The impacts of climate change on European agriculture revenue: weather vs climate data

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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 explains the temporal and spatial variability of agricultural revenues. Our econometric model takes 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

The economic literature has focused considerable attention on climate change impacts on the agricultural sector due to its pre-existing vulnerability to weather conditions. According to Mendelsohn et al. (1999) five main types of approaches could be found in the literature on the impacts of climate change on agriculture: (1) studies that rely on crop simulation models (Ciscar et al., 2011); (2) studies that rely on cross-sectional or intertemporal analyses of yields (Lobell et al.); (3) studies that use CGE (computable general equilibrium) models (Nelson et al., 2014). (4) studies based on cross-sectional analyses of land values per hectare (Mendelsohn et al., 2004, 1994) (5) studies based on panel (intertemporal) analysis of net revenues across weather (Deschenes and Greenstone, 2007). The last two approaches are important approaches used in economic studies to measure climate change impacts on agriculture.

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More recently, Blanc and Reilly (2017) provide an overview of the main approaches assessing the impacts of climate change on agriculture. According to them, statistical tools are favoured by economists to estimate relationship between climate and agricultural outputs. Statistical tools are used both in the Ricardian approach based on land values (Mendelsohn et al., 1994) and in the revenue/profit approach based on production function (Deschenes and Greenstone, 2007). These two approaches are complementary and provide differentiated impacts of climate change on agriculture in terms of short-term and long-term considerations. On one hand, the so-called Ricardian approach assumes that farmers have profit maximizing behaviour in the long-term and that the land values reflect the stream of future revenues that the farmer could gain from the best land allocation. Farmers adapt land allocation to climate averages to achieve the highest revenues. In other words, Ricardian studies examine how long-term climate affects farmland values across space. On the other hand, we have a revenue approach based on farmers annual profits maximising behaviour. The revenue approach is a short-term approach in which the revenue of the observed year is impacted only by weather conditions of this same year (see Auffhammer et al. (2013) for a clear distinction between weather and climate variables). Or, in the literature there are many studies using long term climate averages to estimate agriculture revenues. In other words, within the framework of this approach, we argue that long-term climate averages (often 30 years) lead to incorrect estimations of the impact of climate on agricultural revenues, whereas current weather conditions (annual observations) do not. This is the main argument that this paper develops.

The revenue approach was implemented in several cross-sectional studies in developing country applications due to the availability of data as information on private land owners is often not available to implement the Ricardian approach. Among these studies we could cite Asian (Liu et al., 2004; Wang et al., 2009; Mendelsohn, 2014) and African (Wood and Mendelsohn, 2015) countries as well as a panel data based study on Indian agriculture (Kumar, 2011). All these studies argue that they are using Ricardian approach but instead of taking the land values they take net revenues without calculations of the actualization rates for future revenue expectations. Mendelsohn and Massetti (2017) note that the main advantage of the Ricardian approach is that farmland value reflects the stream of future rents generated by climate, and is less vulnerable to the yearly weather conditions. However, we argue that in the studies where the yearly agricultural output variable is estimated (profits or revenues), it should not be defined as a Ricardian approach, because these studies are not based on future revenue expectations. These studies usually use long term average climate variables, whereas the agricultural revenues for the year of observation should be influenced only by the weather conditions during this same period. Taking long run climate averages could lead to measurement errors.

We start with methodological approach proposed by Deschenes and Greenstone (2007). Deschenes and Greenstone (2007) make the estimation of the impact of climate on US agricultural sector. They argue that cross sectional hedonic equation could be misspecified and suggest to run panel data estimation based on the relation between yearly agricultural profits and weather conditions. They exploit random year-to-year variation in temperature and precipitation to estimate the changes in agricultural profits are higher or lower in years that are warmer and wetter (Deschenes and Greenstone, 2007). The study of Deschenes and Greenstone (2007) was criticised by Fisher et al. (2012) who argue that given the errors in data and the model specification, a better-specified hedonic model produces robust estimates, unlike the results reported in Deschenes and Greenstone (2007). The main limitations reported by Fisher et al. (2012) concern (1) errors in the weather data[5]; (2) biased standard errors due to spatial correlation; (3) the inclusion of state by year fixed effects which does not leave enough weather variation to obtain meaningful estimates of the relationship between agriculture profits and weather. Being aware of these critics, our paper will take a major part of them into account and discuss the possible issues.

