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The effect of policy leveraging climate change adaptive capacity in agriculture

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Abstract

Agricultural adaptation to climate change is indispensable. However, the degree of adaptation depends on adaptive capacity levels and it only takes place if the appropriate resources are present. Cross-sectional climate response models ignore this requirement. This paper adapts the Ricardian method to control for a generic territorial adaptive capacity index. The results for a sample of over 60.000 European farms show a significant non-linear positive relationship between adaptive capacity and climate responsiveness and that some regions in Europe can increase their climate responsiveness significantly. This confirms that improvement of adaptive capacity is an important policy tool to enhance adaptation.

Keywords: Adaptive capacity, adaptation, Europe, cross-sectional, climate change

JEL classification: Q120, O200

1. Accounting for adaptive capacity

Adaptability of farming systems to climate change will prove to be a key aspect of farm survival and food security (Berrang-Ford, Ford and Paterson, 2011; Moore and Lobell, 2014). On average, farm-level adaptation leads to yield benefits of approximately 10 per cent with these benefits of adaptation differing considerably between regions and farms (IPCC, 2007b: WGII AR4 Section 5.5.1). Adaptation has therefore become a key goal in the response to climate change (IPCC, 2014a), as substantial climate change is unavoidable due to past emissions (IPCC, 2007; Stern, 2007). Consequently, climate change studies have to

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account for these adaptive farm measurements instead of merely modelling the biophysical relationship between a crop and its surrounding climate.

The Ricardian Method is the most prominent statistical method for measuring the impacts of climate change on agriculture capturing long-run adaptation to climate (Mendelsohn, Nordhaus and Shaw, 1994). This method, however, does not sufficiently acknowledge the efforts needed before adaptation can take place. Kelly, Kolstad and Mitchell (2005), for instance, point out that adaptation implies adjustment costs but that these are not covered by the Ricardian method. The present paper goes one step further and takes into account that before adaptation can take place, a farmer needs to be 'able' to adapt. This ability is highly influenced by both access to resources and the cost of using these (Kates, 2000; IPCC, 2014b). (Farm) systems must possess the necessary set of natural, financial, institutional and human resources, along with the ability, awareness, expertise and knowledge to use these resources effectively, before they can adapt (IPCC, 2001; Brooks and Adger, 2004). This is defined as adaptive capacity (IPCC, 2001). Adaptive capacity comes before the adaptation itself, as it represents the potential of a system to adapt (Brooks, 2003).

Adaptive capacity has been studied and quantified in previous studies (IPCC, 2001; Yohe and Tol, 2002; Brooks and Adger, 2004; Greiving *et al.*, 2013). However, even though adaptive capacity is measured and discussed in many publications, it is hardly taken into account in studies on the impact of climate change on agriculture. As shown by Vanschoenwinkel, Mendelsohn and Van Passel (2016), this leads to cross-sectional studies being too optimistic regarding autonomous profit-maximising farm adaptation behaviour because it makes adaptation unconditional, making it appear like a somewhat 'easy' solution that does not need a lot of intervention (Lobell, 2014).

Adaptive capacity at the level of the individual farm has been identified as critical for successful climate change adaptation (Wamsler and Brink, 2015). This is because farmers are not responding sufficiently to recent climate changes (Adger *et al.*, 2007; Burke and Emerick, 2016). The Fourth Assessment Report (AR4) evaluates farm level adaptation as inadequate to reduce climate change vulnerability (IPCC, 2007). Even though adaptation plans have been developed at different (sub)national levels, there is still limited evidence of adaptation implementation (IPCC, 2014a). Consequently, there has been a shift in focus that reframes adaptation as capacity building. This in turn calls for a better understanding of the impact of adaptive capacity on adaptation and the ensuing climate response.

This paper examines the relationship between adaptive capacity and the agricultural climate response and quantifies the impact of adaptive capacity on agricultural climate responses. The paper looks specifically to Europe, which has a high capacity to adapt compared to other world regions (IPCC, 2014a). Nevertheless, within Europe, there are large differences in adaptive capacity (Fuentes, 2012; Greiving *et al.*, 2013). In this paper, we examine whether these differences in adaptive capacity will cause marginal climate change effects to differ significantly between more- and less-developed regions. This research question is in part inspired by the latest IPCC report (IPCC, 2014a), which points out that in Europe there is 'a lack of information on the resilience of cultural landscapes and communities, and how to manage adaptation, particularly in low-technology (productively marginal) landscapes' (IPCC, 2014a: 1305). More studies on rural development implications in Europe are needed (IPCC, 2014a) and 'there is a need to better monitor and evaluate local and national adaptation responses to climate change' (IPCC, 2014a: 1304).

In what follows, Section 2 discusses the Ricardian method and explains why this method leads to an overestimation of the effects of adaptation. Section 2 also explains how the Ricardian method can correct for this bias. Next, Section 2 discusses the data and elaborates on adaptive capacity indicators. Sections 3 and 4 present and discuss the results, respectively. The final section concludes the paper.

