



*The World's Largest Open Access Agricultural & Applied Economics Digital Library*

**This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.**

**Help ensure our sustainability.**

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

[aesearch@umn.edu](mailto:aesearch@umn.edu)

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

*No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.*



# The effect of policy leveraging climate change adaptive capacity in agriculture

*S. Van Passel<sup>1</sup>; J. Vanschoenwinkel<sup>2</sup>; M. Moretti<sup>2</sup>*

*1: University of Antwerp, Department of Engineering Management, Belgium, 2: Hasselt University, , Belgium*

*Corresponding author email: [steven.vanpassel@uantwerpen.be](mailto:steven.vanpassel@uantwerpen.be)*

## **Abstract:**

*Agricultural adaptation to climate change is indispensable. Unfortunately, most climate response modeling methods accounting for adaptation are based on economic modelling that assumes simple farm profit-maximization and autonomous farm adaptation. This makes adaptation look like something 'unconditional', explaining why agricultural policy down-sized the attention for adaptation. This is incorrect as adaptation is facing numerous barriers such as low levels of adaptive capacity. This paper therefore captures and quantifies the impact of adaptive capacity explicitly in economic cross-sectional models, showing that those methods can be more policy-oriented. It shows that higher levels of adaptive capacity lead to more positive climate responses.*

*Acknowledgment: This paper was supported by the Horizon 2020 project SUFISA (Grant Agreement No. 635577).*

**JEL Codes:** Q51, Q18

#772



# The effect of policy leveraging climate change adaptive capacity in agriculture

**Abstract:**

Agricultural adaptation to climate change is indispensable. Unfortunately, most climate response modeling methods accounting for adaptation are based on economic modelling that assumes simple farm profit-maximization and autonomous farm adaptation. This makes adaptation look like something ‘unconditional’, explaining why agricultural policy downsized the attention for adaptation. This is incorrect as adaptation is facing numerous barriers such as low levels of adaptive capacity. This paper therefore captures and quantifies the impact of adaptive capacity explicitly in economic cross-sectional models, showing that those methods can be more policy-oriented. It shows that higher levels of adaptive capacity lead to more positive climate responses.

**Key Words:** Adaptive Capacity, Adaptation, Europe, Cross-sectional, Climate Change

## **1. Accounting for adaptive capacity**

Adaptation to climate change is unavoidable [1] as substantial climate change is inevitable due to already unavoidable past emissions [2, 3]. This is especially the case for the agricultural sector who is directly dependent on its surrounding environmental conditions and therefore “arguably the sector mostly affected by climate change” (p.1) [4]. In the EU, one of the worst droughts occurred in 2003: July temperatures went up to 6°C above long-term means and precipitation was 50 percent below the average. This caused a reduction in Europe’s primary crop productivity that was unprecedented [5]. However, this reduction in crop productivity was much lower in Mediterranean countries because they were more adapted to dry and hot summers by means of irrigation and drought-tolerant crops [5]. Clearly, adaptability of farming systems is important and it will prove to be a key aspect of farm survival and food security [6, 7]. On average, adaptation leads to approximately a 10% yield benefits compared with farmers that do not adapt, even though the benefits of adaptation differ between regions and farms (IPCC [3], WGII AR4 Section 5.5.1.). Adaptation has therefore become an important pillar for the response to climate change [8].

Climate change adaptation implies making “adjustments in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities (IPCC (2007) [3]). Historically, farmers responded autonomously to changes of climate [9] and studies examining the impact of climate change therefore realized that they had to account for these adaptive farm measurements instead of merely modeling the natural relationship between a crop and its surrounding climate. The most famous method addressing this point of taking into account adaptation, is the Ricardian Method [10].

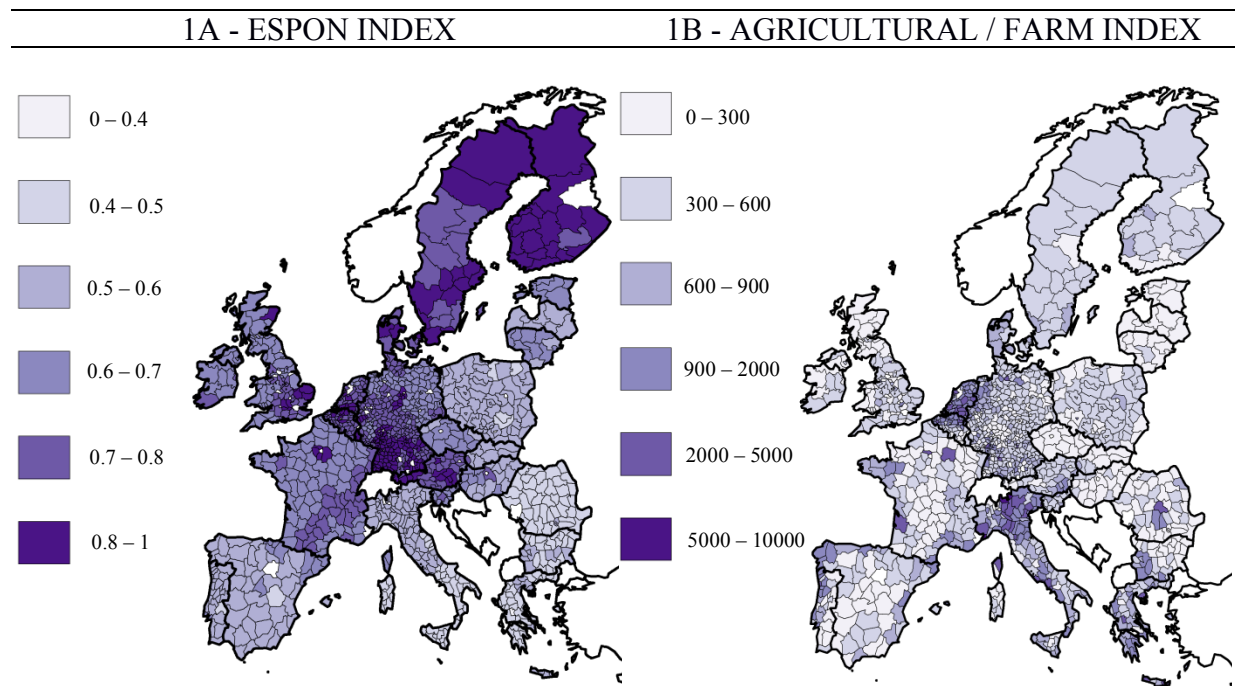
Today, however, it appears that farmers are not responding quickly to recent climate changes anymore [11, 12]. The Fourth Assessment Report (AR4) indicated that the level of adaptation was inadequate to reduce climate change vulnerability [3]. Even though adaptation plans are being developed at different (sub)national levels, there is still limited evidence of

