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A novel way of approaching farm-specific climate change adaptation

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Promoter: Prof. Dr Ir Steven Van Passel

"Anything else you're interested in is not going to happen if you can't breathe the air and drink the water. Don't sit this one out. Do something. You are by accident of fate alive at an absolutely critical moment in the history of our planet." – Carl Sagan

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"You must not let anyone define your limits because of where you come from. Your only limit is your soul." – Ratatouille (2007)

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ENGLISH SUMMARY

The agricultural sector is one of the sectors directly dependent on the climatic conditions of its surrounding environment. With climate change, farmers need to adjust their current farm management practices to adapt to new climatic conditions in order to moderate climate change impacts or exploit beneficial opportunities. To provide insights into these adaptation decisions and processes, it is important to use climate change impact models that account for the numerous adaptation strategies farmers possess to displace no-longer-advantageous activities under new climate conditions. As a result, the microeconomic approach most commonly used to assess the impact of climate change on agriculture is the Ricardian method. The Ricardian method accounts implicitly for adaptation options by assuming that farmers maximize their profits by optimizing all variables within their control. The only variables that then influence yields are exogenous variables outside the farmer's control. The method uses cross-sectional data, as it assumes that farmers today have adapted to their current environment. As such, by looking at how farmers behave in response to their current environment, one can understand how farmers respond to climate change by comparing them with farmers in other climates.

Nevertheless, the Ricardian method's ability to capture adaptation has to be treated with caution because it does not model adaptation explicitly. Endogenous farm management variables are not explicitly modeled by the method, as these are assumed to be optimized. As a result, the user of the results of the Ricardian method gains no insight into how a farmer adapts, making adaptation invisible and undefined. This is unfortunate for adaptation practitioners who need to gain more insight into the adaptation decision and implementation process itself. The goal of this dissertation is therefore specifically to improve the Ricardian method to make its results regarding climate change adaptation more defined and explicit for policy

use (European policy use in particular). This is done by addressing four weaknesses of the Ricardian method.

First of all, the Ricardian method ignores adaptation requirements that need to be in place before a farmer can adapt. The method gives a false feeling of certainty that "farmers will adapt in the most optimal way" even though this is not always realistic, as not all farmers have access to such adaptation strategies. This is because farmers do not always possess all the necessary *adaptive capacity* characteristics such as information, skills, technology, economic wealth, and institutions that help them to implement adaptation strategies. Chapters 2 and 3 both resolve this weakness but in different ways. Chapter 2 suggests clustering farmers or regions based on pre-existing historical conditions that are assumed to influence farmers' ability to adapt. As such, all farmers in one cluster are restricted to uniquely rely on only the adaptation strategies available in that cluster. For European farms, when clustered in Eastern versus Western Europe, this implies that Eastern Europe only has access to the adaptation strategies available in Eastern Europe. Depending on the climate change scenario, this results in an almost 50 percent loss in Eastern European land values compared to a 2 to 32 percent loss for Western Europe. As an alternative, chapter 3 suggests explicitly capturing a measurement of adaptive capacity as an additional variable in the model. This leads to more detailed results as adaptive capacity also diverges within the clusters built in chapter 2. Chapter 3 confirms that not taking into account adaptive capacity leads to too optimistic results, as positive marginal effects of temperature decrease between 2.5 and 5 percentage points in regions with a lower adaptive capacity. Clearly, there is a positive relationship between adaptive capacity and the agricultural climate response, even though chapter 3 shows this relationship is non-linear.

A second weakness of the Ricardian method is that it only accounts for adaptation options that are in the dataset. It does not account for future technological improvements, as these do not yet exist in the data. This is unfortunate for estimations of the impact of climate change on agriculture as technological improvements will play a very important role in climate change adaptation. Chapter 2 shows that by splitting technological development into two types (development due to existing technologies in developed countries, and development due to future technologies), it is already possible to account for technological development in regions in transition, based on existing technologies in more advanced regions. As such, by broadening the dataset with more advanced adaptation strategies from other regions, one can improve the climate response by taking into account future technological development based on existing technologies. The results in chapter 2 show that if Eastern Europe were to apply and implement the same adaptation options as Western Europe by 2100, it could avoid a 50 to 69 percentage point decrease in land value, depending on the climate scenario.

Unlike chapters 2 and 3, which focus on adaptation in general, the second part of this dissertation focuses specifically on one adaptation strategy, irrigation, in order to better understand in which contexts it should be prioritized compared to other adaptation strategies. Irrigation is one of the primary mechanisms by which agriculture can respond and adapt to climate change. Comparing irrigated versus rain-fed agriculture reveals a third weakness of the Ricardian method: There is heterogeneity within the adaptation option that influences its overall effectiveness. Farmers do not simply make one adaptation decision. In the case of irrigation, they consider water management options across a spectrum that ranges from purely rain-fed farms to purely irrigated farms. In between the extremes, there are, among others, farmers that use supplemental irrigation on only part of their field, farmers that apply conservation practices to store water in the soil, farmers that add more surface- or groundwater to their fields, and farmers that irrigate on a very frequent basis. Chapter 4 shows that by taking into account such within-adaptation-option differences (either by means of subsampling, or by means of an interaction term), differences in the effects of marginal changes in climate on farmers at the extremes of the irrigation spectrum can rise up to 30 percentage points, depending on the size of the farm.

Finally, because (as shown in chapter 4) the type of adaptation significantly influences the climate response and a farm has numerous adaptation strategies to choose from, it is important to tackle a fourth weakness of the Ricardian method by revealing the farm adaptation decision process itself. Because each farmer makes numerous decisions at one time, in chapter 5, this dissertation provides a unique simultaneous irrigation-crop decision model to illustrate the farm adaptation decision-making process. The model shows that the irrigation choice is highly crop-specific and that the farm irrigation probability is highly influenced by climate. Specifically, the model reveals that climate and water constraints often hamper the use of irrigation as an adaptation tool. Southern regions, for instance, show decreases in irrigation probability of up to 7 percent in summer, when temperature marginally increases. This shows that those regions adapt through other means than irrigation (for instance by means of crop choice). As a result, the conditional climate response of the different farm adaptation responses differs significantly between irrigated and rain-fed farms. In general, irrigated crops are more resistant to higher temperatures than rain-fed crops in southern regions. However, the model shows there is a difference between large and small farms as small farmers are more dependent on water access before they can irrigate. In addition to the insights this model provides, the model also appears to be more robust when compared to traditional cross-sectional models that do not capture irrigation explicitly.

These four chapters prove that it is possible to adjust the Ricardian method to reveal adaptation more explicitly. This more explicit view is important for policy as it leads to more insight and results that are more robust. It shows that the climate change responses of Western and Eastern Europe could be similar, on the condition that policy, society, and behavior are devoted to bringing forth equal and optimal adjustment and adaptation conditions over both regions. Policy and institutions should increase adaptive capacity to facilitate climate change adaptation. The EU should ensure sufficient investment in water management infrastructure, as well as ensuring water regulations as climate change will limit the usage of adaptation strategies that are dependent rain water. Nevertheless, adaptation through more drought-resilient crops should also be further encouraged as crop choice is a beneficial alternative to irrigation in water-scarce regions. Finally, policy should not merely scale up adaptation strategies that work in one region to a larger region. There are clear differences in the way different adaptation options are implemented, and policy should allow the execution of different adaptation strategies.

NEDERLANDSTALIGE SAMENVATTING

Het klimaat bepaalt in sterke mate de activiteiten en het management van de landbouwsector. Klimaatverandering dwingt landbouwers dan ook tot het aanpassen van hun huidige activiteiten (zoals het veranderen van gewassen of het irrigeren van velden) om de impact van de nieuwe klimaatomstandigheden te minimaliseren of om opportuniteiten te benutten. Het is belangrijk om inzicht te krijgen in deze adaptatiebeslissingen en –processen. Daarom hebben modellen, die de impact van klimaatverandering in kaart brengen en tegelijk deze adaptatiebeslissingen in rekening nemen, de laatste jaren aan populariteit gewonnen. De micro-economische methode die in dit opzicht het meest gebruikt is, is de methode van Ricardo. Deze methode houdt impliciet rekening met klimaatadaptatie in veronderstelling dat landbouwers hun winst maximaliseren door alle winst-beïnvloedende factoren binnen hun controle (bijvoorbeeld de keuze van input en output) te optimaliseren. Concreet betekent dit dat de enige factoren die de winst beïnvloeden, exogene factoren zijn buiten het bereik van de landbouwer (bijvoorbeeld het type grond en klimaat). Door gebruik te maken van cross-sectionele data kan de methode afleiden hoe landbouwers reageren onder verschillende klimaatomstandigheden omdat er verondersteld wordt dat landbouwers gelijkaardig reageren indien alle omstandigheden hetzelfde zijn.

De sterkte van de methode om adaptatie in rekening te nemen, moet echter sterk genuanceerd worden omdat de methode adaptatie niet expliciet meet of toont. Adaptatie wordt namelijk verondersteld optimaal te zijn. Het probleem hierbij is dat ondanks het feit dat de methode adaptatie wel in rekening neemt, de methode geen inzicht geeft in hoe een landbouwer zich aanpast. Adaptatie blijft ongedefinieerd en onzichtbaar en dit maakt de methode minder interessant voor beleidsmakers of beslissingsnemers in adaptatie. Het doel van deze thesis is dan ook om de methode van Ricardo te verbeteren zodat haar resultaten klimaatadaptatie expliciet in kaart brengen en bijgevolg bruikbaarder zijn voor (Europees) beleid. Concreet kaart deze thesis vier tekortkomingen aan van de methode, die een obstakel vormen om adaptatie te visualiseren.