2. Material and methods

The main objective of this paper is to include adaptation in climate response functions in a more realistic way by better accounting for possible barriers to or reinforcements of adaptation (that is, adaptive capacity). Methodologically this implies that we need both a method that measures farm level climate response while accounting for adaptation (Section 2.1.), and also a measurement of adaptive capacity (Section 2.2).

2.1. The Ricardian method

The cross-sectional Ricardian method (Mendelsohn, Nordhaus and Shaw, 1994; Vanschoenwinkel, Mendelsohn and Van Passel, 2016; Van Passel, Massetti and Mendelsohn, 2017) measures the impact of long-run climate on farmland productivity. A key assumption is that farmers maximise profits and fully adapt to the climate they live in. This method can examine farm net revenue (Sanghi and Mendelsohn, 2008; Seo and Mendelsohn, 2008; Kurukulasuriya, Kala and Mendelsohn, 2011) or, as done in this paper, land value[1] (Maddison, 2000; Vanschoenwinkel, Mendelsohn and Van Passel, 2016; Van Passel, Massetti and Mendelsohn, 2017; Vanschoenwinkel and Van Passel, 2018). A second key assumption underlying the method is that farm net revenue or land value reflects the present value of future net income

1 Land values are established or negotiated after an event has taken place (ex post). This explains why land values are robust and show little fluctuation. With regard to adaptation, this means that land values look at the current climate while assuming it will only marginally change, allowing the current adaptation means to be sufficient. As such, land values assume that farmers who are adapted to the current climate will adapt in the same way in the future. That is, their current adaptation means and productivity factors, which are influenced by their current adaptive capacity, influence their future adaptation behaviour to marginal changes in climate. The latter is in line with the fact that farm adaptation is reactive (not anticipating or pro-active); meaning that farm adaptation mostly takes place after an event has taken place. Therefore, we can assume that land values are based on current adaptation means to current climate or to only marginal changes in climate.

(NI) for each farm (Ricardo, 1817; Seo and Mendelsohn, 2008b). As described in Vanschoenwinkel, Mendelsohn and Van Passel (2016), NI of the farm can be described as follows (Mendelsohn and Dinar, 2003; Wang *et al.*, 2009):

$$\text{NI} = \sum P_{qi} Q_i (X_i, L_i, K_i, C, Z, G) - \sum P_x X_i - \sum P_L L_i - \sum P_K K_i \quad (1)$$

where P_{qi} is the market price of crop i, Q_i is the output or production function for crop i, X_i is a vector of purchased inputs for crop i, L_i is a vector of labour for crop i, K_i is a vector of capital, C is a vector of climate variables, Z is a set of soil characteristics, G is a set of socio-economic variables, X_i is a vector of purchased inputs for crop i, P_x is the vector for prices of annual inputs, P_L is the vector for prices for labour and P_K is the rental price of capital. The net present value of NI (V) is as follows (Mendelsohn and Dinar, 2003; Wang *et al.*, 2009):

$$V = \int \Big[\sum P_{qi} Q_i (X_i, L_i, K_i, C, Z, G) - \sum P_x X_i - \sum P_L L_i \\ - \sum P_K K_i \Big] e^{-\varphi t} dt \quad (2)$$

where t denotes time and φ is the discount rate. This paper's focus on land values instead of net revenues is justified by the fact that land value data are more robust and stable over time.

The Ricardian model itself is derived from equation (2) assuming that each farmer maximises NI by choosing the optimal amount for the different endogenous variables (i.e. those that are within his or her control such as inputs and other management choices: Q_i, X_i, L_i, K_i) given the exogenous conditions (i.e. those that are outside the farmer's control such as climate, naturally available water or soil type: P_q, C, Z, G, R, P_x, P_L, P_K) (Mendelsohn, Nordhaus and Shaw, 1994; Maharjan and Joshi, 2013).

$$\text{NI}^* = f\,(P_q,\ C,\ Z,\ G,\ R,\ P_x,\ P_L,\ P_K) \quad (3)$$

$$\text{LV}^* = f\,(C,\ Z, \text{M},\ \text{CD}) \quad (4)$$

$$\text{LV} = \beta_0 + \beta_1 C + \beta_2 C^2 + \beta_3 Z + \beta_4 M + CD \quad (5)$$

Equations (3) and (4) show how exogenous variables only explain variations in the future net value of net income (NI*), and thus land value (LV*) (Mendelsohn, Arellano-Gonzalez and Christensen, 2009). Variables such as labour, capital and crop choice are not included in the Ricardian regression because they are endogenous and assumed to be optimised. The exogenous variables can be grouped in four subgroups (see equation (4)): regional control variables related to soil type and elevation (Z), regional market-related variables including population density, subsidies, distance to ports and cities (M), seasonal climate variables (C) (Mendelsohn, Arellano-Gonzalez and Christensen, 2009) and country dummies variables (CD).