To the best of our knowledge, no previous study applied to European agriculture, adopts a spatial-panel revenue function approach. There are few studies focusing on the study of yields (Benjamin et al., 2017; Iglesias et al., 2012) and the major part of papers are based on Ricardian approach, considering either the whole Europe (Van Passel et al., 2017; Vanschoenwinkel et al., 2016; Vanschoenwinkel and Van Passel, 2018) or a single European country (Bozzola et al., 2017; Lippert et al., 2009; Chatzopoulos and Lippert, 2015). In this paper we will test the use of climate and weather variables in European revenue function approach within a spatial panel framework. The aim is to compare the results and to observe if weather and climate indicators lead to similar estimation results, in order to test the hypothesis that models based on revenue function should be estimated using annual weather data and not long-averaged climate.

Finally, this paper has three main contributions. First, to the best of our knowledge, this study is the first that uses the revenue function approach in European agriculture context. Second, we examine different spatial agricultural revenues interaction models. Finally, we examine and compare the use of yearly whether variations and climate data in the revenue approach.

2 Methodology

The revenue function approach assumes that each farmer have the aim to maximize income, subject to the exogenous conditions of the farm, such as climate, soils and socio-economic conditions. Farmers will choose endogenous inputs X_i, given market prices and exogenous inputs c_i (climate), s_i (soil) and z_i (socio-economic and control variables) to adjust their farming decisions in order to achieve the highest revenue:

$$Max\Pi_i = p_i Q_i(X_i, c_i, s_i, z_i) - wX_i, \tag{1}$$

[5] In their reply to these limitations Deschênes and Greenstone (2012) summarize the new estimates once the errors reported by Fisher et al. (2012) were corrected.

where Π_i is a revenue function of the farmer for the cultivated good i at a given location, p_i is an exogenous price vector of good i, Q_i describes a production technology used by the farmer, and w is an exogenous vector of endogenous input's prices. Knowing that farmers choose the outputs Q and endogenous inputs X that maximize net revenues, the optimal profit or revenue, obtained by deriving the previous equation, could be rewritten in reduced form as a function of exogenous inputs only:

$$\Pi_i^* = \Pi_i^*(c_i, s_i, z_i, p_i, w) \tag{2}$$

We assume that all farmers will have the same structure of prices, the optimal revenue can be rewritten as fallows:

$$\Pi_i^* = \Pi_i^*(c_i, s_i, z_i) \tag{3}$$

The revenue approach, like it was implemented by Deschenes and Greenstone (2007) were very poorly used following its theoretical framework. Many studies estimating net agricultural revenues fallows the so called Ricardian model framework, falsely supposing that the annual net revenues are depending on the long run climate averages. In this paper we argue that annual net revenues are directly dependent on annual weather. The revenue approach is supposed to capture short term farmers response to climate and short term adaptation, differently from Ricardian approach. Thus, in this paper, we estimate the net agricultural revenue using econometric spatial panel data models.

In our study, panel data take into account individual specificities, more precisely, European FADN region specificities in agricultural practices and their behaviour changes over the time. The use of panel data also supposes that the land values are not independent for each year, contrary to cross sectional data use. From a methodological point of view, panel data correspond to observations of individuals repeated over time that enables consideration of heterogeneity over time and between individuals. There are different ways to exploit panel data, some of which we use in our study.
Only one paper, written by Kumar (2011), discussing different spatial models that can be used in revenue approach of Indian agriculture. However, Kumar (2011) argue that the study is based on Ricardian approach, and uses long term climate averages to estimate net agricultural revenues. We argue that the revenue function models should be estimated using annual weather data instead of climate, annual revenues being directly related to the annual weather conditions.

The main advantage of using panel data is to model heterogeneous behaviour. This heterogeneity may appear in the regression coefficients which may vary across individuals and time, in which case we would talk about fixed effects model, or in the structure of the residuals, in which case we would have a random effects model.
The most intuitive way to account for individual or time differences in behaviour, in the context of a panel regression, is to assume that some of the regression coefficients are allowed to vary

across individuals or over time. When these are allowed to vary in one or two dimensions, we have the fixed effects model (Matyas and Sevestre, 1996). The fixed effects model is written as follows:

$$Y_{it} = \beta_1 C_{it} + \beta_2 S_{it} + \beta_3 Z_{it} + \alpha_i + \theta_t + \epsilon_{it}, \tag{4}$$

where α_i represents fixed individual effects and θ_t is the fixed temporal effects coefficient. The fixed effects panel model supposes that each individual (and each year) has its own model, in other words, it states that each individual has its own reaction coefficients which are specific to each time period (Matyas and Sevestre, 1996). Thus, fixed panel data uses the within a single individual (or/and year) type variation, 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 short-run estimates (Kennedy, 2008). Intuitively, the fixed effects models should be the most relevant to estimate short run relations between agricultural revenues and annual weather conditions.