adaptation implementation [13]. This is because compared to the gradual change in climate in the past, climatic events occurring in and predicted for this century are of a larger magnitude, occur fast and discrete, and therefore cannot be readily absorbed [14]. In addition, before adjustments to this level of climate change can take place, a number of requirements need to be fulfilled. One of the key components that is necessary to have in place before adaptation can take place, is a farmer's ability to adapt. This ability is highly influenced by differential resource access and adaptation costs [15-17]. (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 [18, 19]. This is defined as adaptive capacity [19]. As described in the First Assessment Report (FAR), adaptive capacity is dynamic and influenced by social networks, institutions, governance, technology and other resources [12], implying that it can be linked to the theory of innovation economics. Innovation is briefly summarized as the implementation of solutions that fill in new requirements (in this case climate change) [20]. The theory of innovation economics says that economic growth is spurred by innovative capacity [21] and not by merely looking at prices and inputs as claimed by the neoclassicals. Adaptive capacity therefore goes further than the adaptation itself, as it represents the potential of a system to adapt [22].

Given the fact that implementation of adaptation itself goes slowly, there is currently a larger focus on framing adaptation as capacity building [23]. Individual adaptive capacities are being identified as critical for successful climate change adaptation [24]. Apart from merely taking into account adaptation, it is therefore also important to examine or take into account whether the capacity to adapt is appropriate instead of assuming that farmers always adapt autonomously. Adaptive capacity, however, is hardly ever taken into account to study the impact of climate change on agriculture. As shown by Vanschoenwinkel et al. (2016) [25], this leads to cross-sectional studies being too optimistic regarding autonomous profit-maximizing farm adaptation behavior. Not taking adaptive capacity into account gives an overly optimistic image about adaptation because it makes adaptation unconditional, making

it appear like a somewhat “easy” solution that does not need a lot of intervention [26].

This paper therefore 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 compared to other world regions a high capacity to adapt [8]. Nevertheless, within Europe, there are large differences in adaptive capacity distribution [27, 28] (see Figure 1A). In this paper, we examine whether these differences in adaptive capacity will cause climate change effects to differ significantly between more- and less-developed regions. This research question is in part inspired by the latest IPCC report [8] that 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” (p. 1305). More studies on rural development implications in Europe are needed [8] and “there is a need to better monitor and evaluate local and national adaptation responses to climate change” (p.1304).



**Figure 1:** **1A** – ESPON Adaptive Capacity Index (figure adapted from ESPON [27]) – The higher the index, the better; **1B** – Adaptive Capacity Index based on past yield fluctuations (own elaboration using FADN data 2008–2013) – The lower the index, the better.

## 2. MATERIAL AND METHODS

The main focus of this paper is to take into account adaptation in climate response

functions in a more realistic way by better accounting for possible barriers or reinforcements to adaptation (that is, adaptive capacity). In doing so we test whether the farm's climate response differs with different levels of adaptive capacity.

For the methodology used, this implies that we need a measurement of adaptive capacity and a method that measures the farm climate response while accounting for adaptation. As indicated in the previous section, the most famous method to study agricultural productivity while accounting for adaptation is the cross-sectional Ricardian method [10, 25, 29]. Yet, instead of directly looking at productivity or income, the Ricardian method uses data on land value instead. This is because the method assumes that land value reflects the present value of future net income for each farm [30, 31]. A second assumption of the method is that each farmer maximizes net income by choosing the optimal amount of all different endogenous variables that are within his or her control (such as inputs and other management choices) subject to the exogenous conditions that are outside the farm's control (such as climate, water or soil) [10, 32]. As such, the Ricardian model shows how only exogenous variables explain variations in land value [33]. Variables such as labor, capital, and crop choice, are not included in the regression because they are endogenous and assumed to be optimized. This implies that the method assumes that farms today are already adapted to the environment they live in [33]. As such, looking at how farmers behave today in response to their current environment, one can understand how farmers respond to climate by comparing them with farmers in other climates [34]. In this way, adaptation is taken into account as it is captured by the data.

All of this implies that farmers in one location 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) [35, 36]. However, this means the method often ignores regional and individual barriers or requirements to adaptation that might influence farm choices and possibilities. As explained in the introduction, adaptive capacity is a measurement for the ability of a farmer to adapt. It is therefore important to account for this in order to not make



incorrect assumptions about adaptation options available to the farmer. One needs to consider the adaptive capacity of individual farmers and/or regions to get a realistic picture of adaptation [37]. For our model this implies that we should add an additional group of variables to the model to explain adaptive capacity. Given the fact that land value is assumed to be influenced only by exogenous control variable, the model can be summarized as follows:

$$NI^* = f(C, Z, M, \mathbf{AC}) \quad (1)$$

where future net value of net income or land value is presented by  $NI^*$ ,  $Z$  are regional control variables related to soil type and elevation mean and range, and  $M$  are regional market related factors such as population density, subsidies, distance to ports and cities.  $C$  are seasonal climate variables that consist of both a linear and a squared term of seasonal temperature and precipitation [33] since earlier field studies proved the non-linear nature of the net revenue function [10, 38]. Interpreting the climate coefficients should be done by interpreting the marginal effect of climate change (determined separately for precipitation ( $p$ ) and temperature ( $t$ )) for season  $i$  ( $ME_i$ )), which is calculated as follows:

$$ME_i = \frac{\partial V}{\partial C_i} = \beta_{1,i} + 2\beta_{2,i}C_i \quad (2)$$

The annual average marginal effect ( $ME_t$  and  $ME_p$ ) 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 as presented in this paper can be interpreted as the percentage change in 1 hectare land value of a certain region associated with an increase of 1 °C in temperature for  $ME_t$  or an increase of 1cm/mo in precipitation for  $ME_p$ .

Finally, the adaptive capacity explanatory group in equation (1) is presented by  $AC$ . We discuss this in more detail in subsection 2.1. The model is estimated through an ordinary least square regression and can be compared with previous peer-reviewed work [25, 29] because apart from the adaptive capacity index, similar data are used.

## 2.1. Adaptive Capacity

A good measure of adaptive capacity is needed. Adaptive capacity is a complex, multidimensional, and broad concept, consisting of several subcomponents [39]. Data from a wide range of factors such as financing, knowledge, nature, and technology should be captured when measuring adaptive capacity. Given this complexity, we synthesize adaptive capacity in one term or index, making it more comprehensive and operational, and facilitating communication for both academic, political, and practical purposes [40]. However, there are numerous types of adaptive capacity indices differing greatly with regard to geographical scaling, content, interpretation, and timing (e.g. drought versus flood adaptive capacity). This paper will not focus on all the different types of adaptive capacity but instead focus on general climate change adaptive capacities. This is done to maintain the focus on tackling the adaptive capacity ignorance of cross-sectional studies itself, and to give straightforward policy insights. As such, we only distinguish between two types of indices: a generic and a farm adaptive capacity index (ACI).

