Short-term and long-term impacts of climate change on European agriculture revenue: weather *versus* climate data

Abstract

Climate change is now an evidence (IPCC, 2014). Less obvious is the quantification of the impacts on economic indicators whereas it is the main driver of international awareness. We compare in this paper the impacts of long-run climate and short-run weather variations on the economic profitability of agriculture in Europe. This comparison is made within a spatial panel econometric framework that captures the temporal and spatial variability of agricultural revenues. Our econometric models take into account both the non-observable individual heterogeneity of the EU (FADN) regions and the spatial auto-correlation between these regions. We use our estimation results to calculate the marginal impacts of climate and weather variations on agricultural revenues. Our results show that weather indicators should be preferred into revenue function estimations when measuring climate change impacts.

Keywords: Climate change, Revenue function, Spatial panel data, European agriculture
JEL: Q54, C23, Q10

1 Introduction

Agriculture is the key food production, natural resources and environmental sector (EU, 2016). Agriculture provides important natural resources and biodiversity preservation and management and agricultural revenues depend heavily on natural resources availability and quality (e.g. water). Thus, farmers are on the front line in relation to their preservation. In addition, agriculture shapes the landscape and provides the living environment of a large population. Nearly half of the population of the European Union (EU) lives in rural areas. If agriculture were to disappear, many areas would face a land abandonment problem. Finally, many jobs are linked to the agricultural sector. In addition to farmers and farm works, there is employment in the upstream (fuels and fertilizers suppliers, veterinary services, etc.) and downstream (preparation, processing, packaging of foodstuffs) sectors. The agricultural sector counts 22 million workers in the European Union, and if we include the food production sector this number doubles (EU, 2016). Thus, agriculture and food production are essential components of the EU economy.

Climate change is a significant issue. It could have a negative impact on farmers' work, natural resources, and farm productivity, and expose both the agriculture and food production sectors to major vulnerabilities. Agriculture faces the dual challenge of producing food and protecting natural resource, and climate change will exacerbate the difficulty involved in juggling between these two goals. To face the challenges induced by a changing climate EU agriculture will need to make some adaptations.

The last Common Agricultural Policy reform (CAP 2014-2020) is one of the strongest responses to the challenges of food security and climate change in the EU. CAP 2014 aims to increase agriculture resilience by providing guidelines and financial support for farmers to prevent adaptations. Adaptation measures can be short-term or long-term. Long-term adaptation measures include the protection of natural resources such as water which are important for the agriculture, and encouraging investment in R&D to develop new technologies and crops. However, farmers fear that the short-term adaptations required will reduce their revenue. Short-run adaptation options depend on how climate will affect agriculture in the near future. This paper discusses the short-run climate impacts on European agriculture in the context of adaptations in that sector.

There are two main approaches to evaluating the impacts of climate change on agriculture. The Ricardian approach (Mendelsohn et al., 1994) is used to estimate long-run impacts of climate on agriculture. The revenue approach (Deschênes and Greenstone, 2007) is implemented to estimate short-run climate impacts on agricultural sector. However, the literature does not distinguish clearly between these two methods. We suggest a separation between the revenue and Ricardian approaches, based on different perceptions of time. Therefore, in this paper we focus on the revenue approach initially proposed by Deschênes and Greenstone (2007) to capture the short-run relations between climate and agriculture activities.
The revenue approach in its original implementation by Deschênes and Greenstone (2007) tends not to be used due to its lack of an explicit theoretical model. Most estimates of net agricultural revenues adopt the so called Ricardian model framework. This would seem to be due in part to data availability; data on farm revenues are more accessible than data on land prices, and especially in developing country contexts. Also, there is some confusion between the revenue approach and the Ricardian approach in the literature, and this has led to the use of a model that mixes these methods, i.e. uses annual revenues explained by long term average climate.
The revenue approach has been used in several cross-section studies of developing country contexts including Asia (Liu et al., 2004; Wang et al., 2009; Mendelsohn, 2014) and Africa (Wood and Mendelsohn, 2015), while Kumar (2011) studies Indian agriculture using panel data. All these works claim to be using a Ricardian approach but instead of land values they use net revenues. Mendelsohn and Massetti (2017) note that the main advantage of the Ricardian approach is that farmland values reflect future rents and are less affected by yearly weather conditions. We argue that studies that estimate yearly agricultural output (profits and revenues) should not claim to use a Ricardian approach because they are not based on future revenue expectations. These studies usually use long term average climate variables whereas agricultural revenues for the year of observation will be influenced only by the weather condi-

tions in that year.

We start our study with the methodological approach proposed by Deschênes and Greenstone (2007) to estimate the impact of weather fluctuations on the US agricultural sector. They argue that a cross sectional hedonic equation could be misspecified, and suggest panel data estimation based on the relation between annual agricultural profits and weather conditions. They exploit random year-to-year variations in temperature and precipitation to estimate whether agricultural profits are higher in warmer and wetter years (Deschênes and Greenstone, 2007). We take account of individual (European FADN region) specificities in agricultural practices and their changes over time. Use of panel rather than cross section data assumes that revenues are not independent of year. From a methodological perspective, panel data correspond to observations of individuals repeated over time which enable consideration of heterogeneity over time and between individuals. There are different ways to exploit panel data, some of which we use in our study.
The study of Deschênes and Greenstone (2007) was criticized by Fisher et al. (2012) who argue that one of its limitations was biased standard errors due to spatial correlation. We take account of this by introducing spatial interactions in our panel data set. Only one paper, written by Kumar (2011), discusses different spatial models which are used in a revenue approach to the study of Indian agriculture. We argue that in our dataset the main source of autocorrelation is the residuals due to the nature of our climate data which have no geographical boundaries.

To the best of our knowledge, no previous work on European agriculture uses a spatial-panel revenue function approach. A few studies focus on yields (Iglesias et al., 2012), and most papers adopt a Ricardian approach, considering either the whole of Europe (Van Passel et al., 2017; Vanschoenwinkel et al., 2016; Vanschoenwinkel and Van Passel, 2018) or single European countries (Bozzola et al., 2017; Lippert et al., 2009; Chatzopoulos and Lippert, 2015). In this paper we test the use of climate and weather variables in a European revenue function approach within a spatial panel framework. The aim is to estimate and discuss short-term climate change impacts and to propose the ultimate model to capture those impacts.

This paper makes four main contributions. First, to our knowledge, it is the first study to use a revenue function approach in a European agriculture context. Second, we use spatial-panel data models. Third, we examine and compare use of yearly weather variations and climate data in the revenue approach. Finally, we discuss the short-term and long-term impacts of climate change on European agriculture.