The random effects model is interested in heterogeneity in the micro units arising from the unobservable and omitted variables. Indeed, 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, making the random effects model more efficient than the fixed effects model. Since the random effects model uses between variations, it can produce estimates of coefficients of time invariant explanatory variables. Moreover, because the random effects estimator uses both the cross sectional and time series components on the data; it produces estimates that mix the short-run and long-run effects (Kennedy, 2008). The original formulation of the individual random effects model is written as follows:

$$Y_{it} = \beta_0 + \beta_1 C_{it} + \beta_2 S_{it} + \beta_3 Z_{it} + \epsilon_{it}, \tag{5}$$

$$\epsilon_{it} = \alpha_i + u_{it},$$

where the residual term ϵ_{it} is composed of the specific individual random effect α_i and the error term u_{it}. The advantage of the random effects model is that it accounts for time invariant variables which can be important in the studies on climate and agriculture, such as soil quality or altitude.

Fisher et al. (2012) has criticized Deschenes and Greenstone (2007) on biased standard errors due to spatial correlation. We take into account account this criticism by introducing spatial interactions into panel models. The main reason is the possible existence of spatial autocorrelation into residuals. In this case, we assume that we are in a situation where we could have some measurement errors that tend to spill over across the boundaries of the FADN regions or that any unobserved shocks follow a spatial pattern. This type of spatial correlation needs to be implemented with a Spatial Error Model (SEM):

$$y_{it} = X_{it}\beta + \epsilon_{it}, \tag{6}$$

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

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

While working with spatial models, the W takes part of an important component in the spatial analysis. The estimation procedure involves specifying the spatial weight matrix W, which provides a structure to the assumed spatial relationships. There are some types of spatial weight matrix based on different "neighbours" defining criteria: contiguity, queen, distance, k nearest, Gabriel. We tested few of them, but we decided to work with based on 5 nearest neighbours standardized weight matrix. The main issue using other criteria is the geographical structure of European regions. For example, the choice of contiguity (simple or queen) relation based matrix, meaning that the neighbours are those which shares the same boundary, would lead to few isolated regions, because of some Italian regions being islands. Or presenting isolated units the W matrix can't be invertible which can cause some issues in estimations. One other issue was found using distance criteria. The size of European regions is very heterogeneous, for example, in Germany the FADN regions are very small compared to the rest of Europe, and in the Scandinavian countries the FADN regions cover very large areas. Thus, using distance based W matrix creates a lot of spatial relations in the central part of the Europe and very few neighbours for outer regions. The k nearest neighbours criteria allow all regions have same number of relations in order to do not overestimate spatial relations.

In this paper we test following hypothesis: H1) Fixed effects model is the most appropriate to estimate short-run relations; H2) Weather variables are more accurate to use than climatic variables into revenue function model.

First, in order to verify hypothesis H1, we estimate the following econometric spatial panel data models adapted to the net European agricultural revenues per hectare and using annual weather data: Fixed Individual Effects model with Spatial error Autocorrelation (FEi-SEM) and Fixed Temporal Effects with SEM (FEt-SEM), Individual Random Effects model with SEM (RE-SEM1) and with only time variant variables like in Fixed Effects models and Individual Random Effects model with SEM (RE-SEM2) which includes time invariant variables. We then compare the results and models quality.

Second, to test the H2, the FE-SEM and RE-SEM estimation results, based on temperature and precipitation variables represented by year-by-year covering observation period 2004-2012, will be compared to RE-SEM estimation using the long run climate averages to represent temperature and precipitation variables. We will use the RE-SEM estimation for climate based model because the Fixed effects model does not count for time invariant variables.

Finally, the primary hypothesis tests will be completed by the examination and comparison of the marginal impacts between, on one side, FE and RE models, and, on the other side, weather and climate based models. The marginal values are the measure of climate impacts on agriculture and will let us to evaluate the existing differences between these models. The marginal values are calculated as the derivative of the revenue function by climatic variable. For example, for the temperature variable it is written as follows:

$$\frac{dY}{dC_i} = \hat{\gamma_1} + 2\hat{\gamma_2}\bar{C}_i, \tag{7}$$

where γ_1 and γ_2 are combinations of β associated to climate variables and depending on estimated model specification.

3 Data

We are working at the scale of European FADN regions, we have constructed a balanced panel database for N=106 European FADN regions covering T=9 years period (2004-2012).