Eerst en vooral negeert de methode dat adaptatie enkel kan plaatsvinden indien landbouwers aan de minimumvereisten voldoen om zich te kunnen aanpassen. De methode geeft een vals gevoel van zekerheid dat “landbouwers zich zullen aanpassen op de meest optimale wijze” terwijl dit in werkelijkheid niet altijd realistisch is. Niet alle landbouwers hebben toegang tot alle adaptatiestrategieën omdat ze niet altijd beschikken over het nodige aanpassingsvermogen (informatie, kennis, technologie, financiële middelen en instituten). Hoofdstuk 2 en 3 stellen twee verschillende manieren voor om dit op te lossen. Hoofdstuk 2 raadt aan om landbouwers te groeperen op basis van historische eigenschappen die hun aanpassingsvermogen beïnvloeden. Op deze manier erkent de methode dat landbouwers binnen een groep enkel aanspraak maken op adaptatiestrategieën beschikbaar binnen die groep. Voor Europese landbouwers betekent dit dat landbouwers in Oost-Europa enkel gebruik zouden kunnen maken van adaptatiestrategieën beschikbaar in Oost-Europa. Afhankelijk van het klimaatscenario leidt dit voor Oost-Europa in dalingen tot 50 procent in haar netto inkomen, in vergelijking met 2 tot 32 procent verliezen in West-Europa. Een alternatieve methode wordt voorgesteld in hoofdstuk 3 waar het aanpassingsvermogen van de sector expliciet in rekening wordt genomen als een extra variabele in het model. Dit leidt tot meer specifieke resultaten aangezien er zo op een meer gedetailleerde geografische schaal naar verschillen in aanpassingsvermogen gekeken kan worden. Hoofdstuk 3 bevestigt de resultaten van hoofdstuk 2 en concludeert dat positieve marginale temperatuureffecten dalen met 2.5 tot 5 percentagepunten in regio’s met een laag aanpassingsvermogen. Ondanks het positieve verband tussen het aanpassingsvermogen en de agrarische klimaatreactie, is deze relatie niet lineair.

Een tweede zwakte van de methode is dat de methode geen aanpassingsstrategieën in rekening kan nemen die voortvloeien uit technologische ontwikkeling aangezien deze aanpassingsmogelijkheden nog niet aanwezig zijn in de data. Desondanks zal technologische ontwikkeling een belangrijke invloed hebben op toekomstige agrarische aanpassingsstrategieën. Hoofdstuk 2 toont dat technologische ontwikkeling op twee manieren plaatsvindt: ontwikkeling die enerzijds voortvloeit uit vergevorderde technologieën in meer ontwikkelde regio's, en anderzijds uit compleet nieuwe technologieën en kennisstromen. Dit betekent dat het wel mogelijk is om de eerste vorm van technologische ontwikkeling in rekening te nemen indien de dataset uitgebreid wordt met aanpassingsstrategieën uit meer ontwikkelde regio's. Door de datasets van Oost- en West-Europa te bundelen, toont hoofdstuk 2 aan dat, indien Oost-Europa dezelfde adaptatiestrategieën als West-Europa zou kunnen hanteren, het afhankelijk van het klimaatscenario een daling van 50 tot 69 percentagepunten in netto-inkomen zou kunnen voorkomen.

In tegenstelling tot het eerste deel van de thesis, dat de nadruk legt op adaptatie in het algemeen, focust het tweede deel in hoofdstuk 4 en 5 specifiek op één adaptatiestrategie: irrigatie. Het in detail bestuderen van adaptatiestrategieën is noodzakelijk om beter te begrijpen wanneer welke adaptatiestrategieën de voorkeur moeten krijgen. Irrigatie is één van de meest gebruikte adaptatiemechanismes waarmee de landbouwsector reageert op klimaatverandering. Indien irrigatie vergeleken wordt met de niet-irrigerende landbouwsector, is het echter noodzakelijk een derde zwakte van de methode van Ricardo uit te klaren. Landbouwers maken namelijk niet zomaar een ja-neen adaptatiekeuze. In het geval van irrigatie nemen ze watermanagement opties over een wijd spectrum van niet-geïrrigeerde landbouw tot zuiver geïrrigeerde landbouw in overweging. Tussen deze extremen heeft de landbouwer de keuze uit onder andere irrigatie op slechts een gedeelte van zijn akkers, waterconservatietechnieken om water in de bodem op te slaan of het toepassen van verschillende irrigatiefrequenties. Deze verschillende implementatiemogelijkheden van dezelfde adaptatiestrategie kunnen tot sterk verschillende klimaatreacties leiden. Hoofdstuk 4 bevestigt dit door het categoriseren van landbouwers op basis van verschillen in uitvoering van de irrigatie adaptatiestrategie en toont aan dat marginale veranderingen in klimaat tot veranderingen in netto-inkomen kunnen leiden die groter zijn dan 30 percentagepunten tussen de irrigatie-extremen.

Omdat hoofdstuk 4 aantoont dat de keuze van de adaptatiestrategie de klimaatreactie in sterke mate beïnvloedt en een landbouwer bovendien de keuze heeft uit een groot aantal adaptatiemogelijkheden, is het belangrijk om een vierde zwakte van de methode van Ricardo aan te kaarten en op te lossen. De methode geeft namelijk geen inzicht in het adaptatiekeuzeproces van de landbouwer en onthult dus niet hoe een landbouwer zich aanpast. In hoofdstuk 5 stelt deze thesis daarom een uniek adaptatiebeslissingsmodel voor waarin er simultaan twee adaptatiekeuzes van de landbouwer bepaald worden aan de hand van een simultaan irrigatiegewas keuzemodel. Dit is realistischer omdat landbouwers in werkelijkheid ook meerdere beslissingen tegelijk dienen te nemen en omdat de irrigatiekeuze sterk gewasafhankelijk is. Eén van de hoofdresultaten van het model is dat klimaat en waterschaarste vaak de keuze voor irrigatie als een adaptatiestrategie beperken. In Zuid-Europa dalen de kansen op irrigatie tot 7 procent in de zomer als de temperatuur marginaal stijgt. Dergelijke regio's reageren op klimaatverandering op andere manieren zoals het wisselen naar meer droogteresistente gewassen. Bovendien blijkt ook dat landbouwers in meer Noordelijke regio's negatief reageren op temperatuurstijgingen omdat zij zich eerder aanpassen aan veranderingen in neerslag. Ook blijken er grote verschillen te zijn tussen grote en kleine landbouwers, in die zin dat kleine landbouwers meer waterafhankelijk zijn alvorens ze kunnen irrigeren. Tot slot bewijst deze thesis dat het simultaan beslissingsmodel geschat in hoofdstuk 5 robuuster is dan de traditionele schattingen van de methode van Ricardo. Het is daarom belangrijk om adaptatie expliciet te schatten.

Deze vier hoofdstukken bewijzen dat het mogelijk is de methode van Ricardo aan te passen zodat adaptatie expliciet onthuld wordt. Dit leidt niet enkel tot belangrijke inzichten voor beleid, maar ook tot meer robuuste resultaten. De aangepaste methode bewijst dat de klimaatreactie tussen Oost- en West-Europa gelijkaardig zou kunnen zijn indien beleid erin slaagt een gelijk speelveld over de volledige Europese Unie te creëren. Daarom is het belangrijk om het aanpassingsvermogen over beide regio's te vergroten om klimaatadaptatie aan te moedigen. De EU moet bovendien ook voldoende investeren in watermanagementinfrastructuur en waterwetgeving aangezien klimaatverandering de druk tussen vraag en aanbod van water zal verhogen. Adaptatie via meer droogteresistente gewassen zal daarom ook een belangrijke adaptatiestrategie zijn in regio's met waterschaarste. Tot slot moet beleid opletten met het opschalen van adaptatiestrategieën die in een bepaalde regio effectief zijn. Er zijn verschillende manieren waarop adaptatiestrategieën geïmplementeerd kunnen worden en beleid moet erover waken dat deze correct aangepast worden aan de beoogde regio.

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AC	Adaptive Capacity
ACI	Adaptive Capacity Index
ANOVA	Analysis of Variance
AR4	Fourth Assessment Report
CAP	Common Agricultural Program
CC	Climate Change
CO_2	Carbon Dioxide
CRU	Climatic Research Unit
EC	European Commission
ECA	European Court of Auditors
ESPON	European Observation Network for Territorial Development and Cohesion
ESRI	Environmental Systems Research Institute
ESU	Economic Size Unit
EU	European Union
FADN	Farm Accountancy Data Network
FAO	Food and Agriculture Organization
FIML	Full-information maximum likelihood
GCM	Global Climate Model
GDP	Gross Domestic Product
GFCF	Gross Fixed Capital Formation
GSEM	Generalized Simultaneous Equation Model
ICC	Intraclass Correlation
IIASA	International Institute for Applied Systems Analysis
IPCC	Intergovernmental Panel on Climate Change
IRR	Irrigation
JRC	Joint Research Centre
LME	Linear Mixed Effect Model
MEp	Marginal Effect of Precipitation
MEt	Marginal Effect of Temperature
NI	Net Income
NUTS3	Nomenclature of Territorial Units for Statistics regions level 3
OLS	Ordinary Least Squares
p	Precipitation
REML	Restricted Maximum Likelihood
SRES	Special Report on Emissions Scenarios
T	Temperature

UAA	Utilized Agricultural Area
UNEP	United Nations Environmental Program
USD	United States Dollar
USGCRP	United States Global Change Research Program
VSC	Vlaams Super Computer Center

CHAPTER 1. INTRODUCTION –
THE IMPORTANCE OF AGRICULTURAL ADAPTATION TO CLIMATE CHANGE

Chapter 1.
The importance of agricultural adaptation to climate change

"Mitigate we might; adapt we must" - Nordhaus (1994)

ABSTRACT – The goal of this dissertation is to improve the cross-sectional Ricardian method to make its results regarding adaptation more defined and explicit for policy use. This goal is operationalized by focusing in four chapters on four methodological weaknesses of the Ricardian method that impede its understanding of adaptation. First of all, the Ricardian method is too optimistic regarding which adaptation options are available to farmers. This dissertation therefore captures, both explicitly and implicitly, adaptive capacity in order to assess whether a farmer has access to specific adaptation options or not. Secondly, the Ricardian method does not take into account technological development regarding adaptation. By combining datasets of more developed farmers with datasets of farmers in transition, it is possible to take into account technological development, based on existing technologies, in regions that are still making the transition to using more developed technologies. Thirdly, the Ricardian method ignores differences within an adaptation option that might greatly influence the climate response of the farmers. It is therefore important to take into account differences in the implementation of adaptation strategies. Finally, the Ricardian method does not explicitly model the adaptation process. This dissertation therefore explicitly captures one adaptation choice (the irrigation choice) and models this choice simultaneously with one other adaptation choice (the crop choice), because farmers make multiple, simultaneous decisions.