The first index we use is a regional generic index measuring adaptive capacity to climate change. The index is not developed for the agricultural sector specifically, and it can be used over different sectors. It is developed by ESPON on a NUTS 3 European scale and measures economic, sociocultural, institutional, and technological abilities of a region to adapt (see Figure 1A) [27]. In total, 15 indicators were developed to represent the different adaptation dimensions, which were then weighted and aggregated in one index. Even though such an adaptive capacity index is not specific for agriculture or very specific climate events, it is important to take into account, because adaptive capacity at higher geographical and institutional levels has an influential enabling or constraining role in individual farm adaptive capacity [27, 41]. The lower the scale of governance, the more interdependent the capacity is. These type of regional generic indices are often seen as a reflection of a system's socioeconomic status [3], assuming that characteristics of individuals, institutions, and

organizations foster learning in the context of change and uncertainty and allow them to respond more flexibly to change and disturbance [42].

The second index we use is a more farm specific adaptive capacity index. This is because adaptation is often a site-specific action demanding a very specific and local set of resources, depending on the sector in which adaptation is needed [43, 44]. In Germany for instance, inputs explain on average 49% of the total wheat yield volatility [45]. The adaptive capacity index therefore must be specific enough to capture local variation [46] and define farm systems more narrowly [47]. Having a more specific agricultural index allows better understanding of fundamental processes underlying adaptation [39]. This helps to prepare well targeted adaptation policies. Unfortunately, no such ready-made index is available, and no agreed-upon and uncontroversial measure of adaptive capacity in agriculture exists [48]. In addition, scant guidance can be found regarding the selection of the indicator sub-determinants themselves, which causes some subjective interference of the researcher [49]. We believe one issue in building such a farm specific index is related to the question of *when* to measure adaptive capacity. Some sources assume that adaptation is related to *current* farm performance and that *current* management characteristics are therefore good indicators of adaptive capacity [50]. Other sources indicate that past experiences are good indicators of adaptive capacity. Regions build up a higher adaptive capacity to *past* limiting factors and are therefore more prepared when these issues recur [51]. As a result, more unfavorable agricultural areas do not necessarily suffer more as they adapt to the most limiting factors [52, 53]. According to this view, variables such as yield fluctuations over years are good indicators of adaptive capacity: low yield fluctuations and yield stability can be assumed to be indicators of adaptation and thus higher adaptive capacity [54]. Finally, there are authors such as Hinkel (2011) [47] and Dilling et al. (2015) [55] who note that most indices are not forward-looking enough. They state it is not about past or current behavior but instead about their ability to cope with emerging, *future* climate changes. This past-current-future distinction is very important with regard to development of indices. In this paper, we focus on the past view

because the paper's main goal is not the development of the index itself, but rather the improvement of accounting for adaptive capacity in cross-sectional studies.

## **2.2. Data**

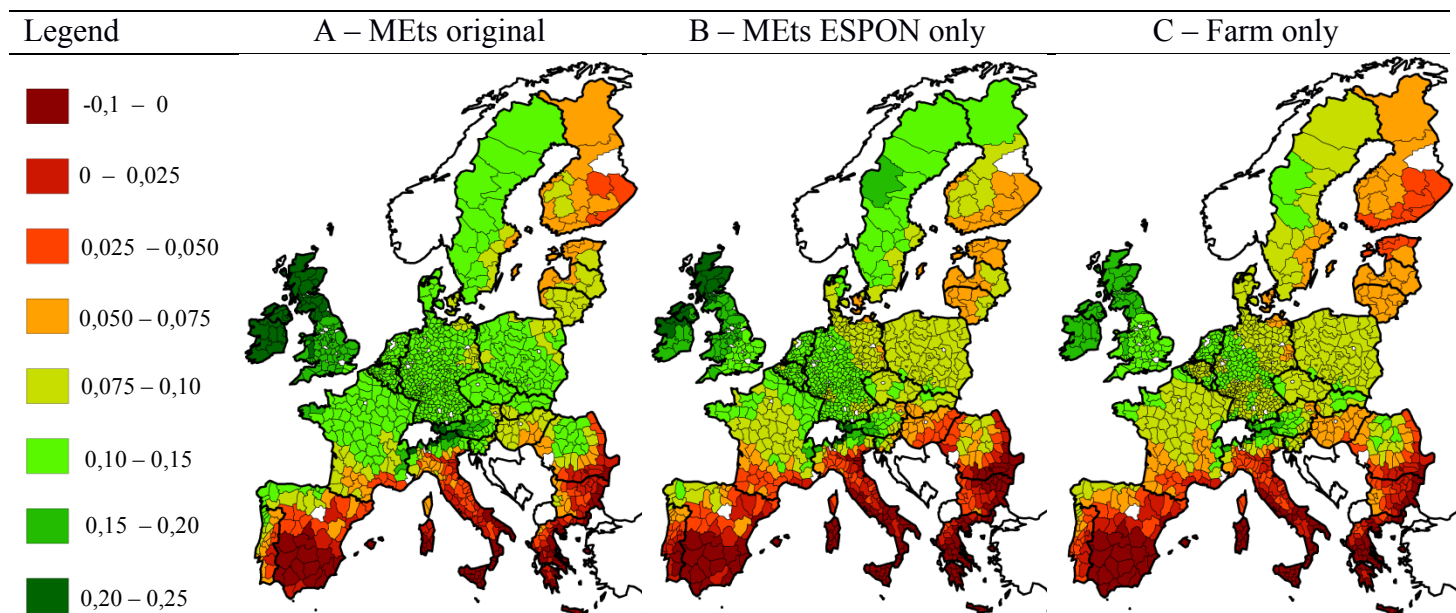
In equation 1, we presented our data in four main groups. Land value data ( $NI^*$ ) are farm-specific data from 2012 and are obtained through the Farm Accountancy Data Network (FADN) [56]. FADN provides farm-specific measures of approximately 80,000 farm holdings in the EU-27, which represent nearly 14 million farms with a total utilized 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 utilize 5,470,490 hectare of farmland and cover by stratification 54 percent of all agricultural areas in the EU-27, situated in 1143 NUTS3 regions. This means that all other variables (climate and control variables) that are not on farm-level are linked on the NUTS3 level. For the climate data, this study uses as a baseline climate the 30-year normal period for temperature and precipitation from 1961–1990 from the Climatic Research Unit (CRU) CL 2.0 [57]. Soil data come 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 [58]. Additional socioeconomic and geographic variables (population density, distance from urban areas, 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 [59-63]. Finally, regarding the AC index, we already indicated that we use the ESPON data for the generic AC index. With regard to the farm specific index, we use variations in yield per hectare per farm for the years 2008-2013 from the FADN data. As such, we capture several different characteristics and decisions of the farmer in one variable, measuring at the

same time how effective farms responded to limitations and changes in different factors of the last years. The fewer the variations, the better the farms are assumed to be adapted to their climate circumstances. In Appendix 1, 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 be found in Vanschoenwinkel et al. (2016) [25] and Van Passel et al. (2017) [29], although this paper uses more recent data from 2012.