This paper examines climate and weather data use in the revenue function provided by JRC data. JRC database is a set gridded climate data generated through the interpolation of daily data from weather stations, providing daily precipitation, minimum and maximum temperature. We use JRC database to construct two sets of data. First, we calculated long term observed climate averages for each FADN region covering the period 1979-2003. Second, we calculate year-by-year weather variables covering the observed period 2004-2012. We consider the challenges of panel data of the agricultural revenue and discuss the use of climate and weather variables, provided by JRC database, in revenue function approach.

In the economic literature, two types of variables are usually used: (i) four seasons' average temperature and precipitation variables, with their squares, and (ii) the 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 are based on four seasons‘ averaged climate variables. Vaitkeviciute et al.[6] compare and discuss the possibility of using climate variables linked to growing season and those related to four seasons, in European agriculture case. They show that both types of climatic variables are valid to use in

[6]Vaitkeviciute, Chakir, van Passel, 2018. Climate variable choice in ricardian studies on European agriculture. *Submitted for publication.*

European based studies with Ricardian evidence. However they prevent there could be some differences in results depending on climate variable choice. Thus, we calculate temperature and precipitation averages for four seasons corresponding to winter (December-February), spring (March-May), summer (June-August) and autumn (September-November).

Net farms revenues are provided by the FADN dataset and are available at the farm level scale. We calculate the aggregated net revenue at the scale of FADN regions. The FADN database also provides information on the Utilised Agricultural Area (UAA), including owned UAA, and rented UAA. In this 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 this FADN database to calculate regional mean values.
Soil variables are also important in farm productivity. We use the European Soil Database for soil texture variables that we calculated for FADN regions. The average altitude for each region was also calculated using this database.

4 Results

We estimate Fixed effects and Random effects models with Spatial Error Model in order to account for individual heterogeneity and spatial autocorrelation. We have tree types of models: three models based on weather data and only with time variant variables (FEi-SEM, FEt-SEM, RE-SEM1), one model using weather data but including time invariant variables (RE-SEM2), and one model based on climate data and including time invariant variables. To confirm the model choice five specification tests are calculated for our models. First, the Spatial Hausman test (SHT) is used to test the efficiency of spatial random effects estimator. Then we also use the joint test for spatial error correlation and random effects (LM-H), a conditional test for spatial error correlation (BSK), and marginal random individual effects (LM1) and spatial autocorrelation (LM2) tests, developed by Baltagi et al. (2003). The specification tests for the models based on weather data and only taking into account time variant variables confirms the existent spatial autocorrelation and do not reject the random effects. In contrary to two other types of models, where the tests reject the hypothesis of spatial autocorrelation in the models. We presume that the country fixed effects may capture information on unobservable spatial variables. The results of these tests are reported in Table 1.

The estimation results for different models using are presented in Table 2. The first hypothesis tests whether if the fixed effects models are the most appropriate to estimate short-run relations between the weather and agriculture revenues. First, we ran some specification tests adapted for spatial panel data as described in previous paragraph an presented in Table 1. These tests do not reject the random effects model, which is a mixed model able to capture short-run and long-run relations. Few additional tests adapted to panel data should be ran to confirm which

Table 1: Specification tests

Hypotheses	FEi-SEM, FEt-SEM, RE-SEM1	RE-SEM2	RE-SEM3
Spatial Hausman test (SHT)			
H_0: SEM-RE is efficient	$\chi^2_{17} = 1.046$	$\chi^2_{17} = 5.421$	$\chi^2_1 = 1,781.6$
H_1: One model is inconsistent	$p = 1$	$p = 0.996$	$p < 0.001$
Joint test for spatial error correlation and random effects (LM-H)			
H_0: $\sigma^2_\mu = \lambda = 0$	$2,867.5$	$2,445.0$	$2,421.4$
H_1: $\sigma^2_\mu \neq 0$ or $\lambda \neq 0$	$p < 0.001$	$p < 0.001$	$p < 0.001$
Conditional test for spatial error correlation (BSK)			
H_0: $\lambda = 0$ (assuming $\sigma^2_\mu \geq 0$)	25.043	20.253	18.503
H_1: $\lambda \neq 0$ (assuming $\sigma^2_\mu \geq 0$)	$p < 0.001$	$p < 0.001$	$p < 0.001$
Marginal test for random individual effects (LM1)			
H_0: $\sigma^2_\mu = 0$ (allowing $\lambda \neq 0$)	53.406	49.422	49.208
H_1: $\sigma^2_\mu > 0$ (allowing $\lambda \neq 0$)	$p < 0.001$	$p < 0.001$	$p < 0.001$
Marginal test for spatial autocorrelation (LM2)			
H_0: $\lambda = 0$	3.907	1.583	-2.568
H_1: $\lambda \neq 0$	$p < 0.001$	$p = 0.113$	$p = 1.99$

model is better.