2 Methodology

In this paper we are interested in farmers' optimal net revenues per hectare of land to capture short-run responses to exogenous environmental shocks. Farmers maximize their net revenues

by choosing the endogenous inputs, given market prices, weather, and other exogenous control variables. The model can be written as $R = f(W, P, Z)$, where R represents net agricultural revenues, W is the annual weather[1] fluctuations, P is market prices, and Z regroups other exogenous variables.
Long-run responses to climate variations are captured using the Ricardian approach, which supposes that the land value, also called Ricardian rent, is equal to the expected net present value of the future stream of income derived from the land. The Ricardian model can be written as $V = f(C, P, Z)$, where V represents agricultural land value per hectare, C regroups long-run climate averages.
Both models suppose that farmers are revenue maximizing and produce the exact supply required to satisfy demand, in conditions of perfect competition and, respectfully, short-term and long-term equilibrium. In the context of climate change, the dependent variables are assumed to be sensitive to weather and climate variations. By examining how agriculture revenues and Ricardian rents shifts with changes in, respectfully, weather or climate variables, the impacts of climate change can be measured by changes in the dependent variables. Thus, by calculating the estimated effects of the perturbing weather and climate variables, wa can project the impact of climate change on economic welfare. Specifically, the environmental change will affect producer's offer on the market and lead to a new equilibrium point. Ricardian and revenue models are partial equilibrium approaches which assumes that changes in the environment will not affect market prices of inputs and outputs. Under this assumption, the consumer surplus is not affected, and producer welfare variation will capture all the environmental change impact. The aim of this paper is to measure climate induced short-run and long-run impacts on European agriculture and, thus, total economic welfare.

We formulate three hypotheses related to evaluating the short-run climate change impacts on European agriculture. Subsection 2.1 presents the empirical model specifications that we estimate in order to test our hypotheses. The hypotheses to be tested are presented in subsection 2.2.

2.1 Empirical model specifications

In this study we argue that annual net revenues depend directly on annual weather, and we test weather and climate variables. For ease of understanding we differentiate between weather and climate as follows: we call *weather* the meteorological conditions observed in a given year, while *climate* is the average weather observed over a long period (here 25 years). We estimate net agricultural revenue using econometric spatial-panel data models.

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2.1.1 Spatial effects

Fisher et al. (2012) criticized Deschênes and Greenstone (2007) biased standard errors due to spatial autocorrelation. We take this into account by introducing spatial interactions in our panel models.

Spatial autocorrelation or spatial dependence can result from a spatial relationship among the values of the dependent (Y) or explanatory (X) variables, or among the residuals (ϵ). Each source of autocorrelation results in different causal effects and needs to be accounted for using different methods to introduce spatial effects into the model. First, the spatial autocorrelation among the dependent variables represents global spillover effects, which are captured by spatial autoregressive (SAR) models (spatial lag on the Y variable). For example, a spatial lag on the revenue dependent variable assumes that the farmer's net revenues are affected by the agricultural revenues of neighbouring farms. In the case of individual data this assumption is important since farmers with similar farming practices usually are located spatially close to one another. For imitation, historical or geographical amenities can also be important. However, in the case of aggregate data, these assumptions make less sense. Second, local spillovers are captured by applying a spatial lag to the explanatory X variables (SLX model). The SLX model assumes for example, that farmers' revenues depend on the weather conditions to which their farms are exposed, and the weather experienced by neighbouring farms (e.g. underground water stocks increased by precipitation). This might be important in the case of individual level data but will not work on the aggregate scale. Also, when working with weather and climate variables which are highly correlated, the SLX model might induce even more collinearity into the regressions. Finally, spatial autocorrelation resulting from spatial dependence among the residuals is captured by a spatial error model (SEM). Spatial autocorrelation in the errors implies the possible presence of measurement errors which tend to spill over across the boundaries of the aggregation unit, omitted variables, or unobserved shocks which follow a spatial pattern. Moreover, the existence of spatial autocorrelation could be explained by the different scales of the data and the aggregation process. Thus, SEM model is better adapted to aggregate data due mostly to the possible existence of spatial autocorrelation in the residuals, due in turn to the construction of our weather data. For example, weather and climate data are constructed based on meteorological weather station data which are not spread uniformly across a space. The "influence" boundaries of each weather station are unclear, and certainly do not coincide with the region or commune limits. Therefore, we use a SEM model which implies the following residual term:

$$\epsilon_{it} = \rho \sum_{k}^{N} w_{ik} \nu_{it} + u_{it}, \tag{1}$$

where the residual term ϵ_{it} is composed of the spatially autocorrelated error term, w_{it} is the generic element of a non negative, NxN spatial-weight matrix W, ρ is the spatial autocorrelation coefficient, ν_{it} is the spatially correlated error term, and u_{it} is the error term.

When working with spatial models, W is an important component in the spatial analysis. The estimation procedure involves specifying the spatial weight matrix W which provides a structure for the assumed spatial relationships. There are some types of spatial weight matrices based on different "neighbours" defining criteria: contiguity (simple, queen), distance, k nearest, Gabriel. The main issue related to these criteria is the geographical structure of European regions. For example, the choice of a contiguity (simple or queen) relation based matrix, meaning that neighbours share the same boundary, could lead to a few isolated regions because some Italian regions are islands. However, in the presence of isolated units the W matrix cannot be invertible which can cause some estimation problems. Another difficulty lies in the use of distance criteria. The sizes of European regions are heterogeneous, e.g. German FADN regions are very small compared to those in the rest of Europe; Scandinavian FADN regions cover very large areas for instance. Thus, using a distance based W matrix creates many spatial relations in the central part of Europe and very few neighbours for outer regions. The k nearest neighbours criteria allow all regions to have the same number of relations in order to not overestimate spatial dependencies. We tested a few of them but decided to work with a standardized weight matrix based on five nearest neighbours.

Table 1: Estimated spatial-panel models' specifications

Equation	Model notation[1]	Full model notation
(2)	FEi-SEM-w	Fixed individual effects with a spatial error model, estimated with weather variables;
(3)	FEt-SEM-w	Fixed time effects with a spatial error model, estimated with weather variables;
(4)	RE-SEM-w	Random effects model with a spatial error model estimated using weather variables;
(5)	REi-SEM-w	Random effects model with a spatial error model estimated using weather variables and controlling for country individual effects;
(6)	REi-SEM-c	Random effects model with a spatial error model estimated with long-time climate averages and controlling for country individual effects;
(7)	REi-SEM-cRi	Ricardian approach based model; Random effects model with a spatial error model estimated with long-time climate averages and controlling for country individual effects;

2.1.2 Panel data model specifications

The main advantage of panel data is that it can be used to model heterogeneous behaviour. This heterogeneity can be represented in the regression coefficients which can vary across indi-

[1]Notes: FE: fixed effects model; RE: random effects model; SEM: spatial error model; i: individual effects; t: temporal effects, w: weather data are used in the model; c: climate data are used; Ri: Ricardian approach.

viduals and time - i.e. a fixed effects model, or according to the structure of the residuals – i.e. a random effects model.

In a panel regression context, individual or time differences in behaviour can be accounted for by assuming that certain individual characteristics refer to the national policy or historical background of a region. Two fixed effects models are estimated in this study:
- Fixed individual effects with a spatial error model (SEM) (FEi-SEM-w):

$$R_{it} = \beta_1 W_{it} + \beta_2 Z_{it} + \alpha_i + \epsilon_{it} \tag{2}$$

$$\epsilon_{it} = \rho \sum_{k}^{N} w_{ik}\nu_{it} + u_{it},$$

where α_i is fixed individual effects, and W_{it} comprises temperature and precipitation variables for four seasons, and their squares.
- Fixed time effects with a SEM (FEt-SEM-w):

$$R_{it} = \beta_1 W_{it} + \beta_2 Z_{it} + \theta_t + \epsilon_{it}, \tag{3}$$

$$\epsilon_{it} = \rho \sum_{k}^{N} w_{ik}\nu_{it} + u_{it},$$

where θ_t is the coefficient of fixed temporal effects.

