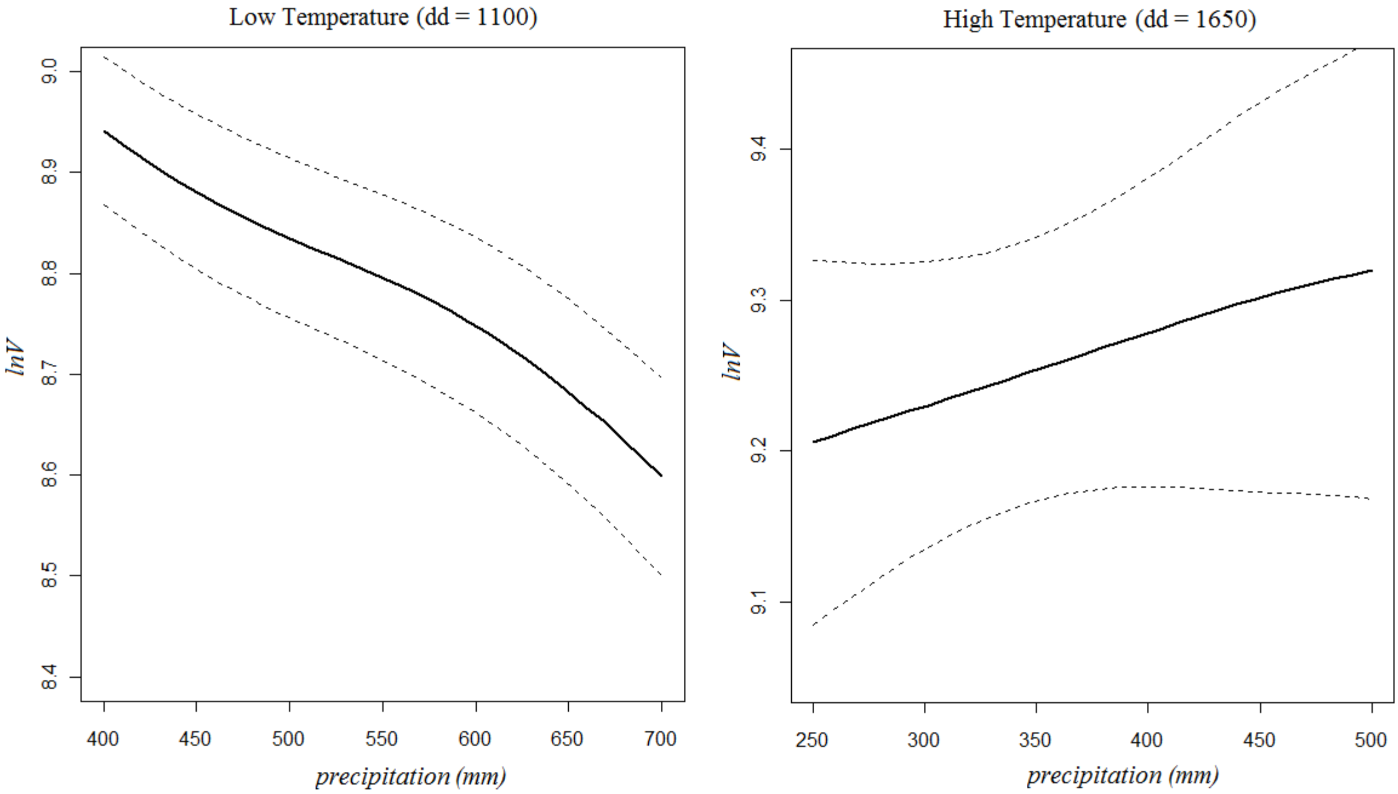
Notes: Weighted statistics (weights = agricultural land area * land value in the baseline). "Q10" indicates the 10% quantile, "Q90" the 90% quantile, "Total" refers to the sum of annual GB farm net revenues assuming a discount rate of 5%, and "std.err" is the standard deviation of the total, calculated via 5000 bootstrap repetitions.