The models estimated coefficients, presented in Table 2, shows that results are very stable and very close between individual fixed effect (FEi-SEM) and individual random effects (RE-SEM1) models, especially for the statistically significant coefficients associated to temperature and precipitation in summer. Both models predicts a concave, increasing but with decreasing rate, relation between mean summer temperature and farmers' revenues. By calculating the optimal summer temperature values for European agriculture, the FEi-SEM model predicts 19.5°C while RE-SEM1 model estimates the optimal summer temperature value to 20°C. The optimal temperature value indicates us in which moment the higher temperatures starts to have a negative impact on agriculture. Knowing that in the observed period summer temperature goes from 10.6°C (minimum) to 26.1°C (maximum), with the average of 18.7°C, we can certify that in Europe the optimal temperature predicted by these model has been already reached and some regions are suffering from too high summer temperatures.

Moreover, we can compare the total marginal impacts of climate on agriculture revenues of all models using weather data and estimating short run climate impacts on agriculture. The total

Table 2: Spatial panel data models estimations

	Dependent variable: Net revenue per 100 ha				
	Weather				Climate
	FEi-SEM	FEt-SEM	RE-SEM-1	RE-SEM-2	RE-SEM-3
Temperature winter	−0.003	−0.633	0.046	−0.020	10.448
	(0.187)	(0.669)	(0.193)	(0.192)	(10.448)
Temperature winter squared	−0.022	−0.132***	−0.021	−0.023	−0.809
	(0.018)	(0.046)	(0.018)	(0.018)	(0.525)
Temperature spring	−0.126	1.476	0.184	−0.361	21.993
	(0.883)	(1.953)	(0.862)	(0.894)	(21.932)
Temperature spring squared	0.017	0.047	0.009	0.024	−0.184
	(0.041)	(0.099)	(0.042)	(0.042)	(0.925)
Temperature summer	4.089**	5.899	4.185**	4.084**	21.659
	(1.899)	(3.737)	(1.985)	(1.965)	(27.704)
Temperature summer squared	−0.105**	−0.202**	−0.105**	−0.108**	−0.720
	(0.051)	(0.098)	(0.053)	(0.052)	(0.704)
Temperature autumn	−1.439	−5.086**	−1.350	−1.751*	−66.277***
	(0.920)	(2.524)	(0.952)	(0.951)	(25.561)
Temperature autumn squared	0.030	0.234**	0.030	0.041	1.958**
	(0.037)	(0.095)	(0.038)	(0.038)	(0.902)
Precipitation winter	0.016	0.100	0.019	0.009	−0.529
	(0.041)	(0.106)	(0.044)	(0.043)	(0.651)
Precipitation winter squared	0.0001	−0.0004	0.00004	0.0001	0.003
	(0.0003)	(0.001)	(0.0003)	(0.0003)	(0.004)
Precipitation spring	−0.067*	0.041	−0.062	−0.072*	0.899
	(0.040)	(0.114)	(0.043)	(0.042)	(1.595)
Precipitation spring squared	0.001**	−0.0001	0.001*	0.001**	−0.010
	(0.0003)	(0.001)	(0.0003)	(0.0003)	(0.011)
Precipitation summer	−0.077**	−0.137*	−0.078**	−0.076**	−0.200
	(0.030)	(0.078)	(0.032)	(0.031)	(1.090)
Precipitation summer squared	0.0004***	0.001*	0.0004**	0.0005***	0.001
	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.006)
Precipitation autumn	−0.043	−0.045	−0.039	−0.047	0.172
	(0.033)	(0.091)	(0.035)	(0.034)	(1.013)
Precipitation autumn squared	0.0002	0.0002	0.0002	0.0002	0.001
	(0.0002)	(0.0005)	(0.0002)	(0.0002)	(0.006)
Rented share	−0.139**	−0.267***	−0.173***	−0.220***	−0.235***
	(0.071)	(0.036)	(0.056)	(0.066)	(0.070)
Population per ha				0.825	0.750
				(0.583)	(0.563)
Clay				−1.299	−2.006*
				(0.954)	(1.061)
Sand				−0.903	−1.045*
				(0.586)	(0.598)
Altitude				0.003	−0.005
				(0.008)	(0.018)
AT				−20.867	−25.787
BE				1.835	−7.062
DE				−8.331	−21.202**
DK				−15.433	−16.944
EL				2.362	26.774
ES				−7.324	7.414
FI				−14.690	11.607
IE				−21.974	−37.076*
IT				2.956	16.379
LT				−19.351	−27.138
LU				−6.486	−16.300
LV				−15.730	−16.787
NL				1.090	−9.142
PL				−14.244	−26.397*
PT				−8.424	−16.066
SE				−23.356**	−26.847
SI				−25.477	−25.765
UK				−19.130**	−30.373**
Constant			−7.277	77.487	229.403
			(18.310)	(49.484)	(170.725)
rho	0.122**	0.251***	0.136**	0.105*	0.118*
	(0.051)	(0.047)	(0.050)	(0.047)	(0.051)
phi			7.214***	5.764**	4.769***
			(1.072)	(0.868)	(0.726)
RMSE	19.502	19.673	19.076	17.117	15.902