The linear and squared terms of the climate variables in the estimation model (equation (5)) are in line with earlier field studies that showed a non-linear response of the net revenue function to climate change (Mendelsohn, Nordhaus and Shaw, 1994; Mendelsohn and Dinar, 2003). Interpreting the climate coefficients from the estimation model follows from the marginal effect of climate change (ME_i), which is calculated as follows:

$$\mathrm{ME}_i = \frac{\partial \mathrm{LV}}{\partial C_i} = \beta_{1,i} + 2\beta_{2,i} C_i \tag{6}$$

The annual average marginal effect of temperature is derived by taking the sum of the average seasonal marginal effects. When presenting the marginal effects, we weighted the average results by a weight reflecting the total amount of farmland that each farm represents in its region. This implies that the marginal effects of temperature, MEt, as presented in this paper can be interpreted as the percentage change in 1 hectare of land value in a certain region associated with an increase of 1°C in temperature (Mendelsohn, Nordhaus and Shaw, 1994).

Note that the regressions also include country fixed effects (CD = country dummy) to capture national characteristics not captured by the other control variables (as these mostly control for regional or farm-level influences on land value). As suggested by Van Passel, Massetti and Mendelsohn (2017), we did not include regional fixed effects (e.g. NUTS3) as these may remove too much of the climate variations in land values.

The model is estimated using ordinary least square (OLS) regression and the results can be compared with previous peer-reviewed work (Vanschoenwinkel, Mendelsohn and Van Passel, 2016; Van Passel, Massetti and Mendelsohn, 2017) because apart from the adaptive capacity index, similar data are used. We corrected for non-normality of land values by log transforming the dependent variable as suggested by Massetti and Mendelsohn (2011) and Schlenker, Hanemann and Fisher (2006). To control for heterogeneity, each farm is weighted using the hectares of owned agricultural land of that farm (Vanschoenwinkel, Mendelsohn and Van Passel, 2016).

Schlenker and Roberts (2009) and Van Passel, Massetti and Mendelsohn (2017) emphasise the importance of using spatially corrected standard errors. Vanschoenwinkel, Mendelsohn and Van Passel (2016) tested this for the FADN data comparing the model used in this paper (country fixed effects model) with a linear mixed effect model. They concluded that there was no significant difference between both models, justifying the use of an OLS model with country fixed effects in our case of a large FADN dataset.[2] The size of the dataset has a positive influence on the robustness of the model with respect to capturing unmeasurable influences on land value (Vanschoenwinkel, Mendelsohn and Van Passel, 2016).

2 The reader can email the author for the specific results of the mixed effect model for this paper.

2.2. Adaptive capacity (index) in the Ricardian method

As explained, the key characteristic of the Ricardian method is that the method implicitly accounts for full adaptation. It is assumed that farms are fully adapted to the environment they live in (Mendelsohn, Arellano-Gonzalez and Christensen, 2009) (this is because the method assumes profit maximisation (Mendelsohn and Massetti, 2017)). As such, looking at how farmers behave in response to their environment provides understanding how farmers will respond to climate change from the comparison of farmers' profit maximising behaviour across climates while controlling for their differences by means of control variables. In this way, adaptation is taken into account as it is captured by the cross-sectional data.

The reasoning above implies that farmers in one location will behave the same as farmers in a second location, if that second location were made to look like the first one (taking into account the control variables) (Timmins, 2006; Lippert, Krimly and Aurbacher, 2009). However, this means the Ricardian method often ignores regional and individual farm level barriers to or requirements for adaptation that might influence farmers' options and choices. Adaptation to climate change takes place in a dynamic biophysical, social, economic, technological and institutional context that varies over time, location and sector. The resulting complex interactions determine the ability of the system to adapt to the changing climate by reducing its vulnerability (Kelly and Adger, 2000; Smit *et al.*, 2000; Smit and Wandel, 2006; Smith *et al.*, 2011) or maintain its resilience (Folke *et al.*, 2010). In this context, adaptive capacity is characterised as the critical system property, shaped by the equilibrium within various social, cultural, political and economic forces that provide the system the ability to reduce its social vulnerability through the realisation of adaptation (Adger and Vincent, 2005; Adger *et al.*, 2005; Smit and Wandel, 2006).

There are numerous ways of defining adaptive capacity given all the natural, financial, institutional and human forces, combined with sector specific, timely and locational influences. Adaptive capacity can differ greatly with regard to geographical scaling, timing and specificity.

For instance, regarding the latter point, in relation to the nature of the hazard to which a socio-ecological system must adapt, adaptive capacity can be generic or specific (Adger and Vincent, 2005; Adger *et al.*, 2005). A generic adaptive capacity index refers to the fact that some attributes of the system (e.g. wealth, economic status, efficient governance and institutions and access to technological innovations) characterise the system's ability to adapt to various, non-specific, potential hazards related to the changing climate stimuli. A specific adaptive capacity index, on the contrary, only measures the factors that will make a socio-economic system less vulnerable to only one specific type of hazard (e.g. drought, flood) and not to others (Adger *et al.*, 2005).