1.1. The climate sensitivity of agriculture

"From the top of the atmosphere to the depths of the oceans" (USGCRP, 2017), there is overwhelming evidence that climate change influences our world as it looks today. There are losses and damages to ecosystems and water resources, threats to food security and human health, sea level rises, increased severity and frequency of hurricanes and storms, infrastructure damages, equity issues, and numerous other impacts on society (Ciscar et al., 2011; Dyurgerov and Meier, 2000; Parmesan and Yohe, 2003; Stocker, 2014). If emissions do not decrease significantly, the effects of climate change will further increase. Ciscar et al. (2014) estimate for instance that in Europe by 2080, without adaptation and under high-emission scenarios, about 200,000 people per year would die due to extreme heats, damage of river floods would exceed 10 billion euros per year and would affect over 290,000 people, costs of droughts would increase to about 150 million euros per year and would mostly affect Southern Europe, forest fires would damage 800,000 ha a year, transport infrastructure damages could reach around 930 million euros a year, tourism losses in Southern Europe could increase up to 7 billion euros a year, and sea-level rise would increase welfare losses to 42 billion per year.

Nevertheless, even though numerous sectors are affected by climate change, "arguably the sector most affected by climate change" (Rosenzweig et al., 2014) is the agricultural sector. The production of both crops and livestock is influenced directly and indirectly by different climate inputs that have an impact on three major parts of the hydrological cycle (Gordon et al., 2008): (i) *the atmosphere* (in which temperature, solar radiation, wind speed, and CO_2 concentrations influence evapotranspiration processes, photosynthetic rates, and water requirements (Falkenmark and Rockström, 2006; Kimball and Idso, 1983; Turral et al., 2011)), (ii) *the aquatic systems* (which determine the runoff of precipitation and the upstream capacity of bodies of water, which together with temperature influence the frequency of floods and droughts), and (iii) *the soil* (which captures and retains some of the rainfall water or water from other sources, which generates soil moisture and natural replenishment of ground water (IIASA/FAO, 2000; Taylor et al., 2013; Turral et al., 2011)).

For all these different climate factors, there exists an optimal range in which crops and animals are the most productive and obtain the highest yield (Figure 1). This is confirmed by different laboratory experiments and field experience (Mendelsohn and Dinar, 2009). As a result, even though there are differences between different species, the relationship between climate and yields is hill-shaped for all the different crop and animal species. Such a hill-shaped relationship explains why there is not a lot of agriculture in the Sahara (too warm and dry) or in the Arctic (too cold). These environments are obviously not ideal for obtaining the highest possible yields of most crops and animals.

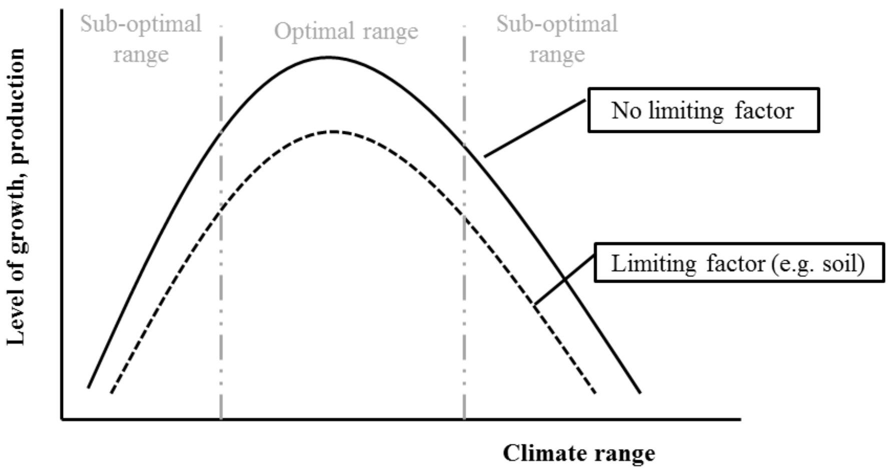

Figure 1 – Impact of climate and limiting factors on growth and production of crops and livestock
(Source: Mendelsohn and Dinar (2009))

With climate change, farmers will move from one point on the function in Figure 1 to another. Because of this, some farmers might face more hostile and less optimal environments to work in. Cows and sheep could suffer, for instance, from heat stress, and could produce less milk or wool in response to increasing temperatures, or crops could suffer from heat stress and shorter growing seasons. Given that agriculture is of major importance to our society (it provides food and clothing, and is a main source of income for many households in developing countries), understanding the impact of such a changing climate on agricultural yields and food security is important. As a result, the agricultural sector is the sector studied the most with regard to the impact of climate change.

Most of the studies executed to examine the impact of climate change on agriculture are based on crop simulation models, the first method used to model the crop impacts of climate change (Mendelsohn and Dinar, 2009). Crop simulation models or agro-economic analyses are based on current scientific knowledge from plant pathology, soil physics, and other disciplines and predict crop growth by means of weather conditions, genetics, soil characteristics, and crop management (Rosenzweig and Parry, 1994). The later implies that these models are based on a deep understanding of agronomic science (Mendelsohn and Dinar, 2009) because the models reflect the crop growth processes based on genetic characteristics of the crop. They can integrate hydrologic conditions, local environments, and carbon dioxide fertilization. An alternative way to model agricultural climate change sensitivity is with production function models or empirical yield models that link water, soil, climate, and economic inputs to crop yields for specific crops (Mendelsohn and Dinar, 2009). These methods are less data-intensive than crop simulation models. A final group of models to model the impact of climate change on agriculture uses the intertemporal or panel net revenue approach. However, those methods focus on short-term responses to weather fluctuations and represent climate change itself less accurately.

1.2. The relationship between climate change and agriculture

The relationship between climate and agriculture is, however, more complicated than the hill-shaped relationship shown in Figure 1. Changes in the natural relationship between crops or animals and the crops' or animals' environment can occur due to interlinkages between atmospheric, aquatic, soil, and biophysical crop systems and as such move the relationship (Figure 1) up or down depending on limiting variables.

However, a natural relationship between a crop or an animal and its environment can also be changed by numerous socio-economic factors. Agriculture is a man-made adjunct to natural ecosystems (Wreford et al., 2010), and the farmer can influence the natural biophysical relationships between production and the environment. As such, when the farmer interferes, the slope of the relationship (Figure 2) can change, making the relationship between climate and yields, for instance, less sensitive and more optimal over a wider temperature range.

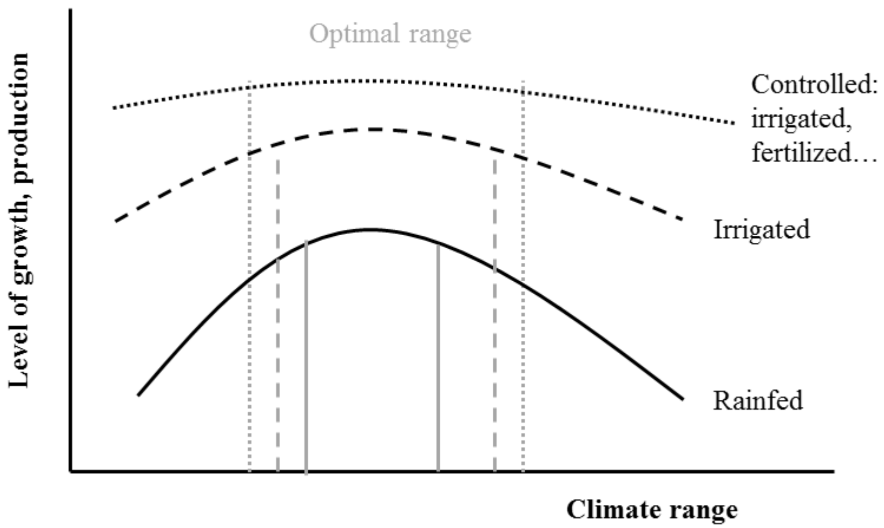

Figure 2 – Schematic presentation of the temperature-yield relationship with various enabling technologies
(Source: Mendelsohn and Dinar (2009))

This farm interference is also referred to as “farm adaptation”, and it implies that farmers make “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, 2007b). One of the most cited examples in the European Union (EU) of the proof of the importance of such adaptation is related to one of the worst droughts in Europe. During the 2003 drought, 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 (Ciais et al., 2005). However, this reduction in crop productivity was much lower in Mediterranean countries because they were more adapted to dry and hot summers and using irrigation and drought-tolerant crops (Ciais et al., 2005). Adaptation to new climate circumstances is therefore important and beneficial.

In summary, each animal and crop is adapted to grow under specific climate conditions. Yet, if the production takes place in less optimal environmental conditions, specific factors can be addressed to make sure that the farm is more adapted to its environment than it would be under natural circumstances. Farmers possess a wide range of adaptation options to improve the natural climate response function if some conditions are suboptimal. They can change their usual management strategies by changing the quantities or quality of their inputs (such as fertilizers, soil moisture, nutrients, and pesticides). Or, for instance, in response to seasonal changes in temperature and water, they can change their sowing or harvesting days. They might add new technologies or infrastructure to their farm such as irrigation or covers, or they can switch between different crops and animals.

Switching between different crops and animals is considered a very effective way to adapt to climate change because the crops and animals continue to be grown in the environment to which they are most adapted. For example, sheep are less sensitive to water supply than cattle (Mendelsohn and Dinar, 2009), while chicken cannot survive if the temperature increases drastically. Figure 3 gives an example of switching farm activities to minimize decreases in yields due to climate change. The graph shows three different farm activities that produce optimal yields under different temperatures or other environmental conditions. Wheat obtains the highest yield under a temperature of B, while corn obtains its highest yield at a temperature of D. If a farmer is currently situated in climate A, wheat will not yet have reached its optimal yield. If climate changes and temperature increases up to B, the farmer will obtain higher yields of wheat. However, beyond point B, the yield of wheat will drop. If temperature increases above point C, a farmer who maximizes his yields will switch from wheat to corn because the yields of corn are higher than the yields of wheat above a temperature of C. Adaptation therefore minimizes the loss of a high yield of wheat that would occur if the farmer persisted in growing wheat under the new climatic conditions. Finally, under the new climatic condition of temperature D, corn would be much more beneficial than wheat.