The fixed effects panel model assumes that the observed individuals have the same slope, and thus the same intercept but not the same reaction. Fixed panel data use the variation within a single individual (or/and year) type, ignoring variations between individuals (or/and years). Since this type of variation is variation within each cross-sectional unit, the fixed effects estimator is sometimes called the "within" estimator. Because the fixed effects estimator is based on the time series component of the data, it estimates the short-run (Kennedy, 2008). Intuitively, the fixed effects models is the most appropriate to estimate short-run relations between agricultural revenues and annual weather conditions.

The random effects model estimates the heterogeneity in micro units arising from the unobservable and omitted variables. There are some unmeasured explanatory variables that affect the behaviour of individuals differently (or uniformly but differently in each time period). Omitting these variables causes bias in the estimation, and the random effects model has the ability to deal with the omitted variable problem (Kennedy, 2008). The random effects estimator uses information from within and between estimators which makes it more efficient than a fixed effects model. Since the random effects model uses between variations, it can produce estimates of the coefficients of the time invariant explanatory variables. Moreover, because the random effects estimator uses both the cross sectional and time series data components it produces estimates that mix short-run and long-run effects (Kennedy, 2008). Three random effects models are

estimated for European agriculture revenues:
– Random effects model with a SEM (RE-SEM-w) including annual weather fluctuations and only time varying variables as in the fixed effects models:

$$R_{it} = \beta_0 + \beta_1 W_{it} + \beta_2 Z_{it} + \epsilon_{it}, \tag{4}$$

$$\epsilon_{it} = \alpha_i + \rho \sum_{k}^{N} w_{ik} \nu_{it} + u_{it},$$

where the residual term ϵ_{it} is composed of the specific individual random effect α_i, and the spatially autocorrelated error term, w_{it} is the generic element of a non negative, NxN spatial-weight matrix W, ρ is the spatial autocorrelation coefficient, ν_{it} is the spatially correlated error term, and u_{it} is the error term.
– Random effects model with a SEM (REi-SEM-w) to consider annual weather fluctuations, and time varying (Z_{it}) and time unvarying (S_i) variables including country dummies introduced to capture individual country effects:

$$R_{it} = \beta_0 + \beta_1 W_{it} + \beta_2 S_i + \beta_3 Z_{it} + \epsilon_{it}, \tag{5}$$

$$\epsilon_{it} = \alpha_i + \rho \sum_{k}^{N} w_{ik} \nu_{it} + u_{it}.$$

The advantage of the random effects model is that it accounts for time invariant variables such as soil quality or altitude which can be important in studies of climate and agriculture.
– Random effects model with a SEM (REi-SEM-c) which considers long-term climate averages (C_i), and time unvarying variables including country individual effects:

$$R_{it} = \beta_0 + \beta_1 \bar{C}_i + \beta_2 S_i + \beta_3 Z_{it} + \epsilon_{it}, \tag{6}$$

$$\epsilon_{it} = \alpha_i + \rho \sum_{k}^{N} w_{ik} \nu_{it} + u_{it}.$$

All five model specifications (equations from 4.3 to 4.7) take net agriculture revenues as the dependent variable to test the first two hypotheses about the short-run climate change impacts on European agriculture. To complete the analysis we estimate a long-run relation function based on the Ricardian approach suggested by (Mendelsohn et al., 1994). This is the last model we estimate; it allows us to test the third hypothesis on the differences among short-run and long-run climate impacts on European agriculture. The random effects with a SEM (REi-SEM-Ri) can be written as follows:

$$ln(V_{it}) = \beta_0 + \beta_1 \bar{C}_i + \beta_2 S_i + \beta_3 Z_{it} + \epsilon_{it}, \tag{7}$$

$$\epsilon_{it} = \alpha_i + \rho \sum_{k}^{N} w_{ik} \nu_{it} + u_{it},$$

Table 2: Tested hypotheses

Hypotheses		Estimated models
H1	Fixed effects model is the most appropriate to estimate short-run relations;	FEi-SEM-w, FEt-SEM-w, RE-SEM-w, REi-SEM-w;
H2	Weather variables are more accurate than climatic variables in a revenue function model;	Models from H1 *vs* REi-SEM-c;
H3	Short-run vs long-run climate effects on agriculture: revenue approach is appropriate to capture short-run climate change impacts on European agriculture.	Models from H1 *vs* REi-SEM-cRi.

where the dependent variable V_{it} represents the land values in the region i at time t, and is expressed in logarithmic form.

Finally, the hypotheses testing is completed by an examination and comparison of the marginal impacts among the different models. The marginal values are a measure of the impact of climate on agriculture and allow an evaluation of the differences among models. Marginal values are calculated as a derivative of the revenue function with respect to the climate variable. For example, the marginal values of the weather variables can be written as follows:

$$\frac{\partial R_i}{\partial W} = \sum(\hat{\gamma_1} + 2\hat{\gamma_2}\bar{W_i}), \tag{8}$$

where γ_1 and γ_2 are combinations of β associated to the climate variables and depending on the model specification estimated, and W_i is a set of explanatory weather variables (temperature and precipitation for four seasons) and their squares. We use the marginal weather and climate values to approximate the changes in economic welfare. Each farm can react differently to the new climate: if total marginal value is positive then the increasing temperature and precipitation is beneficial to the representative farm in region i, it allows farmers to increase their supply and, thus, the producer surplus; if it is negative then warmer and wetter weather will be harmful to the farm, resulting into a negative supply shock reducing producer surplus and economic welfare.

2.2 Hypotheses

In this case study, we test following economic hypotheses: H1 – a fixed effects model is the most appropriate to estimate short-run relations; H2 – in a revenue function model weather variables are more accurate than climatic variables to capture short-run climate change impacts; H3 – climate impacts differ depending on whether the model captures short-run or long-run climate change.

First, to test hypothesis H1, we estimate the following econometric spatial panel data models adapted to net European agricultural revenues per hectare, and using annual weather data: Fixed individual effects model with spatial error autocorrelation (2), fixed temporal effects with SEM (3), individual random effects model with SEM (4) with only time variant variables as in the fixed effects models, and individual random effects model with SEM (5) which includes time invariant variables and controls for country individual effects.

Second, to test H2, the estimation results based on the temperature and precipitation variables represented by year-by-year weather variations during the observation period 2004-2012 (cf. models (2), (3), (4), (5)) are compared to the estimation results using long run climate averages to represent the temperature and precipitation variables (6).

Third, to test H3, we estimate a Ricardian model based on land values (7) which is assumed to capture long-run climate impacts on agriculture. Then we compare the revenue model capturing short-run effects and the land-value model capturing long-run climate impacts on agriculture.

3 Data

We are working at the scale of European FADN regions. We construct a balanced panel database for N=106 European FADN regions covering a nine year period (2004-2012).

This study examines climate and weather data use in the revenue function provided by Joint Research Centre (JRC) data. The JRC database is a set of meteorological grid data generated by interpolation of daily data from weather stations providing daily precipitation, and minimum and maximum temperatures. We use the JRC database to construct two information sets. First, we calculate long term observed climate averages for each FADN region during the period 1979-2003. Second, we calculate year-by-year weather variables for the observed period 2004-2012. We consider panel data issues related to agricultural revenue, and discuss use of climate and weather variables provided by the JRC database, in a revenue function approach. All descriptive statistics are reported in table 6 of the appendix.