On the other hand, adaptive capacity can be considered at different spatial (national, regional, community or individual) levels (Preston and Stafford-Smith, 2009). For instance, government adaptive capacity guarantees and regulates individuals access to and efficient use of resources (Adger *et al.*, 2005). Higher spatial or governance levels influence lower levels as the ability to adapt at individual or local level takes place within a defined institutional context that mediates their access to adaptation opportunities. In addition, national policies may constitute external barriers affecting the possibilities of individuals to develop efficient adaptation strategies (Brooks, 2003).

The fact that national policies have an influence adaptive capacity on lower spatial levels is important as individuals have limited intrinsic ability to cope with discrete deviation in 'normal' climate conditions (that is, the autonomous or reactive adaptive capacity) (Engle, 2011). This is especially the case with the increasing severity of the changes in climate conditions that cause higher ecological, social and economic costs (Ciscar *et al.*, 2011, 2014; IPCC, 2014a). Adaptive capacity is not a static attribute of the system (Smit and Wandel, 2006): it can be improved over time, which makes it an important factor to be examined and discussed from both a research and a policy point of view.

It is therefore important to account for adaptive capacity in order to avoid incorrect assumptions about adaptation options available to the farmer. One needs to consider the adaptive capacity to obtain a realistic picture of adaptation (Marshall *et al.*, 2013). For our model this implies that we should add an additional group of variables to the model to account for adaptive capacity:

$$\mathrm{LV}^* = f(C,\ Z,\ M,\ CD,\ \boldsymbol{AC}) \tag{7}$$

In equation (7), adaptive capacitive is represented by $\boldsymbol{AC}$. This extra control variable is needed as land value (or productivity) is also influenced by adaptive capacity and differences in AC might explain differences in land value across farmers. A good measure of adaptive capacity is therefore needed.

Adaptive capacity is a complex, multidimensional and broad concept, consisting of several subcomponents (Below *et al.*, 2012). A wide range of factors such as finance, knowledge, nature and technology should be captured when measuring adaptive capacity. Given this complexity, adaptive capacity is commonly synthesised in an index, making it more comprehensive and operational, and facilitating communication between academics, policy makers and practitioners (Gallopin, 1997). There are different types of adaptive capacity indices varying with regard to geographical scaling, specificity and timing. For the purpose of this paper, we focus on a more generic climate change adaptive capacity index. This is done to maintain the perspective of tackling the adaptive capacity ignorance of existing cross-sectional studies as such and to provide straightforward policy insights. Whereas a more generic adaptive capacity index is not specific to agriculture or for a specific climate event (e.g. drought), it is important to take adaptive capacity at higher geographical and institutional levels into account because it has an influential enabling or constraining role in individual farm adaptive capacity (Greiving *et al.*, 2013). As such, the adaptive capacity considered in this manuscript is still exogenous to the farmer.

2.3. Data

In equation (7), we presented our data in six main groups (Land Value included). Land value data (LV*) are farm-specific data from 2012 and are obtained through the Farm Accountancy Data Network (FADN) (FADN, 2014). FADN provides farm-specific measures of approximately 80,000 farm holdings in the EU-27, which represent nearly 14 million farms with a total utilised agricultural area of about 216 million hectares. FADN data are collected uniformly and consistently over Europe, which is important in order to correctly compare different regions. For privacy reasons, it is not possible to link these farm holdings to unique locational coordinates, but they can be linked to the different NUTS3 (Nomenclature of Territorial Units for Statistics regions) in the EU. These are homogenous geographic units across all European countries that are identified by the EU. We used a sample of 60,563 commercial farms that utilise 5,470,490 hectares of farmland and cover by stratification 54 per cent of all agricultural areas in the EU-27, situated in 1,143 NUTS3 regions. This means that all other variables (climate and control variables) not observed at the farm-level are specified at the NUTS3 level. For the climate data, this study uses as a baseline climate the 30-year normal for temperature and precipitation for 1961–1990 from the Climatic Research Unit (CRU) CL 2.0 (New *et al.*, 2002). Soil data are from the Harmonized World Soil Database, a partnership of Food and Agriculture Organization (FAO), the European Soil Bureau Network and the Institute of Soil Science (FAO/IIASA/ISRIC/ISSCAS/JRC, 2009). Additional socio-economic and geographic variables (population density, distance from urban areas and distance from ports, mean elevation, elevation range and GDP per capita) were obtained from EuroGeographics Natural Earth Data, the World Port Index, ESRI and Eurostat, respectively (ESRI, 2014; EuroGeographics, 2014; National Geospatial-Intelligence Agency, 2014; Natural Earth, 2014; Eurostat, 2016).