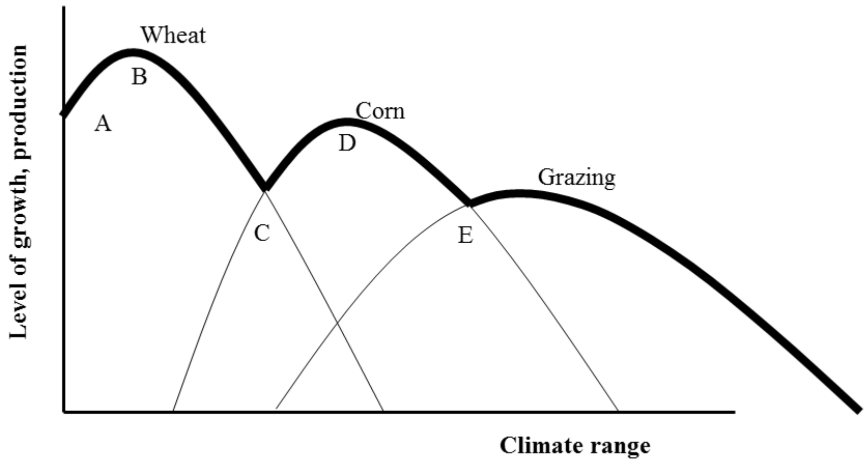

Figure 3 – Comparison of single crop farms versus farms that adapt by switching between crops
(Source: Mendelsohn et al. (1994))

As a result, simply modeling the natural agronomic or biophysical relationship as done by crop simulation models is not enough because human influences are not accounted for. Researchers should instead model the envelope of the most profitable adaptation options to see what the response of farmers to climate change, and therefore the residual impact of climate change after adaptation has taken place, is. It is important to take into account “an infinite variety of substitutions, adaptations and old and new activities that may displace no-longer-advantageous activities” when climate changes (Mendelsohn et al., 1994). Thanks to these adaptive responses, the decrease in yields might be much less rapid then would be the case in the natural crop environment (Mendelsohn et al., 1996). Ignoring these adaptation options and this farm adaptive behavior would imply the “dumb farmer assumption” (Rosenberg, 1992), meaning that the farmer would basically not respond at all to changes in the environment. This is incorrect as farmers have always adapted to changes in their environment. As a result, the relationship between climate and farm productivity should not depend on simply one crop or animal (Figure 1), but should look like Figure 3. If this human reaction to climate change is not taken into account, damages of climate change will be overestimated. When modeling the impact of climate change on agriculture, it is therefore important to take into account all the different adaptation options instead of merely looking at one crop or adaptation option in isolation.

1.3. Modeling climate change impact and adaptation in agriculture

The previous section highlights the important distinction between a farm-raised plant and a naturally growing plant: a farmer possesses a significant number of management and adaptation options to break the natural link between climate and crop growth. As a result, when studying agriculture, it is important not to study one single crop, but to examine the sector as a whole. This reveals some major disadvantages of crop simulation models and other models discussed above. First of all, while the crop simulation approach gives very detailed results on climate sensitivity for individual crops and regions, the results are not easily generalized to wider regions as this would be geographically less precise (Mendelsohn et al., 2009). Moreover, both crop simulation models and empirical yield functions can only model one (or just a few) crop(s) at a time and therefore cannot model crop switching (Wang et al., 2009). These methods assume that the same crops and animals will continue to be grown in the same regions, even if climate changes. Yet as indicated above, each crop and animal has an ideal climate in which it is grown, and crop and animal switching is therefore expected to be an important adaptation strategy in response to climate change.

Not only is crop and animal switching not permitted by the method, adaptation in general is not accounted for. These models basically model the agronomic relationship itself and assume the behavior of the farmer is exogenous or fixed (Mendelsohn and Dinar, 2009).

Alternatively, economic management models (also known as agro-economic simulation models) can be used to model farm behavior (Mendelsohn and Dinar, 2009). Such models assume profit-maximization and look at which farm behaviors lead to the highest profits. Unfortunately, in practice it is too expensive to look at all alternative farming methods, and therefore these models do not capture the full range of farm adaptations (Mendelsohn and Dinar, 2009).

The method used in this dissertation is the Ricardian method, which addresses the weakness of not taking into account a large range of adaptation options. The Ricardian method studies agricultural productivity or net income in a specific region (Mendelsohn et al., 1994). Yet, instead of directly looking at productivity or income, it uses data on land value. This is because of Ricardo's observation that in a competitive market, land value or land rent reflects the present value of future net income for each farm (Ricardo, 1817; Seo and Mendelsohn, 2008b). As a result, land value, or the net present value of net income (V), can be expressed as follows (Mendelsohn and Dinar, 2003; Wang et al., 2009):

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

where P_{qi} is the market price of crop i, Q_i is the output or production function for crop i, X_i is the vector of purchased inputs for crop i, L_i is the vector of labor for crop i, $\mathrm{K_i}$ is the vector of capital for crop i, C is the vector of climate variables, Z is the set of soil characteristics, G is a set of economic variables, X_i is the 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 labor, P_K is the rental price of capital, t is time, and φ is the discount rate.

The explanatory variables in this equation can be divided into two groups: exogenous variables that are outside the farmer's control (such as climate, market prices, and soil characteristics); and endogenous variables that are within the farmer's control (such as farm inputs and the crop type chosen). The Ricardian model is derived from the previous equation by assuming that each farmer maximizes net income by choosing the optimal amount of all different endogenous variables that are within his or her control (Q_i, X_i, L_i, K_i) and by using land with the most suitable climate for the most profitable activity, subject to the exogenous conditions of each farm ($P_q, C, Z, G, R, P_x, P_L, P_K$) that are outside the farmer's control (Maharjan and Joshi, 2013; Mendelsohn et al., 1994). The resulting profit maximizing equation is therefore a reduced function that explains how exogenous variables determine variations in land value, and the value of the land is assumed to be the value of the most profitable use of the land (Mendelsohn et al., 2009). Variables such as labor, capital, and crop choice (that is, farm management tools to adapt to exogenous influences) are therefore not included in the regression because they are assumed to be optimized.

As a result, because farmers adapt by matching farm management decisions (such as inputs and crop choice) to surrounding climate conditions, adaptation is implicitly captured. Because the Ricardian method is based on cross-sectional data, it can look at how farmers in a variety of climates response to their current environment. As such, the method accounts for how farmers respond to climate change by comparing them with farmers in other climates (Mendelsohn et al., 1996). In order to do that, the method assumes that farms are already adapted to the environment they exist in (Mendelsohn et al., 2009). In this way, adaptation is taken into account as it is captured by the data and not because it is explicitly modeled. The advantage of this is that all adaptation options used by farmers in the dataset are taken into account, even if the researcher is not aware of them.

1.4. Dissertation goals and outline

As discussed in the previous section, the Ricardian method is capable of capturing the actual adaptive behavior of farmers in response to climate change (Blanc and Reilly, 2017). The method is popular because it is easy to estimate and because it yields geographically precise values (Mendelsohn, 2007), but it is mostly used because it is "the only method that accounts for full adaptation." In addition, the adaptation captured by the model can be totally different than the adaptation modeled in controlled experiments because the farm practices and conditions in real life might be quite different from those in the experiments (Blanc and Reilly, 2017). As a result, today the method is the most commonly used microeconomic approach to assess the impact of climate change on agriculture and has been applied to different geographical contexts and scales (De Salvo et al., 2014).

The Ricardian method's strong point of capturing adaptation has to be treated with caution, however. This is because the Ricardian method captures adaptation in a "black box." That is, it does not require the explicit modeling of adaptation options, making adaptation invisible and undefined. It merely observes yield or production outcomes instead of identifying adaptation options (Blanc and Reilly, 2017). This is shown in Figure 3, which illustrates how the method models the envelope of the most profitable adaptation options without explicitly distinguishing between them. The method just estimates one climate response function and does not estimate the different climate responses of the different adaptation strategies separately. This implies that researchers, policy makers, and other practitioners that want to use the results of the method will have only limited evidence and knowledge on (1) which adaptation options are used or should be used by farmers, (2) how such adaptation options established themselves and what efforts and requirements were needed before they could be implemented, (3) whether implementation of such adaptation options is homogenous among different farmers, and (4) how farmers decide upon their adaptation choice. Because the traditional Ricardian method does not explicitly model adaptation, it only shows the regional agricultural climate sensitivity, and it gives little to no information on how to improve such climate sensitivity.

Such knowledge on adaptation is necessary as adapting to climate change becomes more complex and expensive with increasing degrees of climate change (see Figure 4). The biggest benefits from adaptation are likely to result from more costly adaptation tools such as the expansion of irrigation of agricultural land and the development of new crop varieties (Rosenzweig and Parry, 1994). Such adaptations require significant investments from numerous stakeholders ranging from farmers to governments (Lobell et al., 2008). Yet, resources are scarce. It is therefore indispensable to direct resources "to those actions with greatest benefits" (Campbell et al., 2016). This implies that it is important to properly quantify the benefits of making adaptation-related investments.