The literature generally uses two types of variables: (i) four season average temperature and precipitation variables, and their squares, and (ii) degree day variables over the growing season, and total precipitation variables (yearly or covering the same growing season) inspired by more agronomic arguments. The majority of European studies use four season averaged climate variables. Vaitkeviciute et al. (2018) compared and discussed the possibility in a European agriculture case of using climate variables linked to the growing season, and to the four seasons. We showed that four season based variables were better adapted to capturing the climate risks to which European agriculture is exposed. Thus, we calculate temperature and precipitation averages for the four seasons corresponding to winter (December-February), spring (March-May), summer (June-August), and autumn (September-November).

Table 3: Specification tests

Hypotheses	RE-SEM-w	REi-SEM-w
Spatial Hausman test (SHT)		
H_0: SEM-RE is efficient	$\chi^2_{17} = 1.046$	$\chi^2_{17} = 5.421$
H_1: One model is inconsistent	$p = 1$	$p = 0.996$
Joint test for spatial error correlation and random effects (LM-H)		
H_0: $\sigma^2_\mu = \rho = 0$	$2,867.5$	$2,445.0$
H_1: $\sigma^2_\mu \neq 0$ or $\rho \neq 0$	$p < 0.001$	$p < 0.001$
Conditional test for spatial error correlation (BSK)		
H_0: $\rho = 0$ (assuming $\sigma^2_\mu \geq 0$)	25.043	20.253
H_1: $\rho \neq 0$ (assuming $\sigma^2_\mu \geq 0$)	$p < 0.001$	$p < 0.001$
Marginal test for random individual effects (LM1)		
H_0: $\sigma^2_\mu = 0$ (allowing $\rho \neq 0$)	53.406	49.422
H_1: $\sigma^2_\mu > 0$ (allowing $\rho \neq 0$)	$p < 0.001$	$p < 0.001$
Marginal test for spatial autocorrelation (LM2)		
H_0: $\rho = 0$	3.907	1.583
H_1: $\rho \neq 0$	$p < 0.001$	$p = 0.113$

Net farm revenues are provided by the FADN dataset and are available at farm level. We calculate aggregate net revenue at the scale of the FADN region. The FADN database also provides information on the utilized agricultural area (UAA) including owned UAA and rented UAA. In our study, we calculate the share of total rented UAA. The FADN database includes information on the representativeness of farms within a given region. We use this information to weight all the variables provided by the FADN database to calculate regional mean values. We use the European Soil Database data to calculate the soil texture variables and altitudes for FADN regions.

4 Results

4.1 Short-term climate change impacts

The estimation results for the different models are presented in table 4. The first economic hypothesis tests whether fixed effects models are the most appropriate to estimate the short-run relations between the weather and agriculture revenues.

We estimate fixed effects and random effects models with SEM in order to account for indi-

Table 4: Short-term impacts estimation

	Dependent variable: Net revenue per 100 ha			
	Weather			
	FEi-SEM-w	FEt-SEM-w	RE-SEM-w	REi-SEM-w
Temperature winter	−0.003	−0.633	0.046	−0.020
	(0.187)	(0.669)	(0.193)	(0.192)
Temperature winter squared	−0.022	-0.132^{***}	−0.021	−0.023
	(0.018)	(0.046)	(0.018)	(0.018)
Temperature spring	−0.126	1.476	0.184	−0.361
	(0.883)	(1.953)	(0.862)	(0.894)
Temperature spring squared	0.017	0.047	0.009	0.024
	(0.041)	(0.099)	(0.042)	(0.042)
Temperature summer	4.089^{**}	5.899	4.185^{**}	4.084^{**}
	(1.899)	(3.737)	(1.985)	(1.965)
Temperature summer squared	-0.105^{**}	-0.202^{**}	-0.105^{**}	-0.108^{**}
	(0.051)	(0.098)	(0.053)	(0.052)
Temperature autumn	−1.439	-5.086^{**}	−1.350	-1.751^{*}
	(0.920)	(2.524)	(0.952)	(0.951)
Temperature autumn squared	0.030	0.234^{**}	0.030	0.041
	(0.037)	(0.095)	(0.038)	(0.038)
Precipitation winter	0.016	0.100	0.019	0.009
	(0.041)	(0.106)	(0.044)	(0.043)
Precipitation winter squared	0.0001	−0.0004	0.00004	0.0001
	(0.0003)	(0.001)	(0.0003)	(0.0003)
Precipitation spring	-0.067^{*}	0.041	−0.062	-0.072^{*}
	(0.040)	(0.114)	(0.043)	(0.042)
Precipitation spring squared	0.001^{**}	−0.0001	0.001^{*}	0.001^{**}
	(0.0003)	(0.001)	(0.0003)	(0.0003)
Precipitation summer	-0.077^{**}	-0.137^{*}	-0.078^{**}	-0.076^{**}
	(0.030)	(0.078)	(0.032)	(0.031)
Precipitation summer squared	0.0004^{***}	0.001^{*}	0.0004^{**}	0.0005^{***}
	(0.0002)	(0.0004)	(0.0002)	(0.0002)
Precipitation autumn	−0.043	−0.045	−0.039	−0.047
	(0.033)	(0.091)	(0.035)	(0.034)
Precipitation autumn squared	0.0002	0.0002	0.0002	0.0002
	(0.0002)	(0.0005)	(0.0002)	(0.0002)
Rented share	-0.139^{**}	-0.267^{***}	-0.173^{***}	-0.220^{***}
	(0.071)	(0.036)	(0.056)	(0.066)
Population per ha				0.825
				(0.583)
Clay				−1.299
				(0.954)
Sand				−0.903
				(0.586)
Altitude				0.003
				(0.008)
AT				−20.867
BE				1.835
DE				−8.331
DK				−15.433
EL				2.362
ES				−7.324
FI				−14.690
IE				−21.974
IT				2.956
LT				−19.351
LU				−6.486
LV				−15.730
NL				1.090
PL				−14.244
PT				−8.424
SE				-23.356^{**}
SI				−25.477
UK				-19.130^{**}
Constant			−7.277	77.487
			(18.310)	(49.484)
rho	0.122^{**}	0.251^{***}	0.136^{**}	0.105^{*}
	(0.051)	(0.047)	(0.050)	(0.047)
phi			7.214^{***}	5.764^{**}
			(1.072)	(0.868)
RMSE	19.502	19.673	19.076	17.117

Note: N=106; T=9; *p<0.1; **p<0.05; ***p<0.01.