Figure 1: The effect of temperature and precipitation on the logarithm of land price: contour plots with iso-value lines (left) and observed climate data (right).



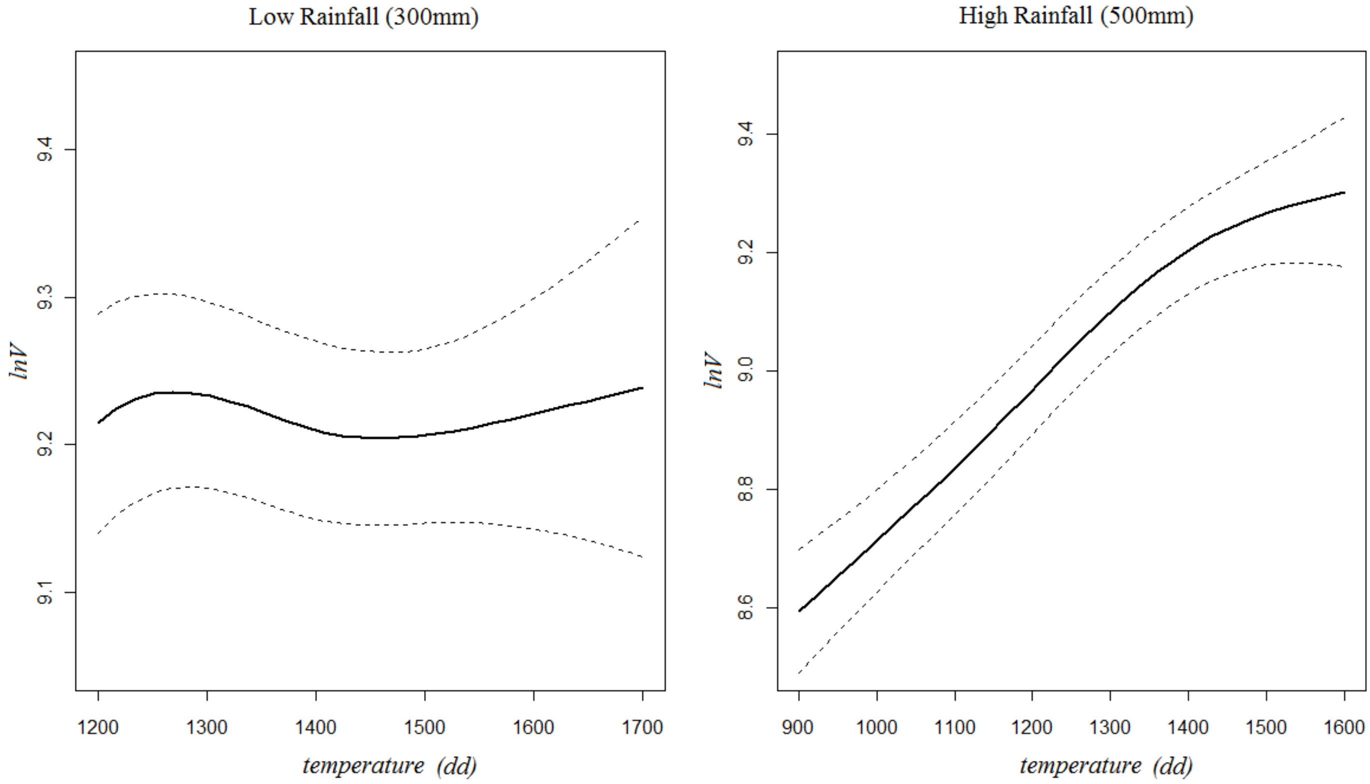
Notes: On the left the estimated effect of precipitation and degree days on the logarithm of land value according to the semi-parametric Model D, on the right the scatter plot of the values of precipitation and degree days within the farm-level sample.