Finally, with regard to the ACI, this paper opted for the ESPON index (Greiving *et al.*, 2013) (the ESPON climate change project), which is based on the five main determinants of a system's generic adaptive capacity as proposed by the third assessment report (IPCC, 2001): knowledge and awareness, technological resources, infrastructure, institutions and economic resources. A set of 15 indicators (see Appendix 1 in supplementary data at *ERAE* online) is used as proxies for these determinants. These individual indicators were normalised in order to have comparable scales for each indicator. The value of each determinant is calculated as the average of the normalised values of the respective indicators. Next, these determinant values are combined as a weighted average, using weights drawn from a Delphi survey conducted as part of the ESPON project (Greiving *et al.*, 2013). The ESPON index is based on the methodology proposed by the ATEAM project (Schröter *et al.*, 2004). Figure 1 visualises the ESPON index by region. Southern and Eastern European regions have the lowest ranking on the generic index. This confirms that generic indices that focus on technology,

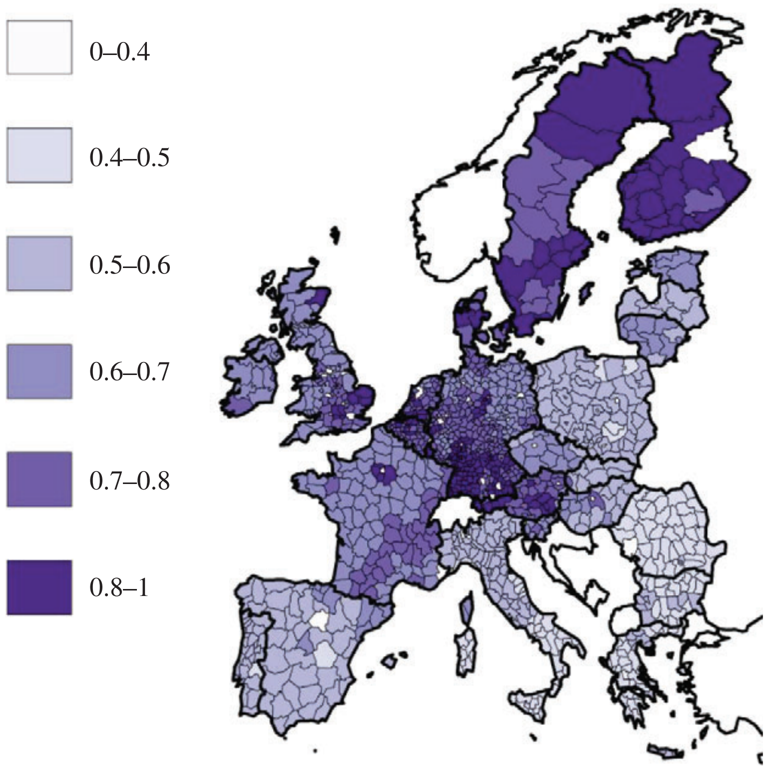

Fig. 1. ESPON Adaptive Capacity Index by region (figure adapted from Greiving *et al.*, 2013) – the higher the index, the better.

knowledge, institutions and economics are highly correlated with socio-economic determinants. Finland has the highest score on the index and is assumed to be best prepared to adapt to marginal climate changes.

Note that we do not make use of climate scenarios. This is because future climate change takes place over a longer time period and adaptive capacity can be assumed to evolve over this time period. While we can measure adaptive capacity today, we do not know how adaptive capacity will change. As such, this paper measures the impact of current adaptive capacity to marginal changes in climate.

In Appendix 2 (in supplementary data at *ERAE* online), an overview of the dependent variable and the explanatory variables with their data sources can be found. Additional information on these data and the method can also be found in Vanschoenwinkel, Mendelsohn and Van Passel (2016) and Van Passel, Massetti and Mendelsohn (2017), although the present paper uses more recent data from 2012.

3. Results

The results of the proposed model show that adaptive capacity has a significant influence on the impact of marginal changes in climate. Table 1 and Figure 2 show the main results and prove that the differences between the models (both at European as at country level) are significant.

The detailed regression results can be found in Appendix 3 (in supplementary data at *ERAE* online). All control variables have the expected signs

Table 1. Marginal effects of temperature of the original model, marginal effects of temperature of the model with the ESPON adaptive capacity index, Standard error of the difference of the marginal effects between models, *t*-value and *p*-value of the difference to see whether the difference between both models is significant.