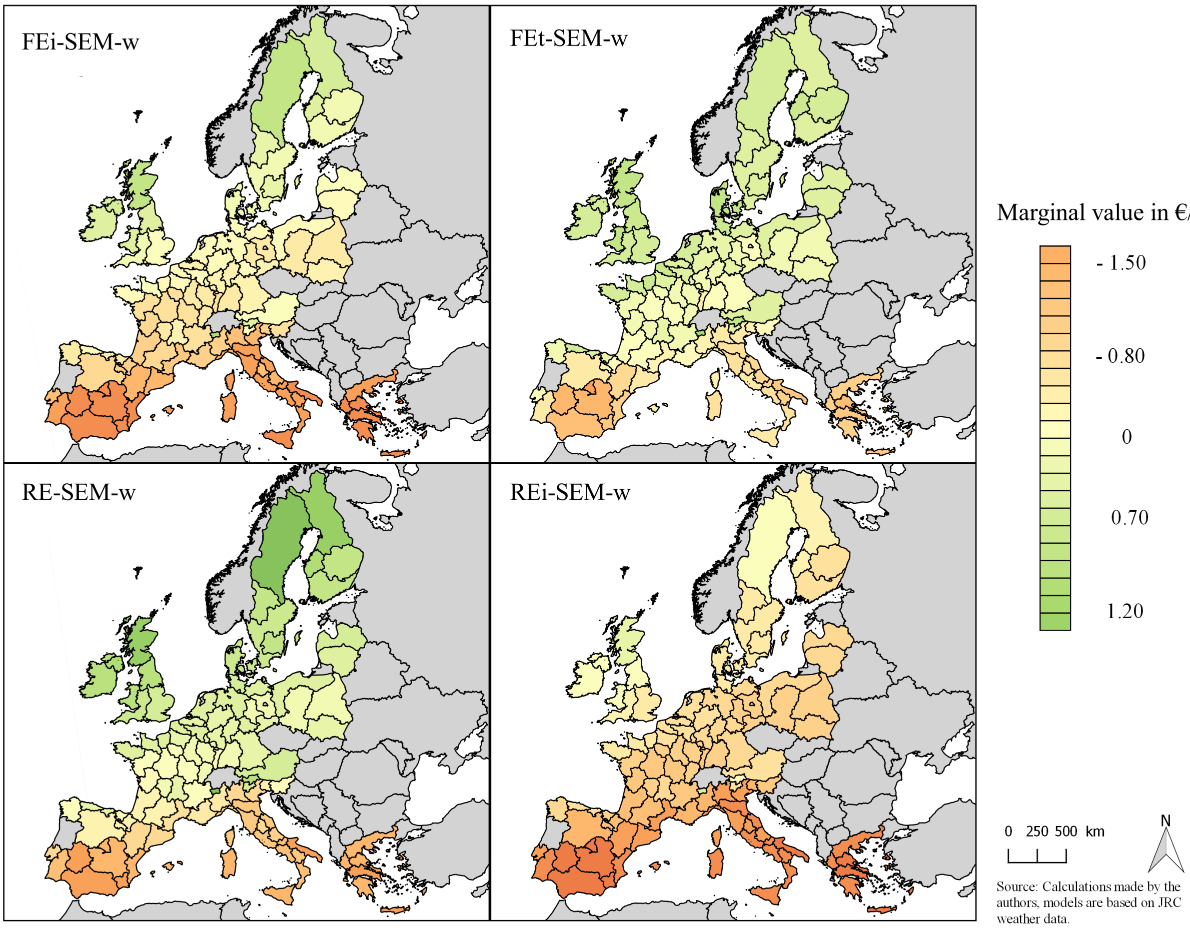

Figure 1: Total marginal weather impacts, in hundreds of euros per hectare

vidual heterogeneity and spatial autocorrelation. We estimate four models for the short-run relations between weather and agricultural revenues: FEi-SEM-w, FEt-SEM-w, RE-SEM-w, REi-SEM-w (cf. table 1). We ran some specification tests adapted to the spatial panel data presented in table 3. First, the spatial Hausman test (SHT) is used to test the efficiency of the spatial random effects estimator. Then we used a joint test for spatial error correlation and random effects (LM-H), a conditional test for spatial error correlation (BSK), and the marginal random individual effects (LM1) and spatial autocorrelation (LM2) tests developed by Baltagi et al. (2003).

The coefficients related to the SHT test are not highly significant at 1%. Thus, the null hypothesis of the consistency of the spatial random effects estimator is not rejected. The model specifications based on weather data and taking account only of the time variant variables confirm the existence of spatial autocorrelation and do not reject random effects. The statistics of all the other tests are significant at 1% confirming spatial error autocorrelation. Also, these tests do not reject the random effects model which is a mixed model able to capture short-run and long-run relations.

Table 5: Total weather and climate marginal values

	Revenue approach					Ricardian approach
Country	FEi-SEM-w	FEt-SEM-w	RE-SEM-w	REi-SEM-w	REi-SEM-c	REi-SEM-cRi
Austria	-0.06€/ha [-0.44 ; 0.33]	0.21€/ha [-0.35 ; 0.77]	0.34€/ha [-0.03 ; 0.72]	-0.43€/ha [-0.82 ; -0.04]	-4.37€/ha [-7.24 ; -1.49]	4.40€/ha [3.71 ; 5.09]
Belgium	-0.18€/ha [-0.57 ; 0.20]	0.25€/ha [-0.31 ; 0.81]	0.19€/ha [-0.19 ; 0.57]	-0.48€/ha [-0.87 ; -0.10]	-2.83€/ha [-5.70 ; 0.05]	54.56€/ha [44.21 ; 64.92]
Germany	-0.22€/ha [-0.60 ; 0.17]	0.11€/ha [-0.45 ; 0.67]	0.17€/ha [-0.21 ; 0.54]	-0.55€/ha [-0.94 ; -0.17]	-4.05€/ha [-6.92 ; -1.17]	63.13€/ha [51.85 ; 74.40]
Denmark	0.04€/ha [-0.34 ; 0.43]	0.51€/ha [-0.04 ; 1.07]	0.46€/ha [0.08 ; 0.83]	-0.31€/ha [-0.70 ; 0.07]	-2.58€/ha [-5.46 ; 0.29]	36.41€/ha [25.25 ; 47.56]
Greece	-1.33€/ha [-1.72 ; -0.95]	-0.74€/ha [-0.29 ; -0.18]	-1.02€/ha [-1.40 ; -0.65]	-1.52€/ha [-1.91 ; -1.14]	2.45€/ha [-0.42 ; 5.33]	6.72€/ha [-0.40 ; 13.85]
Spain	-0.89€/ha [-1.27 ; -0.50]	-0.38€/ha [-0.94 ; 0.18]	-0.56€/ha [-0.93 ; -0.18]	-1.11€/ha [-1.49 ; -0.72]	0.30€/ha [-2.57 ; 3.18]	8.54€/ha [4.19 ; 12.89]
Finland	0.18€/ha [-0.20 ; 0.57]	0.32€/ha [-0.24 ; 0.87]	0.67€/ha [0.30 ; 1.05]	-0.33€/ha [-0.72 ; 0.05]	-6.47€/ha [-9.35 ; -3.60]	4.89€/ha [2.87 ; 6.92]
France	-0.40€/ha [-0.79 ; -0.02]	0.05€/ha [-0.51 ; 0.60]	-0.05€/ha [-0.42 ; 0.33]	-0.68€/ha [-1.07 ; -0.30]	-2.37€/ha [-5.25 ; 0.51]	11.04€/ha [8.29 ; 13.78]
Ireland	0.27€/ha [-0.11 ; 0.66]	0.38€/ha [-0.18 ; 0.94]	0.66€/ha [0.29 ; 1.04]	-0.04€/ha [-0.43 ; 0.35]	-3.83€/ha [-6.71 ; -0.96]	61.07€/ha [47.89 ; 74.26]
Italy	-0.84€/ha [-1.23 ; -0.46]	-0.30€/ha [-0.86 ; 0.26]	-0.50€/ha [-0.88 ; -0.13]	-1.09€/ha [-1.47 ; -0.70]	0.52€/ha [-2.35 ; 3.40]	40.23€/ha [22.23 ; 58.23]
Lithuania	-0.14€/ha [-0.53 ; 0.24]	0.26€/ha [-0.30 ; 0.81]	0.28€/ha [-0.10 ; 0,65]	-0.55€/ha [-0.93 ; -0.16]	-5.54€/ha [-8.42 ; -2.67]	2.30€/ha [1.84 ; 2.75]
Luxembourg	-0.24€/ha [-0.63 ; 0.15]	0.10€/ha [-0.46 ; 0.66]	0.13€/ha [-0.24 ; 0.51]	-0.56€/ha [-0.95 ; -0.17]	-4.45€/ha [-7.32 ; -1.57]	36.94€/ha [30.35 ; 43.53]
Latvia	-0.08€/ha [-0.47 ; 0.30]	0.29€/ha [-0.27 ; 0.85]	0.35€/ha [-0.02 ; 0.73]	-0.50€/ha [-0.89 ; -0.12]	-5.56€/ha [-8.43 ; -2.68]	1.40€/ha [1.06 ; 1.74]
Netherlands	-0.11€/ha [-0.50 ; 0.27]	0.35€/ha [-0.21 ; 0.91]	0.26€/ha [-0.11 ; 0.64]	-0.42€/ha [-0.81 ; -0.03]	-2.14€/ha [-5.01 ; 0.74]	150.17€/ha [120.88 ; 179.46]
Poland	-0.28€/ha [-0.66 ; 0.11]	0.10€/ha [-0.46 ; 0.66]	0.12€/ha [-0.26; 0.49]	-0.64€/ha [-1.03 ; -0.26]	-4.57€/ha [-7.45 ; -1.67]	10.84€/ha [9.02 ; 12.67]
Portugal	-1.01€/ha [-1.39 ; -0.62]	-0.22€/ha [-0.78 ; 0.34]	-0.72€/ha [-1.09 ; -0.34]	-1.14€/ha [-1.53 ; -0.76]	3.12€/ha [0.24 ; 6.00]	5.07€/ha [3.20 ; 6.94]
Sweden	0.22€/ha [-0.16 ; 0.61]	0.26€/ha [-0.30 ; 0.82]	0.69€/ha [0.32 ; 1.07]	-0.25€/ha [-0.64 ; 0.13]	-6.04€/ha [-8.91 ; -3.16]	9.55€/ha [6.52 ; 12.59]
Slovenia	-0.48€/ha [-0.86 ; -0.09]	-0.13€/ha [-0.69 ; 0.43]	-0.12€/ha [-0.49 ; 0.26]	-0.79€/ha [-1.17 ; -0.40]	-3.22€/ha [-6.09 ; -0.34]	32.32€/ha [26.92 ; 37.72]
United-Kingdom	0.24€/ha [-0.15 ; 0.62]	0.44€/ha [-0.12 ; 1.00]	0.64€/ha [0.26 ; 1.01]	-0.09€/ha [-0.47 ; 0.30]	-3.21€/ha [-6.08 ; -0.33]	30.53€/ha [23.62 ; 37.43]