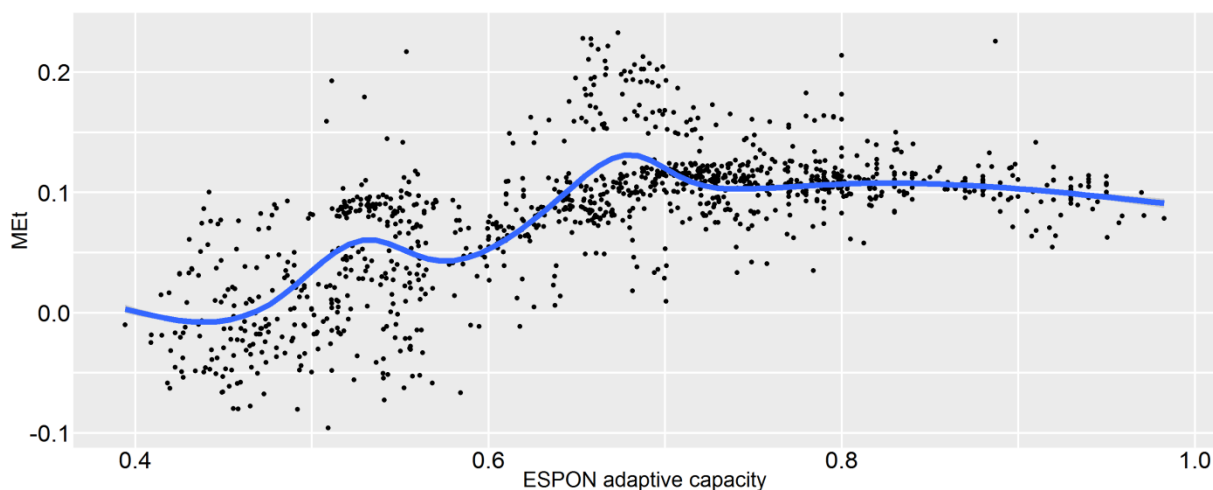
### **3. RESULTS AND DISCUSSION**

The regression results can be found back in Appendix 2. The different columns represent the different regressions whose only differences can be found in the way they do, or do not, take into account adaptive capacity. All control variables have the expected signs (compare with previous peer-reviewed work [25, 29]). In all cases, the coefficients on the adaptive capacity coefficients are highly significant, and the ANOVA tests show that adding adaptive capacity to the regression gives significant information on top of the already-included variables in the original regression. The climate coefficients are analyzed by examining the marginal effects of climate in line with differences in adaptive capacity. As explained by Mendelsohn et al. (1994) [10], marginal effects are interpreted as the percentage change in 1 hectare land value associated with an increase of 1 °C in temperature. Starting with the ESPON index, it can be seen in Figure 1A that Southern and Eastern European regions have the lowest ranking on the generic index. This is in line with the idea that generic indices that focus on technology, knowledge, institutions, and economics, are highly related to socioeconomic determinants. Finland has the highest score on the index and is assumed to be best prepared to adapt to climate change. When comparing the marginal effects of temperature of the model that does not include AC (Figure 2A), with the marginal effects of temperature of the regression which does account for adaptive capacity by means of the ESPON index (Figure 2B), it becomes clear that apart from Finland, all countries show decreasing marginal effects of temperature when adding an ACI. In particular, countries

scoring lowest on the ESPON index register the highest drops in MEts. Clear differences are also noted between Western and Eastern Germany when the ESPON adaptive capacity is taken into account. Yet, also in more developed regions, the estimates 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.



**Figure 2:** Marginal effects of temperature plotted per NUTS 3 region (own elaboration using FADN data 2012); the marginal effects plotted are weighted by a weight reflecting the total amount of farmland that each farm represents in its region. This implies that the marginal effects, as presented in this paper, can be interpreted as the percentage of change in 1 hectare land value of a certain region associated with an increase of 1 °C in temperature; **A** shows the MEts of the original regression, ignoring adaptive capacity; **B** shows the MEts of the original regression when also taking into account ESPON adaptive capacity; **C** shows the MEts of the original regression when also taking into account regional agricultural adaptive capacity index.



**Figure 3:** Evolution of METs compared to adaptive capacity

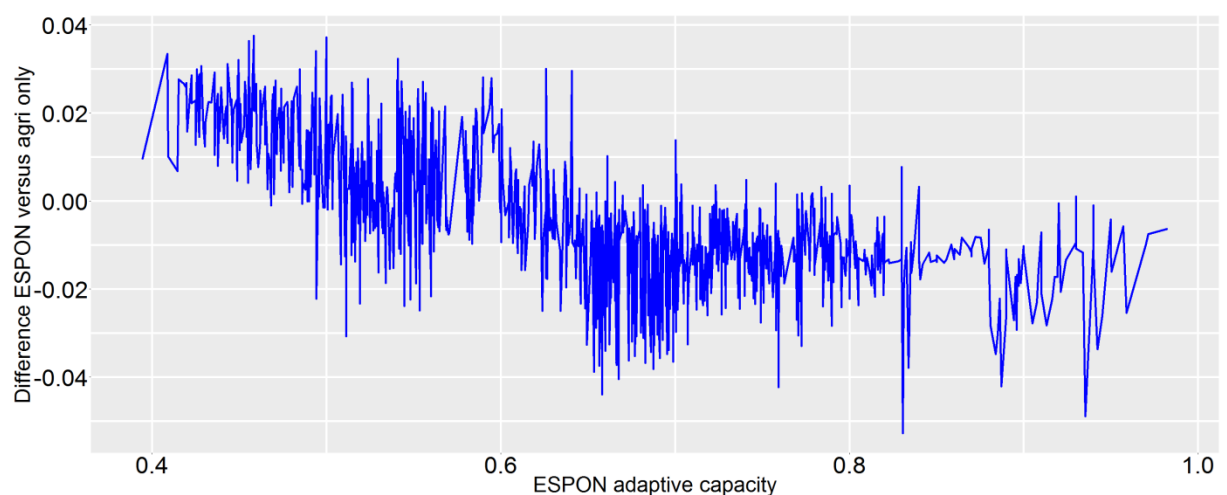
However, looking at Figure 3, it is clear that increasing adaptive capacity does not linearly result in increasing METs. First, a minimum threshold adaptive capacity must be surpassed before adaptive capacity leads to increases in METs. At low levels of adaptive capacity, large efforts are needed before benefits in terms of METs are obtained. Once a threshold is surpassed, benefits in METs increase exponentially. Second, there are multiple thresholds to be surpassed. Increases in METs will flatten out at a certain point, and then large 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, instead of further generic adaptive capacity increases.