The fact that more information on adaptation itself is needed makes the Ricardian method less practical and useful for policy makers, as it does not provide adaptation insights. This is unfortunate, given the fact that the Ricardian cross-sectional method is currently one of the most commonly used methods to examine climate sensitivity. It is therefore important to improve the Ricardian cross-sectional method in such a way that adaptation becomes more explicit and that it becomes clear for policy makers which actions improve agricultural climate sensitivity. This

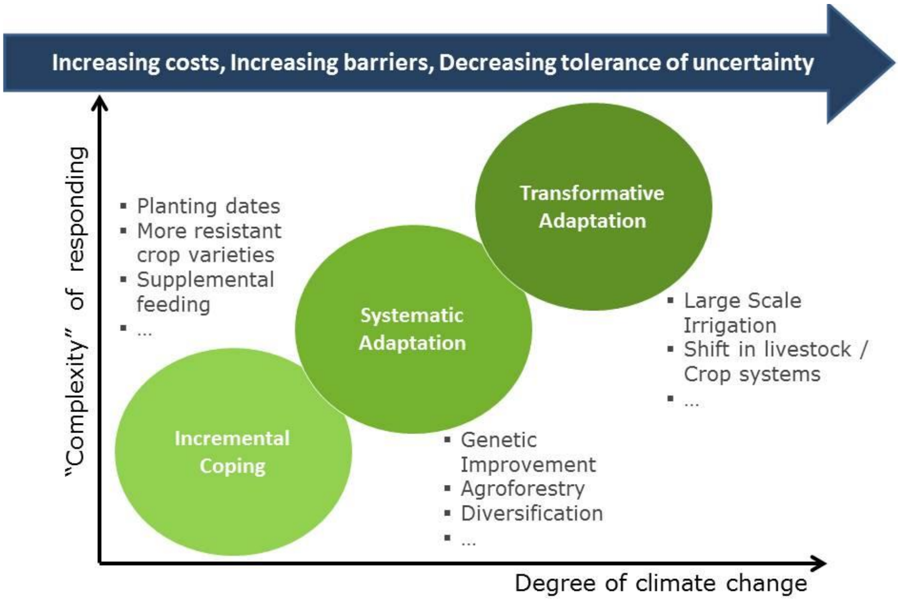

Figure 4 – Transitions in adaptation types in relation to climate change and complexity
(Source: Silvestri (2014), adapted from Howden et al., 2010, and Vermeulen et al., 2013))

dissertation therefore focuses on contributing to the following research question, as well as the questions in the overview below:

1. How can the Ricardian cross-sectional method be improved to make its results regarding climate change adaptation more defined and explicit for policy use?

To answer this question, it is important to understand which characteristics and weaknesses of the Ricardian method cause barriers to better understanding and to taking action regarding adaptation. In the overview below, we present four weaknesses of the Ricardian method for which we suggest solutions in the following four chapters (see also Figure 5). The methodological solutions suggested will provide insights for climate change adaptation policy. The geographical research field of this dissertation is the EU.

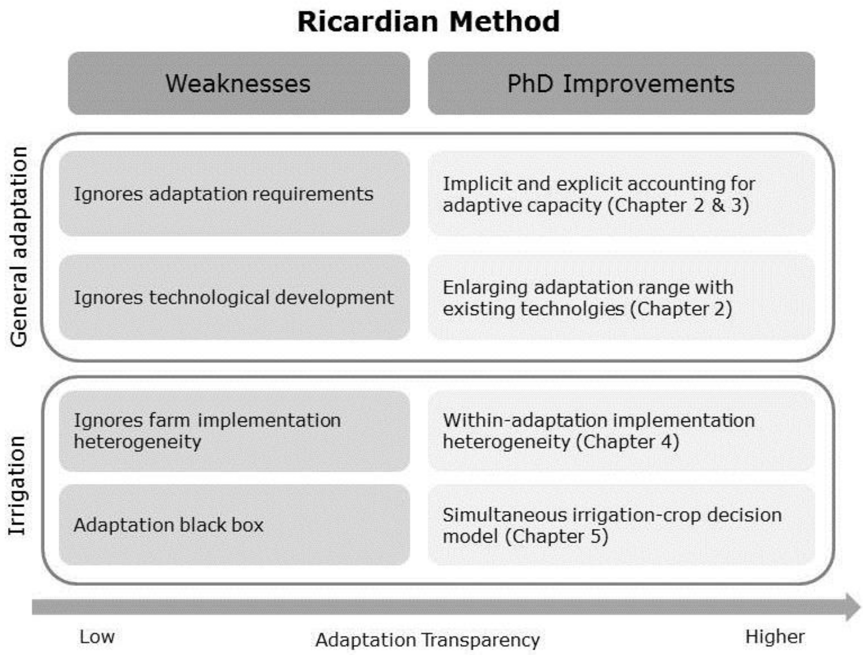

Figure 5 – Structure and content of this dissertation

Chapter 2 – The first weakness of the Ricardian method that this dissertation addresses is that the Ricardian method does not explicitly define which adaptation options are accounted for. The theory of the Ricardian method says that the method accounts for all adaptation options covered by the dataset used for the analysis. This implies that each analysis based on a different dataset probably accounts for a different set of adaptation strategies. For instance, researchers using only data of potato farmers would limit the adaptation options in their dataset to potato adaptation strategies, and they would not account for all adaptation options; they would not allow these potato farmers to switch to other crops or types of agriculture like livestock. As a result, it is the dataset that determines which adaptation options are available to the farmers when estimating their climate response. A large, heterogeneous dataset with wide geographical coverage most likely contains a wider range of adaptation strategies than a small, homogenous dataset with smaller geographical coverage.

The key problem of the fact that adaptation is not visible and fluctuating depending on the dataset is that the Ricardian method has to make assumptions with regard to which adaptation options are available to which farmers. It does so by assuming that farmers in one location behave the same as farmers in a second location would if that second location were made to look like the first one. This implies that the method assumes that farmers at the same latitude, facing the same climate and other geographical factors such as soil and elevation, react similarly to climate change impacts. Translating this assumption to adaptation options means that the Ricardian method assumes that farmers at the same latitude have access to the same adaptation options.

This assumption, however, might be too optimistic in the EU, as there are currently still sizeable socio-economic disparities and technology gaps between Western and Eastern Europe. The regions face significantly different pre-existing historical conditions, as Eastern Europe only switched from a plan to market-oriented economy in 1989 and entered the EU in 2004. These pre-existing conditions might highly affect countries' capability to adapt, influence their adaptation decisions, restrict access to a wide range of adaptation options, and, therefore, make the residual impact of climate change worse than it could have been after adaptation has taken place (Lourenço et al., 2014).

As such, a dataset of Western Europe, a dataset of Eastern Europe, or a dataset of the EU can be expected to contain different ranges of adaptation options. Depending on which dataset is used, climate responses might differ significantly because each dataset possesses different adaptation options. That is, if a dataset of the entire EU is used, the method assumes that all adaptation options in the dataset are accessible to all farmers. Due to pre-existing historical conditions between

Eastern and Western Europe, it might be wrong to assume that Eastern and Western Europe have access to the same adaptation options and consequently react in the same way to climate change. We therefore examine the following research question:

2.1. Do Western and Eastern Europe have the same agricultural climate response?

We will answer this question by comparing the climate responses of the different datasets (Eastern versus Western Europe versus the EU). Once this question is answered, we continue with a second weakness of the Ricardian method that is also related to the dataset used: the Ricardian method does not take into account future technological adaptation improvements. This is because the method only accounts for adaptation options that are currently available in the dataset, and future technological improvements are per definition not yet existing in the data. The fact that the Ricardian method does not take technological improvements into account is unfortunate for estimations of the impact of climate change on agriculture, as technological improvements will play a very important role in climate change adaptation.

There are two types of technological development: (a) development due to existing technologies and knowledge in developed countries, and (b) development due to future technologies. In the case of developing countries or countries in transition, one can already partly take into account technological development by looking at existing technologies in developed regions. We therefore examine whether it is possible to improve the climate response of Eastern Europe by combining the range of adaptation options of Western Europe and Eastern Europe. Some adaptation options that are currently only used in Western Europe will suddenly become available in Eastern Europe. Our second research question therefore is the following:

2.2. Does the agricultural climate response function of Eastern Europe improve if we broaden its range of adaptation options?

The answers to these two research questions (2.1 and 2.2.) will allow policy makers to decide whether Eastern and Western Europe need different climate change adaptation strategies. The original Ricardian method assumes that regions at the same latitude behave the same and therefore does not give insights with regard to potential differences between the eastern and western regions. With regard to the methodology, our approach allows the method to be applied in numerous regions and case studies all over the world, as it does not require additional data. This is a significant advantage of our modification.

Chapter 3 – While answering questions 2.1 and 2.2, we observe that Eastern and Western Europe do not have access to the same adaptation strategies. However, apart from the fact that this conclusion was based on making specific geographical clusters based on historical conditions, there was no explicit measurement of the reason why adaptation differs between the regions. It is therefore important to explicitly capture the cause of the differences in the regions' adaptation behaviors.

There are differences in adaptation behavior between Western and Eastern Europe because adaptation comes at a cost. Numerous efforts are needed before a farm becomes an "adapted" farm. Before adaptation can take place, (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 (Brooks and Adger, 2005; IPCC, 2001). All the costs that go along with this process are generally termed "adjustment or transition costs" (Kelly et al., 2005).

Unfortunately the Ricardian method is a comparative and not a dynamic analysis. It therefore ignores all the efforts and requirements that are needed to go from the pre-adaptation equilibrium to the equilibrium where the farm is adapted. This not only leads to an underestimation of the impact of climate change on agriculture, but it also leads to the assumption that all farmers are equally capable of adapting to climate change, because the cost of adaptation is not accounted for. Yet, a farmer's ability to adapt is highly influenced by resource access and adaptation costs, which vary (Berkhout et al., 2006; IPCC, 2014b; Kates, 2000). "Adaptive capacity" (IPCC, 2001) is "the ability or potential of a system to respond successfully to climate variability and change, and includes adjustments in both behavior and in resources and technologies" (IPCC, 2007a). Adaptive capacity is influenced by characteristics such as information and skills, institutions, equity, technology, and economic wealth, among others (IPCC, 2007a).

Given the fact that adaptive capacity is a requirement for both the design and the implementation of effective adaptation strategies (Brooks and Adger, 2005), differences in adaptive capacity will cause climate change effects to differ significantly between more- and less-developed regions. It is therefore important to identify what exactly are differences in adaptive capacity within Europe. In doing so, it is important to also look at heterogeneity within specific geographical clusters. That is, we should not merely compare Eastern versus Western Europe, but we should also look at differences in adaptive capacity within each of these regions.

3.1. How do adaptive capacity levels differ within the European Union?

Once we have an explicit measurement of adaptive capacity in the EU, we will use this measurement to examine explicitly whether the differences in climate response between Western and Eastern Europe (identified in chapter 2) can be explained by means of differences in adaptive capacity. By explicitly accounting for adaptive capacity, we make the Ricardian method more realistic because we no longer assume that all farmers have access to all the adaptation options in the dataset. Whether they have access to the most optimal adaptation options depends on whether they have a level of adaptive capacity that is high enough to obtain and implement such adaptation options. As such, we examine the following research question:

3.2. What is the effect of adaptive capacity on the impact of climate change on European agriculture, and how does it differ between different regions?