Note: Confidence interval at 95% is presented in parentheses. For revenue approach models, values are presented in hundreds of euros. Marginal values are not directly comparable between revenue and Ricardian approach models, the values are for only illustrative manner to observe positive or negative impacts.

The estimated coefficients of the four models presented in table 4 show that the results are stable and very similar for the individual fixed effects and random effects models, especially for the statistically significant coefficients of summer temperature and precipitation. All the models predict a concave, increasing but at a decreasing rate relation between mean summer temperature and farmer's revenue. For the optimal summer temperature values for European

agriculture, the FEi-SEM-w model predicts 19.5°C and the RE-SEM-w model predicts 20°C. The optimal temperature value indicates when a higher temperature begins to have a negative impact on agriculture. Knowing that in the observed period summer temperatures range from 10.6°C (minimum) to 26.1°C (maximum) with an average of 18.7°C, we note that in Europe the optimal temperature predicted by these models has been reached and some regions are suffering from overly high summer temperatures.
The FEt-SEM-w and REi-SEM-w models suggest significant and decreasing at a increasing rate impacts of autumn temperatures. In the observed EU regions the average autumn temperature ranges between 0°C and 20°C. According to the FEt-SEM-w estimates autumn temperatures below approximatively 11°C temperature increases have harmful short-term impacts on agriculture, and above this threshold have increasing positive impacts. REi-SEM-w model suggests even more severe impacts and a threshold close to 21°C.

To show more precisely how weather affects agriculture revenues we calculate total marginal weather impacts using equation (8). Total marginal values per FADN region for our four short-run models are presented in figure 1, and average values per country are reported in table 5. First, we observe that all the models show that the most harmful short-run weather impacts are in southern European regions. However, their amplitude varies slightly between models. The temporal fixed effects model proposes positive weather impacts with lowest variation in marginal impact values. The FEi-SEM-w model suggests more negative short-run impacts, and estimates harmful marginal weather impacts for the majority of European regions with only a few northern regions benefiting from warmer and wetter weather conditions. The RE-SEM-w model shows a positive impact for northern Europe and negative impacts for southern regions. This model shows the highest variability between the highest and lowest marginal impact values. However, the REi-SEM-w model which includes time in-variant variables and controls for fixed country effects, is more pessimistic than the three previous models and predicts negative marginal impacts for almost all European regions except a few northern FADN regions, and negative impacts for all of Europe based on country averages (5).
The results show that these models seem to be adapted to measuring short run climate impacts on agriculture revenues, and the inter-model variations suggest intervals of possible impacts rather than a single value related to uncertainty. However, based on the confidence intervals of marginal weather impacts, our results suggest that, statistically, the REi-SEM-w model is better than the others because it has the most of significant marginal values.

4.2 Weather data *versus* climate data in revenue models

The second economic hypothesis tests whether the weather variables are more accurate than climate variables in a revenue approach. We start by estimating a REi-SEM-c model which takes account of climate variables instead of weather. The estimation results are reported in appendix table 7. Note first that in the climate based model the estimated statistically significant coefficients of autumn temperature are very high, resulting in an average marginal autumn temperature impact on land value of -2,004€/ha. These are the only statistically significant coefficients in this model, however the autumn temperature should not be the only determinant of agricultural revenues in Europe.

Our tests of H2 are completed by comparing marginal values. The total marginal climate impacts for the REi-SEM-c model are depicted in figure 2 and presented in table 5. Comparing the maps in figures 2 and 1 we observe important differences between the models using weather and those using climate variables. In the climate based model the marginal values have a significantly wider range (from -800 to +800 €/ha) and suggest counter intuitive marginal impacts. This model suggests that a warmer and wetter climate would be harmful to agriculture in central and northern European regions, and that southern regions would benefit from a warmer climate. Thus, the results differ significantly for the models based on weather data and long-term-average climate data. The climate data model seems not to be a good indicator of climate change impacts on annual European agricultural revenues. Thus, we find support for H2.