Next to the generic ESPON index, it is also important to examine more farm-specific indices that account for past behavioral choices that farmers took and that reflect more farm-specific AC. This allows us to see the direction in which the METs are adjusted when an alternative index, not based on purely socioeconomic determinants, is taken into account. When comparing the METs of the regression to the ESPON index alone, with the METs of the regression with the farm index alone (Figure 2), it becomes clear that the farm index gives more negative results for Northwestern regions (see for instance Belgium, Germany, France, Sweden and Finland), while the results are more positive for Eastern regions (see for instance



Slovakia, Hungary, Romania and Slovenia). Clearly, the larger the stereotype ESPON adaptive capacity (which is highly correlated with socioeconomic determinants), the more the ESPON-METs are adjusted downward when using the agricultural index instead of the ESPON index. This implies that for regions with a lower ESPON adaptive capacity, taking into account farm adaptive capacity instead of the socioeconomic adaptive capacity leads to more optimistic results. This indicates that the ESPON socioeconomic index might underestimate the real agricultural adaptive capacity of less-developed regions when looking only at socioeconomic determinants. This is confirmed and visualized more clearly when plotting the difference in METs when going from a regression with a farm specific index to a socioeconomic index (y-axis) and comparing it with the original ESPON index (x-axis) (Figure 4). The higher the ESPON adaptive capacity index, the more METs are adjusted downward when using a regional agricultural index.

Note, however, that Figure 3 and Figure 4 give different types of information as their y-axes are different. Northwestern European regions continue to perform better than other European regions (see Figure 2), and the relationship between METs and adaptive capacity (Figure 3) is positive. However, looking at Figure 4, the point is that the socioeconomic index favors more-developed regions. Looking at another index (in this case a farm index based on past adaptive behavior), the results are upward adjusted for regions in transition with a lower ESPON adaptive capacity, and downward adjusted for regions with a higher ESPON adaptive capacity.





**Figure 4:** Change in METs when using a farm index instead of a socioeconomic ESPON index (y-axis), compared to the original ESPON adaptive capacity (x-axis)

While the results give new insights into the importance of adaptive capacity, further research is needed to understand how farm adaptation is dependent on higher governance levels or whether there is interdependency between different governance levels (i.e. regional versus continental). Further research should also define the different AC thresholds and indicate in which regions increases in adaptive capacity are the 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 [64]), even higher adaptive capacities cannot bring solutions [54]. Adaptive capacity therefore should be further linked to exposure. In this regard, it is very important to specify more impact-specific adaptive capacities such as floods and drought, because these might lead to significantly different results. Finally, there is still a lot more behind adaptation than adaptive capacity. Transition and adjustment costs, the timing of adaptation, specific types of adaptation, adaptive capacity, and different levels of responsibility are important components and even requirements for adaptation. Given the fact that climate change is real, it is important to take these questions more seriously.

#### **4. POLICY IMPLICATIONS**

This paper shows that lower degrees of adaptive capacity lead to larger decreases in the marginal effects of climate change. Policy makers should therefore acknowledge the importance of increasing climate change adaptive capacity. Nevertheless, in Europe, the Common Agricultural Policy (CAP) highly 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 [65]. This paper for the first time shows the effect of denying the importance of adaptive capacity and suggests the following policy points.

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). The Common Agricultural Policy (CAP) explicitly targets rural development through pillar II, but most of the funding goes to pillar I which focusses more on the status quo and does not link funding sufficiently to farm objectives and innovative changes. In addition, farmers benefit from the flexibility to modulate some of their funding between pillar I and pillar II. This paper's results are in favor of a shift from funds from pillar I to pillar II.

Second, we show that the positive relationship between adaptive capacity and the impact of climate change is not necessarily linear. This implies that not all increases in adaptive capacity will lead to positive changes in the impact of climate change. Certain thresholds will need to be exceeded before policy in certain regions has a positive effect on adaptation. Some regions will need to put forth more effort than other regions to increase their climate responsiveness. This is especially important with regard to distribution of funding, emphasizing our previous point about modulation.

Third, it is not only regions with a lower adaptive capacity that should prepare themselves better for climate change, but also regions with a high adaptive capacity should. This paper shows that once a certain generic adaptive capacity has been achieved, no further significant improvements in climate responsiveness occur. This indicates that more-developed regions are less capable of preparing themselves for climate change 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 [5].

Currently however, the CAP gives no clear directions to member states for tackling climate adaptation and adaptive capacity. For instance, apart from setting wrong funding priorities (the majority of funding goes to pillar I), its goals regarding risk management, knowledge transfer, enhancing ecosystems, climate-resilient economy, and resource

efficiency are vague and unspecified, making it hard to measure and evaluate whether the CAP succeeds in its ambitions. In addition, the tools suggested to tackle these issues often overlap in their objectives, and even the two main pillars cannot be separated from one another [66]. Consequently, some measures counteract, instead of reinforce, one another, or are competing for the same funding [67]. We therefore argue that as long as no specific targets are set for which concrete measurements exist against which member states have to deliver, it is highly questionable whether the CAP will bring along significant changes to climate change adaptive capacity. The CAP should specifically target climate change adaptation and climate change adaptive capacity, setting measurable goals for progress.

## **5. CONCLUSION**

Cross-sectional studies might give the impression that autonomous adaptation is a magical solution to tackle climate change impacts or take advantage of its benefits, but this is not the whole truth. The degree of autonomous adaptation highly depends on adaptive capacity levels and it only takes place if the appropriate requirements are present. Policy makers should therefore intervene and provide the appropriate requirements to stimulate adaptive capacity development. It should set clear, non-voluntarily and measurable targets for climate action, against which member states must deliver in order to receive funding. Given the large diversity of the European Union, the different Member State's 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 climate change impacts shows that some member states will have to make larger efforts before they see positive results of adaptive capacity. On the contrary, member states that already have a large socioeconomic adaptive capacity will have to take more diverse measurements in response to specific events such as drought before they see positive increases in climate responsiveness. This is because after a certain threshold, benefits from increasing generic adaptive capacity level out.