Weighted *t*-test of model differences

Mean MEt	Original	ESPON	Std error difference	*t*-value	*p*-value
Annual	0,09163	0,07232	0,00037	52,15055	0,00000
Winter	0,19403	0,15099	0,00035	124,22560	0,00000
Spring	0,38516	0,32800	0,00039	146,11830	0,00000
Summer	−0,18208	−0,18597	0,00039	9,93145	0,00000
Autumn	−0,30548	−0,22069	0,00066	−129,33300	0,00000
Mean MEt/country	**Original**	**ESPON**	**Std error difference**	***t*-value**	***p*-value**
Austria	0,12995	0,10594	0,00098	24,42139	0,00000
Belgium	0,13191	0,11069	0,00027	7,80346	0,00000
Bulgaria	0,01963	−0,00994	0,00103	28,79660	0,00000
Czech Rep.	0,11838	0,09771	0,00024	86,18938	0,00000
Germany	0,11995	0,10145	0,00023	79,24143	0,00000
Denmark	0,11473	0,09070	0,00051	47,42788	0,00000
Estonia	0,06573	0,06280	0,00040	7,29737	0,00000
Greece	−0,00518	−0,03024	0,00055	45,60648	0,00000
Spain	0,01700	0,00726	0,00079	12,29564	0,00000
Finland	0,06133	0,07647	0,00066	−22,78444	0,00000
France	0,11221	0,08988	0,00059	37,59815	0,00000
Hungary	0,07839	0,04801	0,00039	78,22141	0,00000
Ireland	0,21555	0,19713	0,00034	54,57332	0,00000
Italy	0,02490	−0,00131	0,00075	34,97530	0,00000
Lithuania	0,08415	0,06982	0,00025	57,40282	0,00000
Luxembourg	0,01331	0,11836	0,00000	109275	0,00000
Latvia	0,07784	0,06777	0,00033	30,08050	0,00000
The Netherlands	0,14119	0,11820	0,00035	65,79295	0,00000
Poland	0,10636	0,08770	0,00009	199,42870	0,00000
Portugal	0,05192	0,01712	0,00128	27,13889	0,00000
Romania	0,06833	0,03293	0,00096	37,01714	0,00000
Sweden	0,10209	0,10111	0,00074	1,32889	0,00000
Slovenia	0,10480	0,07733	0,00062	44,28790	0,00000
Slovakia	0,11177	0,08328	0,00136	21,01746	0,00000
United Kingdom	0,19220	0,17093	0,00091	23,32718	0,00000

(compare with previous peer-reviewed work (Vanschoenwinkel, Mendelsohn and Van Passel, 2016; Van Passel, Massetti and Mendelsohn, 2017)). The coefficient on the adaptive capacity index is highly significant, and the ANOVA tests[3] show that adding adaptive capacity to the original regression gives significant information on top of the already-included variables in the

3 Analysis of variance *F*-value: 1,653.8 (*p*-value: 0.0000).

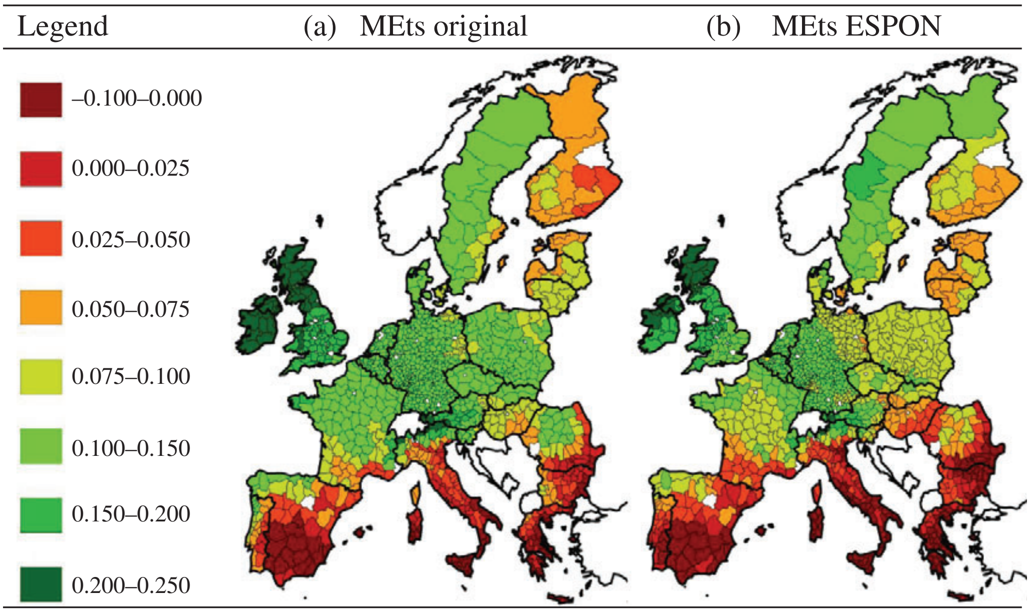

Fig. 2. Marginal effects of temperature plotted by NUTS3 regions (authors' own elaboration using FADN data 2012); the marginal effects are weighted by the hectares of farmland of each farm. This implies that the marginal effects, as presented, can be interpreted as the percentage of change in 1 ha land value in each region associated with an increase of 1°C in temperature; (a) shows the MEts of the original regression, ignoring adaptive capacity and (b) shows the MEts of the original regression when also taking into account ESPON adaptive capacity.

original regression. The climate coefficients are analysed by examining the marginal effects of temperature in line with differences in adaptive capacity.