Given the fact that adaptive capacity is only rarely quantified in climate change impact studies, the shape of the relationship between adaptive capacity and the marginal effects of climate change is not known. This information is important with regard to future investments that are needed. If the relationship is non-linear, certain thresholds might need to be surpassed before adaptive capacity indeed leads to a more beneficial climate response. Moreover, at a certain point, increases in adaptive capacity might not continue to improve agricultural climate response. It is important to be aware of such potential pitfalls. We therefore also examine the following question:

3.3. What is the relationship between adaptive capacity and the marginal agricultural climate response?

Chapter 4 – By answering questions 2.1 to 3.3, we show the importance of increasing adaptive capacity in order to allow adaptation to occur. Higher levels of adaptive capacity should lead to more positive climate responses. However, the truth is that greater adaptive capacity does not always automatically lead to adaptive action (Adger and Barnett, 2009; Moser and Ekstrom, 2010). Different farm characteristics influence the adaptation decision and implementation process, making farmers behave differently under similar circumstances.

It is therefore important to examine specific adaptation options in more detail to better understand how they are selected by farmers, and how they are implemented. This dissertation focuses on one specific type of adaptation: irrigation. Irrigation is currently already one of the primary mechanisms for agriculture to respond and adapt to climate change (Howden et al., 2007). With climate change causing more severe and more frequent drought events (Dai, 2012), the role of irrigation will become increasingly important. Especially in Europe, significant changes in irrigation are to be expected because currently approximately 85 percent of European irrigated land is concentrated in the lower latitude Mediterranean area (Giannakis et al., 2016). However, irrigation is now also spreading to regions at higher latitudes due to climate-driven drought and water scarcity. This implies that investments in irrigation and water infrastructure are needed in a significant part of the EU. Insights in irrigation as an adaptation tool to climate change are therefore required.

Looking at irrigation, however, it becomes clear that there is no such thing as “irrigation.” Farmers nowadays consider water management options across a spectrum that ranges from purely rain-fed farms to purely irrigated farms. In between the extremes, there are, among others, farmers that use supplemental irrigation on only part of their fields, farmers that apply conservation practices to store water in the soil, farmers that add more surface- or groundwater to their fields, and farmers that irrigate on a very frequent basis (Molden, 2007). This implies that two farmers who “irrigate” can have significantly different irrigation efficiencies and effectiveness, which might explain differences in their climate responsiveness. Not taking into account these farm-to-farm differences might unintentionally lead to inconsistent results regarding the impact of irrigated versus rain-fed farming, or regarding the farm decision process. For policy, this leads to uncertainties and confusion regarding which adaptation options should be used. We therefore examine the following research question:

4.1. Does ignoring the continuous spectrum from purely rain-fed to purely irrigated agricultural farms influence climate change impact results?

Chapter 5 – In chapter 4, we show that the farm irrigation decision is not merely a “yes” or “no” decision determining whether to irrigate or not. Instead, the farm irrigation decision consists of a number of decisions concerning the irrigation technology, the water application rate, and the share of irrigated land. These decisions lead to a range of water management options that lead to a wide range of climate responses depending on the degree of adaptation.

Given the large number of adaptation decisions a farmer can take, and given the fact that such decisions influence the farm’s climate response and sensitivity, it is important to gain more insight into the farm decision-making process. Remarkably, however, only few studies examine farm irrigation decisions explicitly. And, the Ricardian method, as explained previously, does not explicitly model adaptation. Adaptation is implicitly accounted for and not revealed to the researcher. As such, the adaptation process is a “black box,” which makes it hard to better understand and act on it.

The goal of this chapter is therefore to open this black box to better understand the farm irrigation decision process. However, before doing so, it is important to clearly set the scope of this chapter, as it is impossible to model all farm irrigation decisions. We therefore present a framework consisting of three levels. The first level captures the binary irrigation decision itself: will the farmer irrigate or not? A complication here is that farmers (and decision makers in general) make multiple decisions at the same time. In the case of irrigation, the decision to irrigate depends highly on water requirements, which depend on how much water a crop needs. As a result, the irrigation decision is dependent on the crop choice of the farmer. And, the farm crop choice in turn depends on how much water is available to a crop. This water availability and reliability depends in its turn on the farm irrigation decision. As a result, the first level of the framework consists of a simultaneous irrigation-crop choice model, as both decisions are made simultaneously. Depending on this irrigation-crop decision, a number of successive decisions will be made in the second level of the framework. That is, if a farmer decides to irrigate, he will have to decide on the size of the irrigated land, adoption of different irrigation technologies, adjustments in water application rates for specific crops, and allocation of land to different crops. Finally, depending on all these choices, a farmer will face a conditional climate response in the third level of the framework.

Ideally, this entire framework should be modeled as one mixed, simultaneous decision model in which all decisions are jointly modeled. However, this chapter will focus on only the first and the third levels of the framework. That is, we will estimate the farm's simultaneous irrigation-crop decision and its conditional climate response. This is done because estimating the entire framework at once would be computationally very challenging and data-intensive. In addition, we do not possess sufficient data to model the successive decisions in the second level of the framework. Furthermore, we are aware of at least one study (Olen et al., 2016) that models such successive decisions (even though separately and not in a joint, simultaneous model). This study of Olen et al. (2016) suggests that researchers focus on building a mixed, simultaneous decision model that estimates the irrigation and crop decisions simultaneously, as currently the majority of researchers examining the farm irrigation decision do not take into account the simultaneous crop decision. We therefore focus on building a simultaneous irrigation-crop decision model. In doing so, we answer the following question:

5.1. Does crop choice influence irrigation choice?

The irrigation-crop decision model in the first level of the framework provides more information than only the relationship between crop and irrigation choice. Given the fact that climate change is causing more periods of drought and higher levels of water scarcity, it is also important to examine how farmers choose adaptation options in response to such climatic changes. We therefore answer the following question:

5.2. Do climatic influences increase a farm's probability to opt for irrigated farming? And if so, how?

Once it is determined how farmers make irrigation decisions, farmers can endogenously categorize themselves in one of the two decision categories (rain-fed versus irrigated farms). As such, it will be possible to compare the different conditional climate responses with one another to evaluate the effectiveness of the farm adaptation decision.

5.3. Do irrigated and rain-fed farms have different climate response functions? And if so, how do the functions differ?

Finally, it should be noted that accounting for irrigation in cross-sectional methods has been subject to numerous discussions in the past. A recurring question was whether traditional cross-sectional methods take into account irrigation properly and whether estimates are biased if irrigation is not modeled explicitly. We therefore also compare our model, which explicitly models irrigation, with the traditional model that does not explicitly model irrigation, and we answer the following question:

5.4. Do traditional cross-sectional models properly capture irrigation?

Conclusion – The final chapter of this PhD dissertation contains general conclusions and the answers to the above research questions. It discusses these findings regarding further research and policy implications.

CHAPTER 2.
DO WESTERN AND EASTERN EUROPE HAVE THE SAME AGRICULTURAL CLIMATE RESPONSE? – TAKING ADAPTIVE CAPACITY INTO ACCOUNT

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CHAPTER 2.

Do Western and Eastern Europe have the same agricultural climate response? – Taking adaptive capacity into account

"Climate change increasingly poses one of the biggest long-term threats to investments." – Christiana Figueres (UNFCCC)

Abstract – This dissertation's first sub-research question relates to the question to which extent differences in adaptation and investment efforts are needed in different European regions and whether it is possible to improve regional climate responses. Current cross-sectional methodologies measuring climate change impacts namely assume that regions at the same latitude face a similar climate response and therefore have the same adaptive capacity. This chapter proves that assumption to be erroneous in the European Union. It does so by ameliorating the Ricardian methodology by restricting which farmers (and therefore which adaptation options) are allowed in the dataset. In doing so, a comparative Ricardian methodology is suggested that makes it possible to examine, for the first time, how the climate responsiveness of a region changes if adaptive capacity changes. The chapter combines climate, soil, geographic, socio-economic, and farm-level data in a linear mixed-effect model and examines whether Eastern and Western Europe have the same climate responses and how these responses change if regional adaptive capacity increases. The results show that when both regions rely independently on autonomous profit-maximizing farm behavior, depending on the climate change scenario this leads to an almost 50 percent loss in Eastern European land values compared to a 2–32 percent loss for Western Europe. This is because both regions do not have the same means to adapt to climate change. However, it is possible to improve the agricultural climate response function of Eastern Europe by broadening its range of adaptation options up to the same level as Western Europe. If Eastern Europe were to apply and implement the same adaptation options as Western Europe by 2100, it could avoid a 50–69

percentage points decrease in land value depending on the climate scenario.

2.1. Introduction

It is a striking statistic that between 2011 and 2013, agricultural labor productivity in Eastern Europe was only 19 percent of agricultural labor productivity in Western Europe (EC, 2013). This is despite investment of approximately 20 billion euro of European Union (EU) and national funds to modernize Eastern European agriculture between 2000 and 2012 (Erjavec, 2012). Clearly, there continue to be sizeable socio-economic disparities and technology gaps between Western and Eastern Europe, even though Eastern European countries entered the EU as early as 2004 (Swinnen and Vranken, 2009). In contrast with this slow transition process, the United Nations Environment Program (UNEP) points to the urgent need to close this type of technology gap in less-developed regions because climate change will have a disproportionate impact if their adaptive capacity does not increase quickly enough (IPCC, 2014b; UNEP, 2014). Indeed, "those with the least resources have the least capacity to adapt and are the most vulnerable" (p.8) (IPCC, 2001).

Nevertheless, most studies in this area have focused on the impact of climate change on agriculture in developed countries, not representing developing countries (Sanghi and Mendelsohn, 2008) or countries in transition such as those in Eastern Europe. Furthermore, studies that have looked at developing countries have ignored the technological development and steep learning curve those countries continue to face. Consequently, they are unable to distinguish climate change impacts from losses due to a lack of adaptive capacity. Although there has been a lot of criticism related to this ignorance of technological development, the criticism has failed to differentiate between (a) development due to existing technologies and knowledge in developed countries, and (b) development due to future technologies. However, in case of developing countries or countries in transition, one can already partly take into account technological development by looking at existing technologies in developed regions.