	Variable	Description	Units	Mean	Min	Max	Sd	Source
Farm-specific	Agricultural land value	Valued on the basis of prices (net of acquisition costs) that apply in the region for non-rented land of similar situation and quality sold for agricultural purposes. The replacement value is divided by the amount of land owned.	€/ha	12,420	50.00	654,000	22,883	FADN
	Land owned	Land in the owner's occupation and land in share-cropping	ha	41.95	1.00	4,857.00	95.27	FADN
	UAA	Utilized agricultural area consists of land in owner occupation, rented land, land in share-cropping.	ha	109.40	1.00	11,930	311.33	FADN
	Farms represented	Sum of weighting coefficients of individual holdings in the sample	number	61.66	1.00	7,665	132.01	FADN
	Subsidies	Subsidies on current operations linked to production (not investments) per UAA	€/ha	29.92	0.00	4,967.00	103.00	FADN
	Share rented land	Total leased land out of the total utilized agricultural land	ha/ha	0.35	0.00	0.995	0.33	FADN
Soil	Gravel	Volume % gravel (materials in a soil larger than 2 mm) in the topsoil	%vol	8.29	2.44	18.35	2.78	WSD
	Sand	Weight % sand content in the topsoil	%wt	47.39	18.19	83.02	10.84	WSD
	Silt	Weight % silt content in the topsoil	%wt	30.81	10.83	45.93	6.60	WSD
	Clay	Weight % clay content in the topsoil	%wt	21.3	5.80	44.53	5.00	WSD
	pH	pH measured in a soil-water solution		6.20	4.18	7.88	0.66	WSD
Geographic and socioeconomic	Distance to cities	Distance from cities with population > 500,000	km	113.7	0.90	842.80	74.62	NED
	Distance to ports	Distance from medium and large ports	km	202.5	0.90	636.20	137.59	WPI
	Elevation mean	Elevation mean	m	324.3	0.00	2,092.00	293.15	ESRI
	Elevation range	Elevation range	m	911.2	1.00	4,255.00	845.61	ESRI
	Population density	Population density in 2010	cap/km <sup>2</sup>	139.3	2.00	8,058.00	230.67	Eurostat
Adaptive capacity	ESPON index	Generic adaptive capacity index on NUTS 3 level based on awareness, ability, and action	scale	0.607	0.394	0.983	0.125	ESPON
	Agricultural index	Weighted average per NUTS 3 region of the standard deviation of output per hectare from 2008–2013	€/ha	580.60	28.11	972.3	572.74	FADN
Climate	Seasonal precipitation	Baseline climate measured by temperature and precipitation. A 30-year normal period from 1961–1990 is used	mm	5.83	5.70	6.47	6.45	CRU
	Seasonal temperature		° C	1.47	8.31	18.02	10.63	CL 2.0

**Appendix 1: descriptive statistics data and resources** ; WSD = Word Soil Database [58]; NED = Natural Earth Data [59]; WPI = World Port Index [60]; Climatic Research Unit (CRU) CL 2.0 [57]; Eurostat [63]; ESRI = Environmental Systems Research Institute [61]; ESPON = European Spatial Planning Observation Network [27]

	A - Original		B - ESPON only		C - Agri only	
	Coef	Std. Err	Coef	Std. Err	Coef	Std. Err
(Intercept)	2.639***	0.428	2.525***	0.422	2.874***	0.422
Precip. Winter	-0.041**	0.014	0.044**	0.014	-0.014	0.014
Precip. Winter Squared	0.000	0.001	-0.001**	0.001	-0.001	0.001
Precip. Spring	-0.041	0.026	-0.148***	0.026	0.005	0.026
Precip. Spring Squared	0.003*	0.001	0.006***	0.001	-0.001	0.001
Precip. Summer	0.151***	0.018	0.181***	0.018	0.110***	0.018
Precip. Summer Squared	-0.001	0.001	-0.003***	0.001	0.000	0.001
Precip. Autumn	0.067***	0.013	0.012	0.013	0.027**	0.013
Precip. Autumn Squared	-0.005***	0.001	-0.004***	0.001	-0.003***	0.001
Temp. Winter	0.184***	0.016	0.112***	0.016	0.192***	0.016
Temp. Winter Squared	0.002**	0.001	0.010***	0.001	0.001	0.001
Temp. Spring	0.126***	0.030	0.134***	0.029	0.071**	0.029
Temp. Spring Squared	0.015***	0.002	0.011***	0.002	0.013***	0.002
Temp. Summer	0.368***	0.055	-0.007	0.055	0.311***	0.054
Temp. Summer Squared	-0.015***	0.001	-0.005***	0.001	-0.013***	0.001
Temp. Autumn	-0.112*	0.057	0.290***	0.057	-0.128**	0.056
Temp. Autumn Squared	-0.009***	0.002	-0.024***	0.002	-0.007**	0.002
Population density	0.140***	0.019	0.019	0.019	0.067***	0.018
Distance to ports	-0.613***	0.047	-0.661***	0.047	-0.498***	0.047
Distance to cities	-1.332***	0.069	-1.328***	0.068	-1.393***	0.068
Rented land	0.159***	0.013	0.196***	0.013	0.183***	0.013
Elevation mean	-0.279***	0.043	-0.365***	0.043	-0.267***	0.043
Elevation range	-0.03**	0.010	-0.011	0.010	-0.034***	0.010
Subsidies	0.460***	0.015	0.447***	0.015	0.455***	0.015
Gravel	-0.012***	0.003	-0.011***	0.003	-0.007**	0.003
pH	0.305**	0.097	0.021	0.096	0.431***	0.096
pH squared	-0.004	0.008	0.017**	0.008	-0.017**	0.008
Silt	-0.006***	0.002	-0.005**	0.002	-0.001	0.002
Sand	-0.006***	0.001	-0.005***	0.001	-0.006***	0.001
Belgium	2.354***	0.051	2.260***	0.051	2.171***	0.051
Bulgaria	1.287***	0.047	1.917***	0.048	1.229***	0.046
Czech Republic	1.105***	0.035	1.414***	0.035	1.144***	0.034
Germany	2.304***	0.033	2.291***	0.033	2.247***	0.033
Denmark	3.930***	0.041	3.519***	0.042	3.758***	0.041
Estonia	0.651***	0.053	0.693***	0.053	0.594***	0.053
Greece	3.297***	0.056	3.901***	0.057	2.778***	0.056
Spain	2.185***	0.049	2.697***	0.050	2.001***	0.048
Finland	3.413***	0.070	2.389***	0.074	3.311***	0.069
France	1.259***	0.044	1.428***	0.043	1.232***	0.043
Hungary	0.792***	0.042	1.127***	0.042	0.914***	0.042
Ireland	2.484***	0.063	2.455***	0.062	2.544***	0.062
Italy	3.538***	0.044	4.310***	0.047	3.232***	0.044
Lithuania	0.804***	0.045	0.918***	0.044	0.812***	0.044
Luxembourg	2.391***	0.052	2.196***	0.051	2.404***	0.051
Latvia	0.411***	0.048	0.556***	0.048	0.430***	0.047
The Netherlands	3.590***	0.048	3.422***	0.047	3.102***	0.049
Poland	2.01***	0.035	2.545***	0.037	2.077***	0.035
Portugal	0.648***	0.059	1.254***	0.060	0.642***	0.058
Romania	0.484***	0.043	1.198***	0.046	0.535***	0.042
Sweden	3.057***	0.050	2.432***	0.052	2.852***	0.049
Slovenia	1.832***	0.054	2.351***	0.055	1.891***	0.053
Slovakia	0.825***	0.050	1.213***	0.050	0.864***	0.049
United Kingdom	2.273***	0.050	2.228***	0.049	2.313***	0.049
ESPON NUTS 3 index			3.205***	0.079		
Agricultural NUTS 3 index					0.465***	0.011
ANOVA F-test			1,656.2***		1,745.1***	
Adjust R <sup>2</sup>		0.709		0.718		0.718