Figure 2B visualises the marginal effect of temperature for the model without AC (adaptive capacity) (Figure 2A) and the marginal effect of temperature of the regression that does account for adaptive capacity by means of the ESPON index. It is clear that apart from Finland, all countries show decreasing marginal effects of temperature when adding an AC index. In particular, countries scoring low on the ESPON index register the highest drops in MEts. Clear differences are also noted between Western Germany (MEt = 10–15 per cent) and Eastern Germany (MEt = 7.5–10 per cent) when the ESPON adaptive capacity is taken into account. Yet, also in more developed regions, the original cross-sectional coefficients are significantly overestimated and adaptive capacity does not seem to be sufficient for all the adaptation options needed. The relationship between MEts and the ESPON index is therefore clear in the sense that higher adaptive capacities lead to lower drops in MEts, indicating that higher adaptive capacity levels allow support of the necessary adaptation options needed to avoid decreases in MEts. This is a clear indication that the original cross-sectional estimates were too optimistic because they disregard the fact that adaptive capacity is a requirement for adaptation and that adaptation cannot simply autonomously take place.

However, looking at Figure 3, it is clear that increasing adaptive capacity does not result in a proportional increase in MEts. First, a minimum threshold adaptive capacity must be reached before adaptive capacity leads to increases in MEts. At low levels of adaptive capacity, large efforts are needed before benefits in terms of MEts are obtained. Once a threshold has been crossed, benefits in MEts increase exponentially. Second, there are multiple thresholds. Increases in MEts will flatten off at a certain point and then further increases in adaptive capacity are again necessary before benefits are visible. Third, at a certain point, further increases in ESPON adaptive capacity do not lead to increases in MEts. These regions will probably benefit more from increases in specific adaptive capacity with regard to floods and droughts for example, rather than from further increases in generic adaptive capacity.

4. Policy implications and discussion

The estimation results show the effect of ignoring the importance of adaptive capacity in Ricardian studies of European agriculture and climate change and suggest the following policy implications. First, within Europe there is a clear need for adaptive capacity development in a significant number of agricultural areas (mostly Southern and Eastern European countries). Nevertheless, in Europe, the Common Agricultural Policy (CAP) has ignored the importance of climate-change-specific adaptation and adaptive capacity. There are no compulsory legislative forces at the European level to compel climate adaptation, and policy has mostly focused on mitigation (Jordan *et al.*, 2012).

Second, we show that the positive relationship between adaptive capacity and the impact of marginal changes in climate is not necessarily linear. This implies that not all increases in adaptive capacity will lead to positive effects in terms of the impact of marginal changes of climate. The results suggest that adaptive capacity needs to reach a threshold before a policy intervention in a certain region will have a positive effect on farm level adaptation. Some regions will need to put in more effort than others to increase climate responsiveness. This is an important insight, especially important with regard to distribution of funding, emphasising our previous point.

Third, it is not just regions of currently lower adaptive capacity that should prepare better for climate change. Regions with a higher adaptive capacity should as well. This paper shows that once a certain generic adaptive capacity level has been achieved, no further significant improvements in climate responsiveness can be expected. This indicates that more-developed regions are less capable of preparing themselves to marginal climatic changes through their conventional tools. They should increase their adaptive capacity to more specific events (such as droughts) in order to see more positive effects in their response to climate change. Countries such as Spain have already shown to be better adapted to drought than more northern regions (Ciais *et al.*, 2005).

While the results give new insights into the importance of adaptive capacity, further research is needed to understand how farm adaptation depends on incentives at higher governance levels or whether there is interdependency between incentives at different governance levels (i.e. regional versus (supra-) national). Further research should also define the different AC thresholds and