Related to this is the problem of large-scale agricultural climate change impact studies (e.g. Cline (2007)) ignoring East–West differences. In doing so, these studies assume that regions at the same latitude facing the same climate (and holding environmental and other factors fixed) have the same adaptive capacity or climate response, and thus face similar climate change impacts. This assumption is erroneous given that adaptive capacity is context-specific and differs from country to country (Smit and Wandel, 2006). In addition, adaptive capacity is not static; it changes over time. Therefore, both developed and developing countries can enhance their adaptive capabilities to cope better with climate change (IPCC, 2001). In this respect, Haddad (2005) noticed that adaptive capacity development paths in response to climate change are highly influenced by national socio-political aspirations and priorities. In the case of the European Union, it seems that the latest Common Agricultural Policy (CAP) reform is not sufficiently encouraging (Eastern European) countries to increase their rural climate change adaptive capacity. This could be due to the fact that differences in European adaptive capacity to climate change have not received significant attention, even though such attention is a prerequisite for understanding differences in adaptive capacities for successful targeting interventions (Vincent, 2007).

The present paper examines these warnings for the EU by separating it into Eastern and Western Europe: a region in transition and a developed region, respectively. The most recent large-scale study of climate change impacts in Europe already examined Western Europe (Van Passel et al., 2017). This paper builds on their work by testing whether Western and Eastern Europe have similar climate responses. We defined climate response using the Ricardian technique and ameliorated it in order to take into account differences in adaptive capacity. The Ricardian technique is a statistical cross-sectional regression method that measures the sensitivity of comparable land values to climate and other factors by using historical data about existing farms that face different climate and soil conditions (Mendelsohn and Dinar, 2003; Mendelsohn et al., 1994). As a result, this method takes into account hidden human, climatic, agronomic and other mechanisms that have already been presented in the regional climates (Sanghi and Mendelsohn, 2008). The main advantage of the Ricardian technique, compared to other approaches, is that it takes adaptation into account in its estimations because farmers have already adapted to the climate in which they live (Mendelsohn et al., 2009). To date, however, the methodology has never distinguished between differences in adaptive capacity within the sample examined, or how the climate responsiveness would change if adaptive capacity increases. The present paper is the first to study farmers' actual and potential climate response by estimating the same model twice, but using different datasets: the first dataset includes all Eastern and Western European farms, while the second dataset contains the same farms, but splits them in separate sub-datasets (one with only Eastern European farms and one with only Western European farms). In this way, the paper improves on the traditional Ricardian method and economically valuates the benefits of unlocking Eastern European potential adaptive capacity. As such, it provides an understanding of how climate change impacts could be moderated by increasing adaptive capacity.

Sections 2–6 discuss (2) the Ricardian technique, its assumptions and this paper's improvement; (3) the data and model estimation; (4) the empirical findings and projections of different climate scenarios; (5) the discussion; and (6) the conclusion.

2.2. Methodology and modeling

This section begins with a general overview of the Ricardian method and then clarifies how this paper's approach is different from previous studies that have assumed farm development and adaptive capacity to be the same within regions at the same latitude or climate zone.

In its original form, the Ricardian model explains variation in land value per hectare of land in different regions (Mendelsohn et al., 1994). The method assumes that land value reflects the present value of future net income for each farm (Ricardo, 1817; Seo and Mendelsohn, 2008b). Net income (NI) of the farm can be described as follows (Mendelsohn and Dinar, 2003; Wang et al., 2009):

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

where P_{qi} is the market price of crop i, Q_i is the output or production function for crop i, X_i is the vector of purchased inputs for crop i, L_i is the vector of labor for crop i, K_i is the vector of capital, C is the vector of climate variables, Z is the set of soil characteristics, G is a set of economic variables, X_i is the 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 labor, and P_K is the rental price of capital.

The net present value of net income (V) is as follows (Mendelsohn and Dinar, 2003; Wang et al., 2009):

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

where t is time and φ is the discount rate. The Ricardian model is derived from the latter equation by assuming that each farmer maximizes net income by choosing the optimal amount of all different endogenous variables that are within his or her control (Q_i, X_i, L_i, K_i) and by using land with the most suitable climate for the most profitable activity, subject to the exogenous conditions of each farm ($P_q, C, Z, G, R, P_x, P_L, P_K$) that are outside the farmer's control (Maharjan and Joshi, 2013; Mendelsohn et al., 1994).

This profit-maximization assumption is the key to explaining how the Ricardian method takes adaptation into account: the method assumes that farmers in one location behave the same as farmers in a second location would if that second location were made to look like the first one (Lippert et al., 2009; Timmins, 2006). Referring to the example illustrated in the paper of Mendelsohn et al. (1994), this means that if a change in climate lowers the value of producing wheat, a profit maximizing farmer will adapt and switch to corn if these revenues are higher than those of wheat in the new climate.

This knowledge of *how* adaptation is taken into account is indispensable to understand the strengths and limitations of the model. However, it is even more important to understand *which* adaptation options are taken into account. The Ricardian method, which corresponds to the idea of Hedonic Pricing of environmental attributes, automatically takes into account all possible adaptation options of which data of other farmers are available in the dataset (Lippert et al., 2009). Therefore, it is the dataset on which the Climate-Response Function is based that determines the size of the adaptive capacity available per farmer. All Ricardian papers acknowledge that this implies that the methodology is very optimistic with regard to climate change adaptation because it disregards transition costs and efforts. Nonetheless, we are not aware of a Ricardian paper that tests whether the dataset or chosen sample has an influence on the result and how this would change the climate response. Still, this is important to know in case certain regions in the study have no or less access to adaptation options that are available in the dataset anyway and are thus incorrectly assumed to be at the disposal of the region.

Given that there are large differences between Eastern and Western Europe, this paper specifically tests the consistency and robustness of the European Climate-Response Function over different farmers at the same latitude and tests how the function changes if available adaptive capacity changes. This is done by comparing two models: a Single Climate-

Response Model and a Double Climate-Response Model. The Single Climate-Response Model estimates one single overarching relationship, assuming that climate coefficients are the same for both Eastern and Western Europe. This means that all the Eastern and Western European farms in the dataset are taken into account to estimate the climate response. The Double Climate-Response Model repeats the Single Climate-Response Model, but also allows climate coefficients to vary between the two regions. This is done by multiplying a dummy for Eastern and Western Europe by each variable. This implies that the Eastern European Double Climate-Response model is based entirely and only on the Eastern European part of the dataset, and the Western European Double Climate-Response model is based entirely and only on the Western European part of the dataset. Therefore, the only difference between the Single and Double models is the datasets that they use. Thirdly, as an additional robustness test to further justify and test the results of the models, we applied the coefficients of the Double Climate-Response Model from one region to predict what would happen in the other region. In this way, we recognize that Eastern and Western Europe have a slightly different base climate.

In order to address the question of whether Eastern and Western Europe have the same climate response, we do not compare Eastern and Western Europe directly. Instead, we compare the Single and the Double Climate-Response Models with each other, which are identical apart from the dataset they use. If there is one consistent Climate-Response function in Europe, the Single and the Double Climate-Response Models should not be significantly different from each other. Nevertheless, for the control variables, we do compare Eastern and Western Europe directly by comparing the coefficients of the Double Climate-Response Model for each region. Finally, in order to answer the research question of how a regional Climate-Response function changes if its adaptive capacity increases, the response of one region in the Single model is compared with its own response in the Double model.

Independent of the dataset applied to the model, the profit-maximization assumption still implies that all the endogenous variables within the farmer's control are optimized and that the Ricardian model therefore only consists of a set of exogenous variables that affect the future net value of net income (NI*), and thus land value (V).

$$NI^* = f(P_q, C, Z, G, R, P_x, P_L, P_K)$$
$$V = \beta_0 + \beta_1 C + \beta_2 C^2 + \beta_3 Z + \beta_4 G$$

These exogenous variables can be grouped in three subgroups: climate variables (C), exogenous control variables (Z) and socio-economic variables (G). For the first subgroup, (C), we use temperature and precipitation to describe climate. These climate data are averaged into four seasons because there is a high correlation in climate data from month to month. Linear and quadric terms are introduced for both temperature and precipitation since earlier field studies proved the non-linear nature of the net revenue function (Mendelsohn and Dinar, 2003; Mendelsohn et al., 1994). Due to the quadratic climate term, the marginal impact of a climate variable i on the value of farmland depends upon the level of the climate, $\mathrm{C_i}$, in which the farm is already located (Mendelsohn et al., 2009). Therefore, 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 ($\mathrm{ME_i}$)), which is calculated as follows:

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

The annual average marginal effect (MEt and MEp) is derived from the previous 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 MEt or an increase of 1cm/mo in precipitation for MEp.
Having estimated the Ricardian model, we can calculate what the estimated value of the land under the new climate will be (C_1) and compare this with the current climate (C_0). The difference between the two is the change in welfare (ΔW) after climate has changed from C_0 to C_1 (Mendelsohn et al., 2009). GCM models can be used to calculate this non-marginal climate change impact.

In this paper specifically, when comparing the Single and the Double Climate-Response, above all, the marginal effects of climate have to be examined before interpreting climate change impacts from the GCM models. This is important because changes in climate are slightly different in Eastern and Western Europe. The marginal effects allow us to compare the same increase in temperature and precipitation over both Eastern and Western Europe. This allows for an interpretation of possible differences between the Single and the Double Climate-Response Models that are not related to differences in climate change. We can then draw, ceteris paribus, conclusions for climate change scenarios that differ between the regions.

Finally, land value was not only influenced by a group of climate variables, but also by a group of exogenous control variables and socio-economic variables. These are needed in order to isolate climate factors from fixed, unmeasured and climate-correlated factors (Chen et al., 2013). Because land values are used, it is necessary to account for population density, GDP per capita, elevation, and distance to ports and cities to control for market access for farm products and the opportunity cost of land utilization (Chen et al., 2013). In addition, different soil characteristics must be controlled for because these undoubtedly have an influence on productivity. Finally, since the paper is on a continental scale, it is also important to control for continental influences. A special concern in Europe is whether the EU Common Agricultural Policy (CAP) distorts climate sensitivities. Therefore, we also control for CAP subsidies at the farm level. These subsidies have a linear effect on land value because they are decoupled from production in order to reinforce market orientation and to improve environmental and social conditions (Schmid et al., 2007).