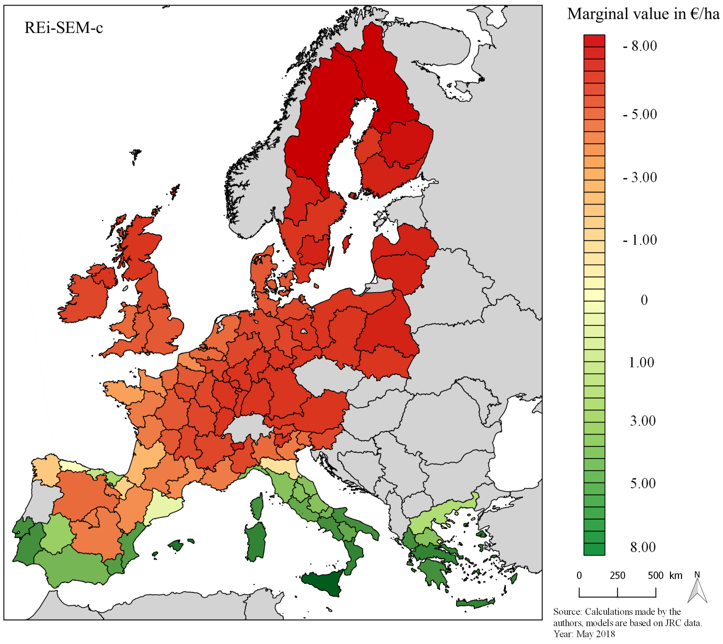

Figure 2: Total marginal effect of climate in a revenue model, in hundreds of euros per hectare

4.3 Short-run and long-run climate change impacts on European agriculture

Finally, we compare the results obtained so far for short run impacts with the results estimated for long-run impacts (see H3). We estimate a Ricardian model based on land values and long-

term average climate conditions (cf. model (??)). We compare marginal values for short-run impacts in the revenue approach presented in section 4.4.1. to the estimated long-run impacts from the Ricardian model.
These long-run estimated total marginal values are depicted in figure 3 of appendix and presented in table 5. The Ricardian model assumes that farmers implement some adaptations based on their observation of the changing climate which triggers maximizing behaviour. Thus, the long-term impacts are estimated to be beneficial to European agriculture, with some harmful impacts on a few southern European regions. These results are similar to those found in previous studies (Van Passel et al., 2017; Vanschoenwinkel et al., 2016).
Table 5 presents total marginal values for short-run and long-term impacts. Average long-run impacts by country are estimated to be positive in all European countries. We observe smaller impacts for southern countries, e.g. only 0.06% of farmland value per hectare for Greece (equal to 6.72€/ha), and 0.13% of land value per hectare for Spain (8.54€/ha). Although those impacts are positive, these smaller values show that for southern regions it will be more difficult to adapt in order to benefit from climate change.

Table 5 presents heterogeneous but mostly negative short-term impacts across European countries. Short-term impacts imply no adaptations by farmers, or anticipation of future climate conditions. Thus, farmers experience revenue gains or losses due to weather fluctuations. For example, the FEi-SEM-w model estimates negative short-term marginal impacts for the majority of European countries, and the REi-SEM-w model predicts that in the short-term warmer and wetter weather will be harmful to all European regions, especially the countries of southern Europe, with the highest losses for Portugal and Greece in the FEi-SEM-w model, and for Greece, Spain, Italy and Portugal in the REi-SEM-w model. However, three of the four short-term models estimate positive short-run marginal climate change impacts for northern European countries, implying that even with no adaptive behaviour northern agriculture will benefit from a warmer and wetter climate.

Finally, if we compare short-run and long-run climate change impacts on European agriculture we observe negative impacts in the former case and more positive impacts in the latter case. These results confirm the importance of adaptation measures to face climate change. Indeed, the short-run impacts model do not take account of potential adaptations and show only gross impacts. In the context of no adaptation measures, these short-run impacts could persist. However, the long-run model includes farmers' adaptations, and offers a more optimistic vision of climate impacts while increasing public awareness of the impacts of climate change on agriculture and the importance of adaptations.

5 Conclusion

Understanding the potential effects of climate change on economic outcomes in agriculture is central to identifying areas of adaptation to climate change. Our study provides an evaluation of climate change impacts at the EU level using an agricultural revenue approach in a spatial panel framework. We compare the impacts of short-run weather variations on the economic profitability of European agriculture using fixed effects and random effects with SEMs. Our models are estimated at the EU scale, and employ balanced panel data for 106 European FADN regions covering a 9 year period (2004-2012).

Our study makes four main contributions to the literature. First, it is the first study to use a revenue approach to measure the impacts of climate on European agriculture. Previous European studies use a Ricardian approach to estimate long-run relationships between climate and agricultural activity. Our models show negative climate impacts on agricultural revenues for southern regions, and positive impacts for northern regions.

Second, we estimate climate change impacts taking account of spatial autocorrelation and individual heterogeneity among EU regions. The revenue function approach was proposed by Deschênes and Greenstone (2007) to estimate the short-term impacts of climate on agriculture. Their paper was criticized because it took no account of spatial autocorrelation. We account for spatial autocorrelation and estimate SEMs. We ran some statistical specification tests to confirm the presence of spatial autocorrelation in our models.

Third, we discuss the relevance of variables based on annual weather variations rather than climate data in a revenue function approach. This was one of the main motivations for our study. The most common application of agricultural revenue as the dependent variable is in work based on a Ricardian framework, and thus, long term climate averages. We argue that agriculture revenues are affected directly by annual weather conditions, and not by 25 or 30-year average past climate. In this study we compared estimations based on weather and climate data. Our results show significant differences in the estimated impacts. It suggests caveats to the use of climate data in a revenue function based analysis of European agriculture.

Finally, comparison of short-run and long-run climate change impacts shows that the northern European countries will benefit from a changing climate in both cases. However, our results point to the importance of adapting to climate change to avoid harmful impacts on agriculture which could result in important revenue losses.

References

Baltagi, B. H., Song, S. H. and Koh, W. (2003). Testing panel data regression models with spatial error correlation. *Journal of econometrics* 117: 123–150.

Bozzola, M., Massetti, E., Mendelsohn, R. and Capitanio, F. (2017). A ricardian analysis of the impact of climate change on italian agriculture. *European Review of Agricultural Economics* 45: 57–79.

Chatzopoulos, T. and Lippert, C. (2015). Adaptation and climate change impacts: A structural ricardian analysis of farm types in germany. *Journal of Agricultural Economics* 66: 537–554.

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

EU (2016). The European Union Explained: Agriculture. Tech. rep.

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

Iglesias, A., Garrote, L., Quiroga, S. and Moneo, M. (2012). A regional comparison of the effects of climate change on agricultural crops in europe. *Climatic Change* 112: 29–46.

IPCC (2014). Climate change 2014: Impacts, adaptation, and vulnerability. part a: Global and sectoral aspects. contribution of working group ii to the fifth assessment report of the intergovernmental panel on climate change.

Kennedy, P. (2008). *A guide to econometrics*. MIT press.

Kumar, K. K. (2011). Climate sensitivity of indian agriculture: do spatial effects matter? *Cambridge Journal of Regions, Economy and Society* 4: 221–235.

Lippert, C., Krimly, T. and Aurbacher, J. (2009). A ricardian analysis of the impact of climate change on agriculture in germany. *Climatic Change* 97: 593–610.

Liu, H., Li, X., Fischer, G. and Sun, L. (2004). Study on the impacts of climate change on china's agriculture. *Climatic Change* 65: 125–148.

Mendelsohn, R. (2014). The impact of climate change on agriculture in asia. *Journal of Integrative Agriculture* 13: 660–665.

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

Mendelsohn, R. O. and Massetti, E. (2017). The use of cross-sectional analysis to measure climate impacts on agriculture: Theory and evidence. *Review of Environmental Economics and Policy* 11: 280–298.