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

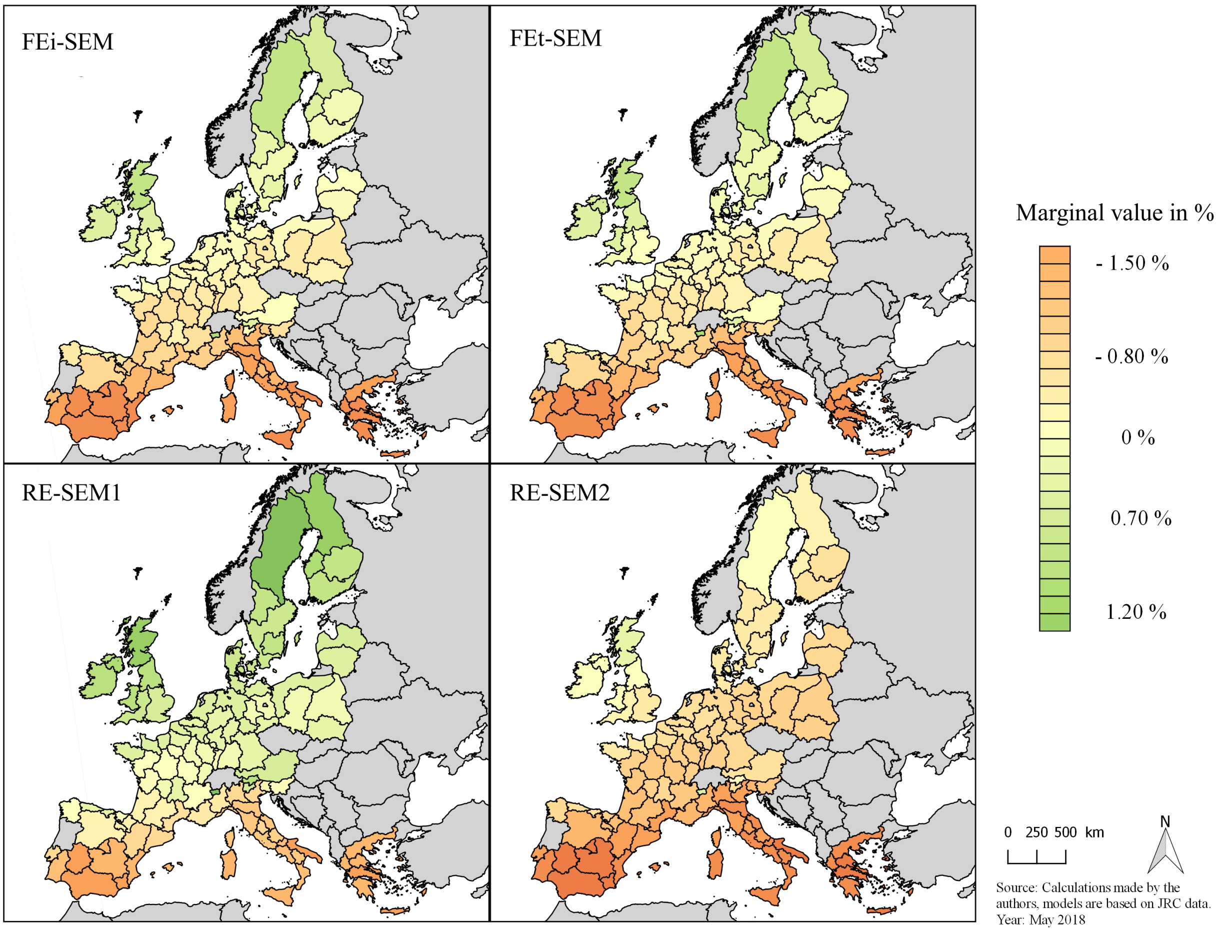

Figure 1: Total marginal effect of weather on agricultural revenues

marginal values per FADN region for these models are presented in Figure 1 and the average values per country are reported in Table3. The fixed effects models as well as the RE-SEM1 model predict similar marginal impacts, with positive impact for the northern Europe and the negative impacts in Southern regions. However, the RE-SEM2 model, which includes time invariant variables and controls for fixed country effect, is more pessimistic than previous tree models. RE-SEM2 predicts negative marginal impacts for almost all the European regions, except few northern FADN regions, but negative impacts for all Europe if looking at averages by countries(3).
Based on these results it is not possible to to favour one of the models, unless one relies on economic intuitions. Noticing the stability of results for the models FEi-SEM, FEt-SEM and RE-SEM1, these models seems to be all adapted to measure short run climate impacts on agriculture revenues. We will favour the FEi-SEM model for further comparison.

The second hypothesis tests whether the weather variables are more accurate to use in the revenue function than the climate variables. We start to examine this hypothesis by approaching the estimated RE-SEM3 model in the Table 2. First, we notice that estimated statistically

Table 3: Total weather and climate marginal values in percentage of net agricultural revenue per 100 ha

Country	FEi-SEM	FEt-SEM	RE-SEM1	RE-SEM2	RE-SEM3
AT	$-0,06$	$0,21$	$0,34$	$-0,43$	$-4,37$
BE	$-0,18$	$0,25$	$0,19$	$-0,48$	$-2,83$
DE	$-0,22$	$0,11$	$0,17$	$-0,55$	$-4,05$
DK	$0,04$	$0,51$	$0,46$	$-0,31$	$-2,58$
EL	$-1,33$	$-0,74$	$-1,02$	$-1,52$	$2,45$
ES	$-0,89$	$-0,38$	$-0,56$	$-1,11$	$0,30$
FI	$0,18$	$0,32$	$0,67$	$-0,33$	$-6,47$
FR	$-0,40$	$0,05$	$-0,05$	$-0,68$	$-2,37$
IE	$0,27$	$0,38$	$0,66$	$-0,04$	$-3,83$
IT	$-0,84$	$-0,30$	$-0,50$	$-1,09$	$0,52$
LT	$-0,14$	$0,26$	$0,28$	$-0,55$	$-5,54$
LU	$-0,24$	$0,10$	$0,13$	$-0,56$	$-4,45$
LV	$-0,08$	$0,29$	$0,35$	$-0,50$	$-5,56$
NL	$-0,11$	$0,35$	$0,26$	$-0,42$	$-2,14$