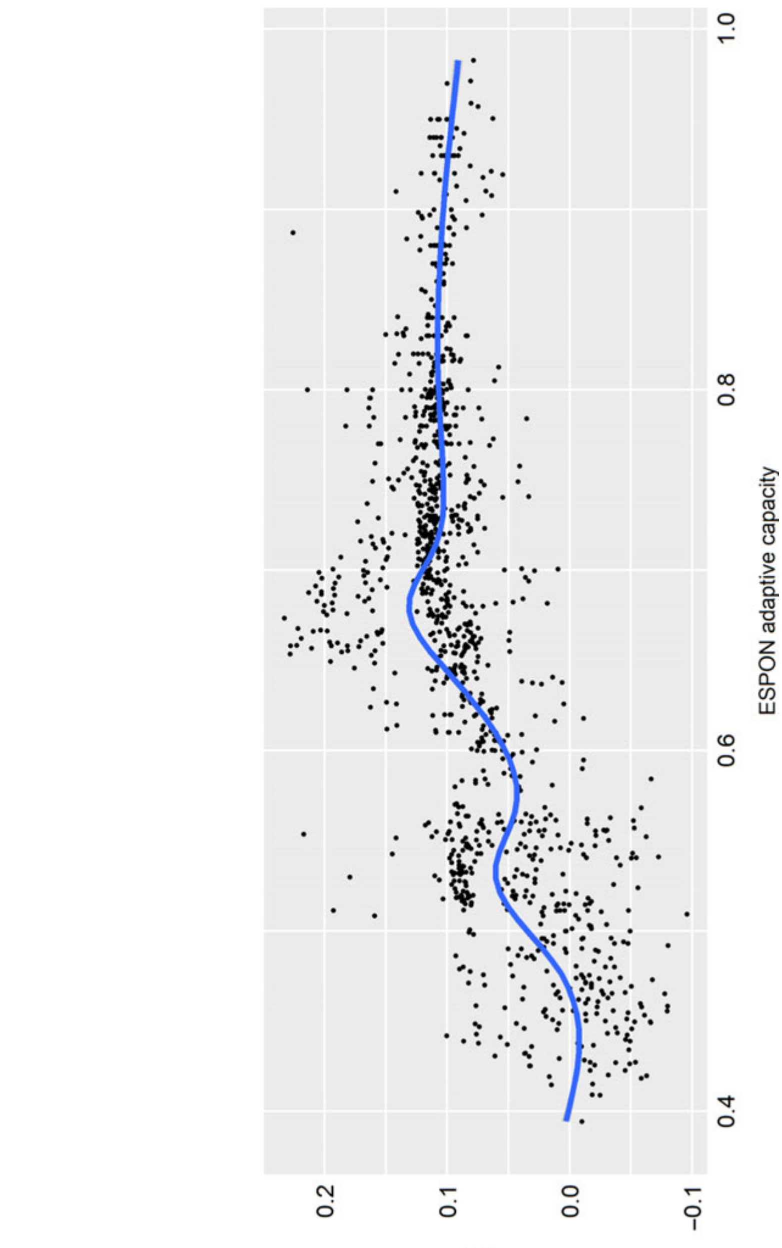

Fig. 3. Evolution of MEts compared to adaptive capacity.

indicate in which regions increases in adaptive capacity are most cost efficient. However, the opposite reasoning is also important: in certain regions, even though adaptive capacity might seem high, if exposure exceeds a certain threshold (e.g. tipping points), even higher adaptive capacities cannot bring solutions (Reidsma and Ewert, 2008). Adaptive capacity development therefore should be further linked to exposure. In this regard, it is very important to specify more impact-specific adaptive capacities, such as with regard to floods and drought, because these might lead to significantly different results. Finally, adaptive capacity is only one part of the complex process of climate change adaptation. Transition and adjustment costs, the timing of adaptation, specific types of adaptation and different levels of responsibility are important components and even requirements for adaptation.

With regard to the robustness of our results, it should be pointed out that the country fixed effect included in the model potentially captures some effect of the adaptive capacity. The difference between the two empirical models therefore might describe only part of the difference in adaptive capacity. The real effect of adaptive capacity might therefore be larger, making it even more important. Nevertheless, including country dummies to control for differences in land market policies and regional agricultural policies (Pillar 2 of the CAP) between member states is indispensable in the model. Furthermore, it should also be noted that some variables that are usually included in the Ricardian model are not included in this paper. For instance, our baseline model does not correct for local GDP per capita, nor does it correct for the regional length of roads. This is because these variables are already included in the ESPON index. We therefore did not these include variables to avoid correlation between the ESPON index and these other variables. However, we did test the baseline model with the variable GDP/capital and motorway length included. Including the variables did not change the results or the conclusion. This is in line with the findings of Vanschoenwinkel, Mendelsohn and Van Passel (2016): their baseline model with the variable GDP/capital and motorway length gives the same results as our baseline model without these variables.

5. Conclusion

Agricultural adaptation to climate change is indispensable. However, the degree of adaptation depends on adaptive capacity levels and it only takes place if the appropriate resources are present. Cross-sectional climate response models ignore this requirement. In this paper, we adapted the Ricardian method to control for a generic territorial adaptive capacity index. Our results for European farms show a significant non-linear positive relationship between adaptive capacity and climate responsiveness and that some regions can still increase their climate responsiveness significantly. This suggests that improvement of adaptive capacity is an important policy tool to enhance adaptation.

Policy makers in Europe should therefore intervene and provide the appropriate resources to stimulate adaptive capacity development. They should set clear, non-voluntary and measurable targets for climate action, against which member states must deliver in order to receive funding. Given the large diversity within the European Union, the different Member States' needs and the fact that adaptation is a local action, flexibility in policy implementation should still be allowed, but this should not undermine common objectives and goals. The non-linear relationship between adaptive capacity and marginal climatic change impacts suggest that in some Member States additional effort will be required before positive results of improved adaptive capacity can be expected. In Member States where current generic adaptive capacity is already substantial, more diverse policy intervention might be needed regarding specific climate events such as drought. This is because after a certain threshold the benefits from generic adaptive capacity level off.

Supplementary data

Supplementary data are available at *European Review of Agricultural Economics* online.

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Competing financial interests

The authors declare no competing financial interests.

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