**Appendix 2:** linear regression results for the different regressions; **A** - Original = original regression without taking into account adaptive capacity; **B** - ESPON only = original regression when ESPON adaptive capacity is taken into account; **C** - Agri only = original regression with only taking into account NUTS 3 agricultural adaptive capacity

## 6. REFERENCES

1. Berrang-Ford, L., J.D. Ford, and J. Paterson, *Are we adapting to climate change?* Global environmental change, 2011. **21**(1): p. 25-33.
2. Stern, N.H., *The economics of climate change: the Stern review*. 2007: cambridge University press.
3. IPCC, *Climate Change 2007 - Impacts, Adaptation and Vulnerability. Contribution of working group II to the Forth Assessment report of the Intergovernmental Panel on Climate Change*. 2007.
4. Rosenzweig, C., et al., *Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison*. Proceedings of the National Academy of Sciences, 2014. **111**(9): p. 3268-3273.
5. Ciais, P., et al., *Europe-wide reduction in primary productivity caused by the heat and drought in 2003*. Nature, 2005. **437**(7058): p. 529-533.
6. Darnhofer, I., et al., *Adaptiveness to enhance the sustainability of farming systems. A review*. Agronomy for Sustainable Development, 2010. **30**(3): p. 545-555.
7. Moore, F.C. and D.B. Lobell, *Adaptation potential of European agriculture in response to climate change*. Nature Clim. Change, 2014. **4**(7): p. 610-614.
8. Field, C.B., et al., *Climate change 2014: impacts, adaptation, and vulnerability*. Vol. 1. 2014: Cambridge University Press Cambridge and New York.
9. Wreford, A., D. Moran, and N. Adger, *Climate change and agriculture. Impacts, Adaptation, and Mitigation*. 2010, OECD.
10. Mendelsohn, R., W.D. Nordhaus, and D. Shaw, *The impact of Global Warming on Agriculture: a Ricardian Analysis*. American Economic Review 1994. **84**(4): p. 753-771.
11. Burke, M. and K. Emerick, *Adaptation to Climate Change: Evidence from US Agriculture*. American Economic Journal: Economic Policy, 2016. **8**(3): p. 106-40.
12. Adger, W.N., et al., *Assessment of Adaptation Practices, Options, Constraints and Capacity*. , in *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, M.L. Parry, et al., Editors. 2007, Cambridge University Press: Cambridge, UK.
13. IPCC, *Climate Change 2014-Impacts, Adaptation and Vulnerability: Regional Aspects*. 2014: Cambridge University Press.
14. Anwar, M.R., et al., *Adapting agriculture to climate change: a review*. Theoretical and Applied Climatology, 2013. **113**(1): p. 225-245.
15. IPCC, *Summary for policymakers, in 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*, C.B. Field, et al., Editors. 2014d, Cambridge University Press: Cambridge, United Kingdom and New York, NY, USA. p. 1-32.
16. Kates, R.W., *Cautionary Tales: Adaptation and the Global Poor*. Climatic Change, 2000. **45**(1): p. 5-17.
17. Berkhout, F., J. Hertin, and D.M. Gann, *Learning to Adapt: Organisational Adaptation to Climate Change Impacts*. Climatic Change, 2006. **78**(1): p. 135-156.
18. Brooks, N. and W.N. Adger, *Assessing and enhancing adaptive capacity*. Adaptation policy frameworks for climate change: Developing strategies, policies and measures, 2005: p. 165-181.
19. IPCC, *Climate Change 2001: Working Group II: Impacts, Adaptation and Vulnerability, Summary for Policymakers*. 2001, Cambridge University Press: New York.
20. Maranville, S., *Entrepreneurship in the Business Curriculum*. Journal of Education for Business, 1992. **68**(1): p. 27-31.
21. Antonelli, C., *The economics of innovation, new technologies and structural change*. 2014: Routledge.
22. de Assumpcao, C.R.M., et al., *Enhancing adaptive capacity of the agricultural communities across regions-the role of institutions*. 2017.