PL	$-0,28$	$0,10$	$0,12$	$-0,64$	$-4,57$
PT	$-1,01$	$-0,22$	$-0,72$	$-1,14$	$3,12$
SE	$0,22$	$0,26$	$0,69$	$-0,25$	$-6,04$
SI	$-0,48$	$-0,13$	$-0,12$	$-0,79$	$-3,22$
UK	$0,24$	$0,44$	$0,64$	$-0,09$	$-3,21$

significant coefficients in climate based model (RE-SEM3), associated to autumn temperature, are very high, giving the average marginal value of autumn temperature equal to -20.4%. Moreover, these coefficients are the only ones statistically significant in this model, or the temperature in autumn should not be the only determinant for the agricultural revenues in Europe.

The tests of the H3 can be completed by the comparison of marginal values presented in Figure 2. We calculated the total marginal impacts for two of our models: FEi-RE[7] using weather data and RE-SEM3 based on climate data. Comparing maps we observe an important differences between model using weather and the one using climate variables. In the climate based model the marginal values have significantly larger range (from -8% to +8%) and proposes a counter

[7]We chose to compare climate based results with a fixed effects model because we argue that fixed effects models are the best adapted to estimate short run relations between weather and agriculture revenues. Nevertheless, a similar comparison can be made with other estimates models and their marginal values presented in Table 2 and in Figure 1.

intuitive marginal impacts. This model suggests that warmer and wetter climate would be harmful to the agriculture in the central and northern European regions, and that southern regions would benefit from the warmer climate.

Weather based model is represented on the left of the Figure **??**. The predicted marginal values are more intuitive than in climate based model. Thus, the results differ significantly for models based using weather data and the model using climate data. We accept the H2 based on the analysis. This is the major contribution of this paper and proves that the climate impacts estimations based on revenue function approach should not use the climate variable but the annual weather data which is directly related to annual farmers revenues.