Vaitkeviciute, J., Chakir, R. and Van Passel, S. (2018). Climate variable choice in ricardian studies on european agriculture (submitted for publication in 2018) .

Van Passel, S., Massetti, E. and Mendelsohn, R. (2017). A ricardian analysis of the impact of climate change on european agriculture. *Environmental and Resource Economics* 67: 725–760.

Vanschoenwinkel, J., Mendelsohn, R. and Van Passel, S. (2016). Do western and eastern europe have the same agricultural climate response? taking adaptive capacity into account. *Global Environmental Change* 41: 74–87.

Vanschoenwinkel, J. and Van Passel, S. (2018). Climate response of rainfed versus irrigated farms: the bias of farm heterogeneity in irrigation. *Climatic Change* 147: 225–234.

Wang, J., Mendelsohn, R., Dinar, A., Huang, J., Rozelle, S. and Zhang, L. (2009). The impact of climate change on china's agriculture. *Agricultural Economics* 40: 323–337.

Wood, S. A. and Mendelsohn, R. O. (2015). The impact of climate change on agricultural net revenue: a case study in the fouta djallon, west africa. *Environment and Development Economics* 20: 20–36.

Table 6: Descriptive statistics

Variable	Units	Mean	Min	Max	Source
Net revenues per ha	€/ha	1,380.00	-494.9	22,760.00	FADN
Land value per ha	€/ha	15,240.00	301.3	215,600.00	2004-2012
Log land value per ha		9.04	5.70	12.28	
Rented land share	%	35.63	0.91	85.34	
Climate					
Temperature Winter	°C	3.55	-12.14	11.71	JRC
Temperature Spring	°C	9.93	-1.05	15.57	1979-2003
Temperature Summer	°C	18.00	11.68	23.77	
Temperature Autumn	°C	11.71	0.21	18.99	
Precipitation Winter	cm	5.83	2.63	15.31	
Precipitation Spring	cm	5.48	2.25	10.63	
Precipitation Summer	cm	5.42	0.47	11.71	
Precipitation Autumn	cm	6.98	3.02	13.52	
Weather					
Temperature Winter	°C	3.65	-15.23	12.86	JRC
Temperature Spring	°C	10.64	-1.49	17.50	2004 - 2012
Temperature Summer	°C	18.77	10.62	26.12	
Temperature Autumn	°C	12.39	0.09	20.25	
Precipitation Winter	cm	5.94	0.46	16.60	
Precipitation Spring	cm	5.37	0.57	17.33	
Precipitation Summer	cm	5.62	0.00	23.41	
Precipitation Autumn	cm	6.82	1.21	21.56	
Population per ha	nb/ha	1.97	0.04	22.86	Eurostat
					2004-2012
Silt	%	31.22	16.79	38.08	European Soil
Clay	%	20.85	11.63	32.71	Database
Sand	%	45.78	28.69	67.83	2012
Altitude	m	292.70	5.92	1,691.00	

Table 7: Estimation results using climate data

	REi-SEM-c	REi-SEM-cRi
Temperature winter	10.448	0.278
	(10.448)	(0.242)
Temperature winter square	-0.809	-0.030^{**}
	(0.525)	(0.012)
Temperature spring	21.993	-0.872
	(21.932)	(0.536)
Temperature spring square	-0.184	0.074^{***}
	(0.925)	(0.021)
Temperature summer	21.659	1.252^{*}
	(27.704)	(0.645)
Temperature summer square	-0.720	-0.046^{***}
	(0.704)	(0.016)
Temperature autumn	-66.277^{***}	-0.373
	(25.561)	(0.606)
Temperature autumn square	1.958^{**}	0.010
	(0.902)	(0.022)
Precipitation winter	-0.529	-0.045^{***}
	(0.651)	(0.016)
Precipitation winter square	0.003	0.0002^{***}
	(0.004)	(0.0001)
Precipitation spring	0.899	0.009
	(1.595)	(0.036)
Precipitation spring square	-0.010	-0.0002
	(0.011)	(0.0002)
Precipitation summer	-0.200	0.006
	(1.090)	(0.026)
Precipitation summer square	0.001	0.0001
	(0.006)	(0.0001)
Precipitation autumn	0.172	0.037
	(1.013)	(0.025)
Precipitation autumn square	0.001	-0.0002
	(0.006)	(0.0001)
Rented share	-0.235^{***}	-0.001
	(0.070)	(0.002)
Population per ha	0.750	0.047^{***}
	(0.563)	(0.012)
Clay	-2.006^{*}	0.0004
	(1.061)	(0.024)
Sand	-1.045^{*}	-0.010
	(0.598)	(0.014)
Altitude	-0.005	0.0003
	(0.018)	(0.0005)
Austria	-25.787	-1.294^{***}
Belgium	-7.062	1.061^{***}
Germany	-21.202^{**}	1.357^{***}
Denmark	-16.944	1.462^{***}
Greece	26.774	2.112^{***}
Spain	7.414	0.557^{*}
Finland	11.607	1.930^{***}
Ireland	-37.076^{*}	1.435^{***}
Italy	16.379	1.612^{***}
Lithuania	-27.138	-0.517
Luxembourg	-16.300	0.668^{*}
Latvia	-16.787	-0.917
Netherlands	-9.142	1.868^{***}
Poland	-26.397^{*}	-0.220
Portugal	-16.066	-0.963^{**}
Sweden	-26.847	1.147^{*}
Slovenia	-25.765	0.126
United Kingdom	-30.373^{**}	0.628
Constant	229.403	3.922
rho	0.118^{**}	0.659^{**}
phi	4.769^{***}	2.250^{***}
Note:		*p<0.1; **p<0.05; ***p<0.01

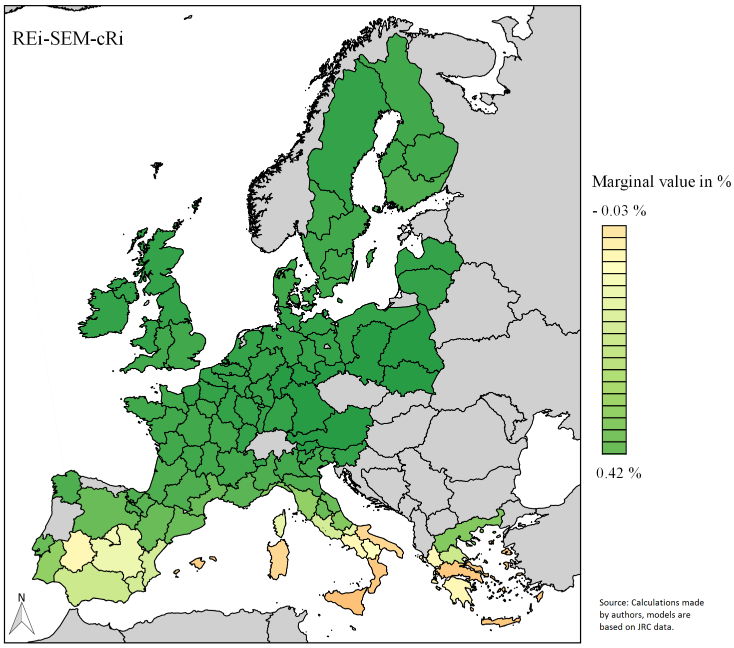

Figure 3: Total marginal effects of climate in a land value model