23. Smith, M.S., et al., *Rethinking adaptation for a 4°C world*. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences., 2011. **369**(1934): p. 196-216.
24. Wamsler, C. and E. Brink, *The role of individual adaptive practices for sustainable adaptation*. International Journal of Disaster Resilience in the Built Environment, 2015. **6**(1): p. 6-29.
25. Vanschoenwinkel, J., R. Mendelsohn, and S. Van Passel, *Do Western and Eastern Europe have the same agricultural climate response? Taking adaptive capacity into account*. Global Environmental Change, 2016. **41**: p. 74-87.
26. Lobell, D.B., *Climate change adaptation in crop production: Beware of illusions*. Global Food Security, 2014. **3**(2): p. 72-76.
27. ESPON, *ESPON Climate - Climate Change and Territorial Effects on Regions and Local Economies Applied Research 2013/1/4 2011*, ESPON & IRPUD, TU Dortmund University.
28. Fuentes, M., *The EU agricultural Policy - delevivering on adaptation to climate change*. 2011, European Commission - DG for Agricultural and Rural Development.
29. Van Passel, S., E. Massetti, and R. Mendelsohn, *A Ricardian Analysis of the Impact of Climate Change on European Agriculture*. Environmental and Resource Economics, 2017. **67**(4): p. 725-760.
30. Seo, S.N. and R. Mendelsohn, *A Ricardian Analysis fo the impact of climate change on south american farms*. Chilean journal of agricultural research, 2008b. **68**(1): p. 69-79.
31. Ricardo, D., *On the Principles of Political Economy and Taxation*. Works and Correspondence of David Ricardo, ed. P. Sraffa. Vol. I. 1817: Cambridge University Press.
32. Maharjan, K.L. and N.P. Joshi, *Climate Change, Agriculture and Rural Livelihoods in Developing Countries*. Advances in Asian Human-Environmental Research, ed. M. Nüsser. 2013, Japan: Springer.
33. Mendelsohn, R., J. Arellano-Gonzalez, and P. Christensen, *A Ricardian analysis of Mexican farms*. Environment and Development Economics, 2009. **15**: p. 153-171.
34. Mendelsohn, R., W. Nordhaus, and D. Shaw, *Climate impacts on aggregate farm value: accounting for adaptation*. Agricultural and Forest Meteorology, 1996. **80**(1): p. 55-66.
35. Timmins, C., *Endogenous Land use and the Ricardian Valuation of Climate Change*. Environmental and Resource Economics, 2006. **33**(1): p. 119-142.
36. Lippert, C., T. Krimly, and J. Aurbacher, *A Ricardian analysis of the impact of climate change on agriculture in Germany*. Climatic Change, 2009. **97**(3-4): p. 593-610.
37. Marshall, N.A., et al., *Climate change awareness is associated with enhanced adaptive capacity*. Agricultural Systems, 2013. **117**: p. 30-34.
38. Mendelsohn, R. and A. Dinar, *Climate, Water, and Agriculture*. Land Economics, 2003. **79**(3): p. 328-341.
39. Below, T.B., et al., *Can farmers' adaptation to climate change be explained by socio-economic household-level variables?* Global Environmental Change, 2012. **22**(1): p. 223-235.
40. Gallopin, G.C., *Indicators and their use: information for decision-making*. Scienfitic Committee on Problems of the Environmental International Council of Scientific Unions, 1997. **58**: p. 13-27.
41. Jordan, A., et al., *Climate change policy in the European Union: confronting the dilemmas of mitigation and adaptation?* 2010: Cambridge University Press.
42. Armitage, D., *Adaptive Capacity and Community-Based Natural Resource Management*. Environmental Management, 2005. **35**(6): p. 703-715.
43. Adger, W., N.W. Arnell, and E.L. Tompkins, *Successful adaptation to climate change across scales*. Global Environmental Change, 2005. **15**(2): p. 77-86.
44. Smit, B. and J. Wandel, *Adaptation, adaptive capacity and vulnerability*. Global Environmental Change, 2006. **16**(3): p. 282-292.
45. Albers, H., C. Gornott, and S. Hüttl, *How do inputs and weather drive wheat yield volatility? The example of Germany*. Food Policy, 2017. **70**: p. 50-61.
46. Vincent, K., *Uncertainty in adaptive capacity and the importance of scale*. Global Environmental Change, 2007. **17**(1): p. 12-24.
47. Hinkel, J., *"Indicators of vulnerability and adaptive capacity": Towards a clarification of the science-policy interface*. Global Environmental Change, 2011. **21**(1): p. 198-208.



48. Grasso, M. and G. Feola, *Mediterranean agriculture under climate change: adaptive capacity, adaptation, and ethics*. Regional Environmental Change, 2012. **12**(3): p. 607-618.
49. Brooks, N., W. Neil Adger, and P. Mick Kelly, *The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation*. Global Environmental Change, 2005. **15**(2): p. 151-163.
50. Reidsma, P., F. Ewert, and A. Oude Lansink, *Analysis of farm performance in Europe under different climatic and management conditions to improve understanding of adaptive capacity*. Climatic Change, 2007. **84**(3): p. 403-422.
51. Niles, M.T., M. Lubell, and M. Brown, *How limiting factors drive agricultural adaptation to climate change*. Agriculture, Ecosystems & Environment, 2015. **200**: p. 178-185.
52. Challinor, A., et al., *Assessing the vulnerability of food crop systems in Africa to climate change*. Climatic Change, 2007. **83**(3): p. 381-399.
53. Reidsma, P., et al., *Adaptation to climate change and climate variability in European agriculture: The importance of farm level responses*. European Journal of Agronomy, 2010. **32**(1): p. 91-102.
54. Reidsma, P. and F.A. Ewert, *Regional Farm Diversity Can Reduce Vulnerability of Food Production to Climate Change*. Ecology and Society, 2008. **13**(1): p. 1-16.
55. Dilling, L., et al., *The dynamics of vulnerability: why adapting to climate variability will not always prepare us for climate change*. Wiley Interdisciplinary Reviews: Climate Change, 2015. **6**(4): p. 413-425.
56. FADN. *FADN Homepage*. 2014; Available from: <http://ec.europa.eu/agriculture/rica/>.
57. New, M., et al., *A high-resolution data set of surface climate over global land areas*. Climate reserach, 2002. **21**(1): p. 1-25.
58. FAO/IIASA/ISRIC/ISSCAS/JRC, *Harmonized World Soil Database Version 1.1*. 2009: FAO, Rome, Italy and IIASA, Laxenburg, Austria.
59. Natural Earth. *Natural Earth Data Homepage*. 2014; Available from: <http://www.naturalearthdata.com/>.
60. National Geospatial-Intelligence Agency. *World port index 2014*; Available from: [http://msi.nga.mil/NGAPortal/MSI.portal?\\_nfpb=true&\\_pageLabel=msi\\_portal\\_page\\_62&pubCode=0015](http://msi.nga.mil/NGAPortal/MSI.portal?_nfpb=true&_pageLabel=msi_portal_page_62&pubCode=0015).
61. ESRI. *Homepage ESRI*. 2014; Available from: <http://www.esri.com/>.
62. EuroGeographics. *Homepage EuroGeographics*. 2014; Available from: <http://www.eurogeographics.org/>.
63. Eurostat, *Database*, E. Commision, Editor. 2016.
64. Lenton, T.M., et al., *Tipping elements in the Earth's climate system*. Proceedings of the National Academy of Sciences, 2008. **105**(6): p. 1786-1793.
65. Jordan, A., et al., *Understanding the paradoxes of multilevel governing: Climate change policy in the European Union*. Global Environmental Politics, 2012. **12**(2): p. 43-66.
66. Bureau, J. and L. Mahé, *Was the CAP reform a succes?*, in *The Political Economy of the 2014-2020 Common Agricultural Policy - An Imperfect Storm*, J. Swinnen, Editor. 2015, Rowman & Littlefield International, Ltd.: London.
67. Swinnen, J., *The Political Economy of the 2014-2020 Common Agricultural Policy: Introduction and key conclusions*, in *The Political Economy of the 2014-2020 Common Agricultural Policy - An Imperfect Storm*, J. Swinnen, Editor. 2015, Rowman & Littlefield International, Ltd.: London.