Figure 2: The effect of precipitation on the logarithm of land value for different levels of temperature



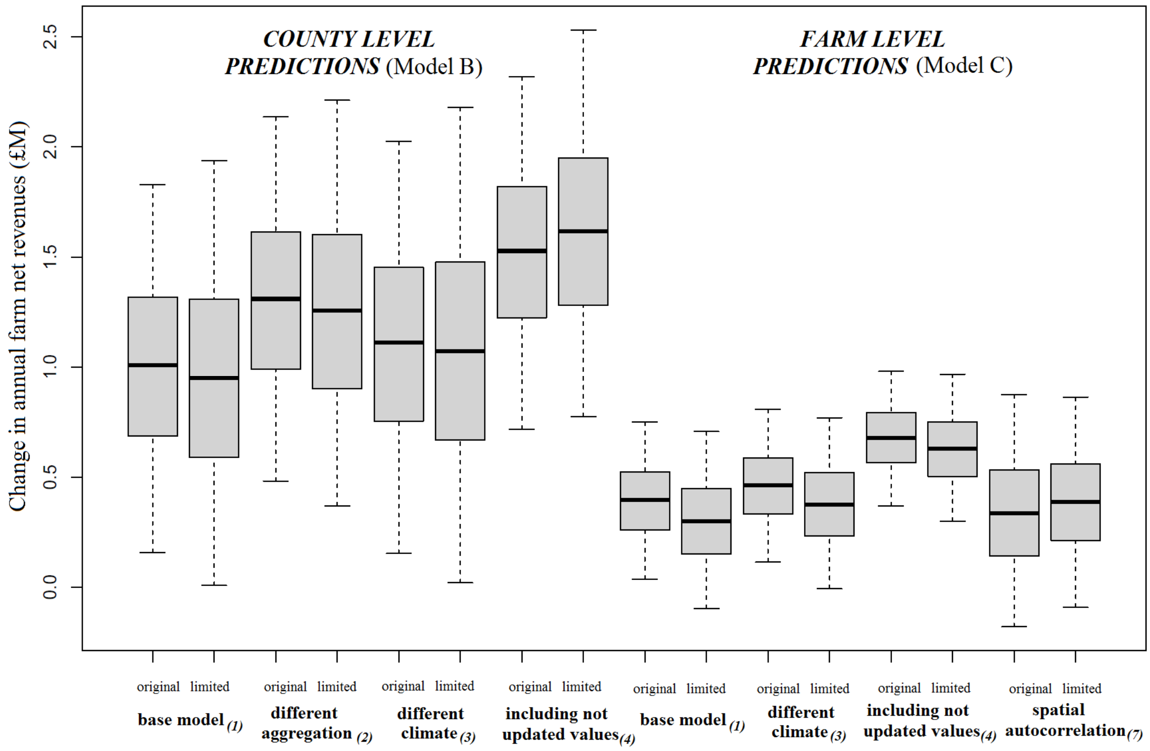
Note: on the left the estimated effect of precipitation when temperature is low (1100 °C degree days in the growing season), on the right the estimated effect of precipitation when temperature is high (1650 °C degree days in the growing season). Solid line = mean estimate according to the semi-parametric Model D, dotted line = ± 1 standard error.

Figure 3: The effect of temperature on the logarithm of land value for different levels of precipitation



Note: on the left the estimated effect of temperature when precipitation is low (300 mm in the growing season), on the right the estimated effect of precipitation when temperature is high (500 mm in the growing season). Solid line = mean estimate according to the semi-parametric Model D, dotted line = ± 1 standard error.

Figure 4: Estimated total impact of climate change on GB agriculture in the 2020-2049 UKCIP medium emission scenario in different model specifications



Notes: The boxplots represent the confidence intervals for the change in total GB annual farm net revenues, calculated with 5000 bootstrap repetitions. The gray box indicates the 1st and 3rd quartile, the whiskers the 95% confidence interval. The models estimated on county level data (Model B) and farm level data (Model C) are based on five different specifications reported in Table 5 (rows 1,2, 3, 4 and 7, in parenthesis). "original" indicates the original climate change scenario, "limited" indicates the "limited" climate change scenario.

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