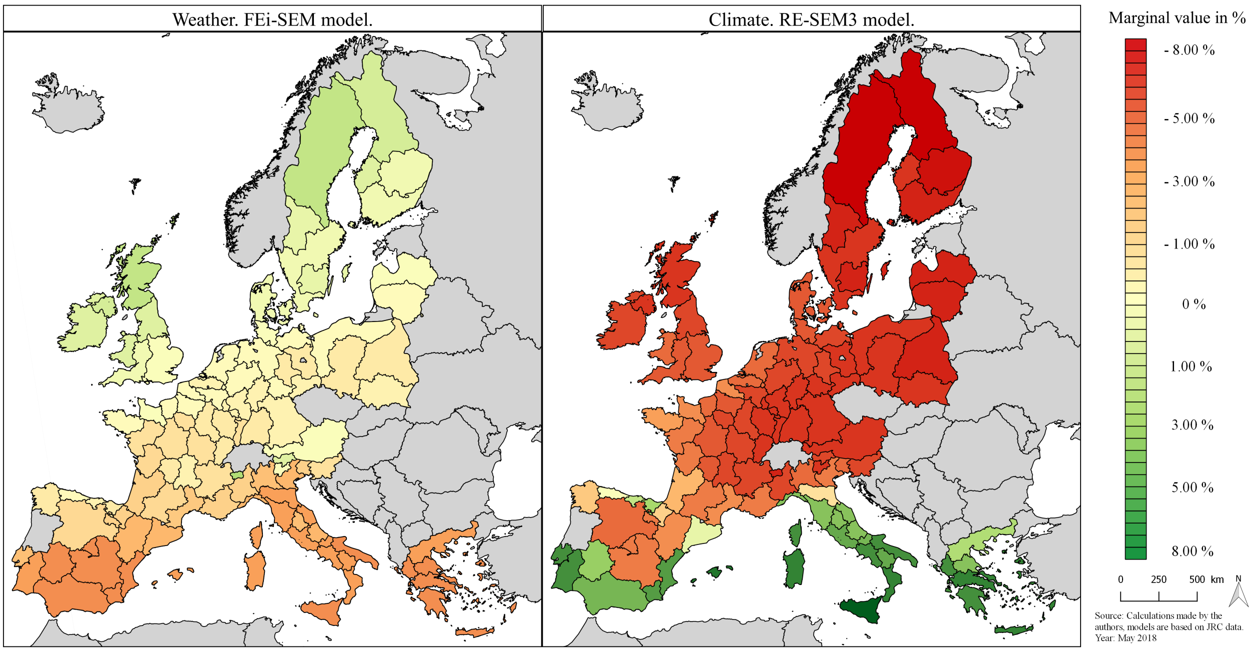

Figure 2: Total marginal effect of weather and climate

5 Conclusion

Understanding the potential effects of climate change on economic outcomes in agriculture is central to identify levers for adapting to the changing climate. Our study proposes a climate change impacts valuation at the EU level using agricultural revenue approach in a spatial panel framework. We compared the impacts of short-run weather variations on the economic profitability of European agriculture using Fixed effects and Random effects with Spatial Error models. Our models are estimated at the EU scale using a balanced panel database for N=106 European FADN regions covering T=9 years period (2004-2012).

Our paper has tree main contributions to the literature. First, this is the fist paper adopting the revenue approach to measure climate impacts on European agriculture. Previous European studies used Ricardian approach to estimate long-run relationship between climate and agricultural activity. We found that our models estimates negative climate impacts on agricultural revenues for southern regions, and negative impacts for Northern regions. It is interesting to notice, that even if other studies made on European agriculture used different methods, we found similar results.

Second, we estimate climate change impacts taking into account for spatial autocorrelation and individual heterogeneity of EU regions using the revenue function approach. The revenue function approach was proposed by Deschenes and Greenstone (2007) to estimate short-term impacts of climate on agriculture. Their paper was criticized because it did not took into account the spatial autocorrelation. We took this critique into account and we estimated all of our models with Spatial Error Model. We also ran some statistical specification tests to confirm the presence of spatial autocorrelation in our models.

Third, we discuss the relevance of using variables based on annual weather variations instead of climate data in the revenue function approach. This hypothesis was one of our main motivation for this study. The revenue function approach was implemented by Deschenes and Greenstone (2007), but it was very poorly used as their initial model. The most common use of the agricultural revenues as the dependent variable was in the studies based on Ricardian framework, and, thus, long term climate averages. We argue that agriculture revenues are the annual data directly impacted by the annual weather conditions, and not by the 25 or 30-years average past climate. In this study we compared the estimations based on weather data and those based on climate data. our results show a significant differences in the estimated impacts. Thus, we argue that climate data is not relevant to use in our revenue function based analysis on European agriculture.

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