2.3. Data and estimation method

In this section we explain which data and estimation methods are used. With regard to the farm-specific data (agricultural land value, subsidies and land rented), we relied on farm accountancy data collected in 2007 by the FADN (Farm Accountancy Data Network) (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 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. The USD–Euro exchange rate fluctuated in 2007 between 0.672 and 0.770 Euro per 1 USD (ECB, 2016).

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. Consequently, the farm sample data are clustered within different countries, which means that our dataset has a nested structure. This can lead to random effects that influence the variance of the dependent variable because the agricultural land values of observations in the same country may be more related to each other than to agricultural land values of observations in other countries (Crawley, 2007). Especially for this study, due to this large geographic dispersion, and given that there are multiple unmeasurable differences between Eastern and Western

Europe, it is important to take into account the added variation caused by the differences between the countries. This study uses the Linear Mixed Effect Model (LME), which consists of fixed effects (that are equivalent to the Ordinary Least Squares estimates), and random country effects that make it possible to take into account differences between countries by allowing for a random shift around the intercept. This implies that the model assumes that the variation around the intercept is normally distributed for each country and with a certain variance (Zuur et al., 2009). As such, the LME model creates underlying different intercept values that capture the differences between the different countries. Alternatively, we could have used 25 country dummy variables to build a country fixed-effects model, but this would have cost 24 degrees of freedom and the results are almost identical to the results of the LME Model. This implies that national influences are captured by the model, while the paper’s models still have to control for regional or individual influences on land value. The LME model is estimated by means of the Restricted Maximum Likelihood (REML). Finally, it should be noted that we can use a unique and large dataset, which has a positive influence on the robustness of the model with respect to capturing unmeasurable influences on land value.

Furthermore, the paper corrects for non-normality by taking the log transformation of the dependent variable. This is also suggested by Massetti and Mendelsohn (2011b) and Schlenker et al. (2006) since land values are log-normal. In addition, each farm is weighted using the total amount of owned agricultural land in that farm to further control for heteroskedasticity. Finally, outlier tests were conducted. The open software R was used to run the regression model and graph the results (R Core Team, 2014).

All of the information about fixed effects (climate and control variables) is linked on the NUTS3 level. The baseline climate should be representative for the recent average climate in the study region and should be of a sufficient duration to encompass a range of climatic variations (Carter and La Rovere, 2001). This study uses the 30-year normal period for temperature and precipitation from 1961–1990 from the Climatic Research Unit (CRU) CL 2.0 (New et al., 2002). These long-run climate estimates are stable.

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 (FAO/IIASA/ISRIC/ISSCAS/JRC, 2009). 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 (ESRI, 2014; EuroGeographics, 2014; Eurostat, 2016; National Geospatial-Intelligence Agency, 2014; Natural Earth, 2014). An overview and detailed description of all model variables and sources can be found in Appendix A. An overview of the distribution of the sampled farm land that we used can be found in Appendix B.

Once the Single and the Double Climate-Response Models had been built, we determined the marginal effects of temperature and precipitation and used Wald chi-square tests (comparable with F-tests in country fixed effects models) to compare both models and to test whether the climate responses of both models differ significantly. We then used the estimated parameters of the Ricardian regression to simulate impacts from future climate change. This is done based on plausible climate change scenarios. A common method to develop climate scenarios is to use the output of Global Climate Model experiments (Carter and La Rovere, 2001). To construct GCM-based climate change scenarios, an emission scenario that predicts atmospheric greenhouse gas and aerosol concentrations should be chosen (Goodess, 2014). This paper uses GCMs that are used in the AR4 and that use the well-known IPCC-approved A2 SRES scenario (Nakicenovic et al., 2000): the ECHO-G (Legutke and Voss, 1999) and

NCAR PCM (Washington et al., 2000) climate models for 2071-2100. These two climate scenarios represent a moderate and a mild possible change in climate, respectively. The mean temperature and precipitation in Eastern and Western Europe of each scenario can be found in Appendix A.

Mean differences between the control climate and the future climate are calculated from these climate models (Carter and La Rovere, 2001). The standard approach in climate science literature is then to add these GCM projections of regional climate change of the control period to the subregional baseline. This method preserves subregional variation and avoids regression toward the mean is avoided (Fisher et al., 2012). Ratios (future climate/control climate) are used for temperature variables, differences (future climate minus control climate), and for precipitation variables (Carter and La Rovere, 2001). Finally, the climate generated by GCMs is attributed to each NUTS3 region centroid by interpolating the four closest grid points of the GCM scenario using inverse distance weights.

2.4. Results

This section presents the two regressions that have been modeled in this paper and introduced in section 1 (see Table 1). Both regressions consist of the same variables; however, unlike the Single Climate-Response Model, the Double Climate-Response Model allows the climate response in Europe to differ between Eastern and Western Europe. This is done by means of an interaction between each variable and a dummy indicating whether the farm is located in Western or Eastern Europe. As such, in the Double Climate-Response Model, the coefficients of Eastern Europe are estimated using the Eastern European part of the dataset, and the coefficients of Western Europe are estimated using the Western European part of the dataset. In the Single Climate-Response Model, the climate response of Eastern and Western Europe is assumed to be identical and therefore estimated using one dataset combining all Eastern and Western European farms.

Comparing both models as a whole, the ANOVA test gives a Chi square value of 2208.8, which implies a significant difference between the Single and the Double Climate-Response Models. Looking specifically at the

Table 1 – Single and Double Climate-Response Mixed Effect Regressions

	Single			Double Climate-Response							
	a) East + West			b) East			c) West			d) Difference	
	Coef	Sig	St Er	Coef	Sig	St Er	Coef	Sig	St Er	Coef	Sig
(Intercept)	-0.822		0.524	-0.966		2.331	2.955		2.398	3.921	
T Winter	-0.010		0.017	-0.511	***	0.049	-0.017		0.021	0.494	***
T Winter²	0.002	*	0.001	-0.021	**	0.009	0.006	***	0.001	0.027	***
T Spring	0.223	***	0.033	1.565	***	0.141	0.082	*	0.044	-1.484	***
T Spring²	0.018	***	0.002	-0.054	***	0.009	0.025	***	0.002	0.079	***
T Summer	0.414	***	0.061	-2.143	***	0.349	0.446	***	0.075	2.589	***
T Summer²	-0.019	***	0.002	0.043	***	0.010	-0.018	***	0.002	-0.06	***
T Autumn	0.144	**	0.060	1.065	***	0.304	0.338	***	0.069	-0.727	**
T Autumn²	-0.015	***	0.003	-0.031	**	0.015	-0.026	***	0.003	0.005	
P Winter	0.055	***	0.015	-0.026		0.116	0.110	***	0.016	0.136	
P Winter²	0.001		0.001	0.017		0.013	0.000		0.001	-0.017	
P Spring	-0.218	***	0.025	-0.197		0.136	-0.202	***	0.029	-0.005	
P Spring²	0.008	***	0.001	-0.006		0.012	0.006	***	0.002	0.012	
P Summer	0.130	***	0.018	-0.438	***	0.076	0.115	***	0.020	0.552	***
P Summer²	0.000		0.001	0.024	***	0.004	0.002	*	0.001	-0.022	***
P Autumn	0.145	***	0.014	-0.022		0.095	0.127	***	0.015	0.149	
P Autumn²	-0.011	***	0.001	0.002		0.007	-0.011	***	0.001	-0.014	*
Elev range	-0.017		0.011	0.002		0.036	-0.011		0.012	-0.013	
Elev mean	0.204	***	0.045	0.732	***	0.176	0.018		0.049	-0.714	***
Subsidies	0.431	***	0.016	-0.003		0.050	0.464	***	0.017	0.467	***
Distance ports	-0.900	***	0.051	-1.104	***	0.106	-0.563	***	0.072	0.541	***
Distance cities	-0.701	***	0.073	0.057		0.178	-0.953	***	0.085	-1.009	***
Pop density	0.498	***	0.033	-0.366	**	0.159	0.476	***	0.034	0.842	***
GDP/inhabitant	0.003	***	0.001	0.046	***	0.005	0.001		0.001	-0.044	***
Freight transport	0.003	***	0.001	0.011	**	0.004	0.003	***	0.001	-0.007	
Rented land	0.130	***	0.014	0.485	***	0.023	-0.084	***	0.018	-0.569	***
pH	1.191	***	0.104	5.294	***	0.301	0.163		0.121	-5.131	***
pH squared	-0.075	***	0.008	-0.410	***	0.023	0.010		0.010	0.42	***
Gravel	-0.009	***	0.003	0.022	**	0.009	-0.037	***	0.003	-0.059	***
Silt	-0.013	***	0.002	0.018	***	0.004	-0.022	***	0.002	-0.039	***
Sand	-0.013	***	0.001	0.004	*	0.002	-0.022	***	0.001	-0.026	***
AIC			195204							193253	
BIC			195501							193830	
Random effect countries (Std. Dev)			1.397			0.8347			1.150	1.039	
Random effect residual (Std. Dev)			5.011			5.0272			4.875	4.922	
ICC			0.038			0.027			0.053		
Std. Dev (ICC)			0.002			0.007			0.003		
Number of farms			60563			18577			41986	60563	

***p<0.01,**p<0.05,*p<0.1

Double Climate-Response Model, using the Wald chi-square test to determine whether the Eastern European coefficients are jointly significantly different from the Western European coefficients gives a value of 2229.2, indicating a significant difference between the two regions.

2.4.1. Control variables

For both models and regions, most of the control variables have the expected signs: higher GDP per capita, smaller distance from cities and ports, higher subsidies and a higher pH value, and a positive impact on land values. However, when comparing Western and Eastern Europe in the Double Climate-Response Model, it must be noted that subsidies do not significantly influence Eastern European land values. This could imply that subsidies have been spent on unproductive farms (Mendelsohn and Reinsborough, 2007). Furthermore, distance from cities does not have a significant impact for Eastern Europe. It should also be noted that a higher share of rented land has a negative impact on land values in Western Europe, but a positive impact in Eastern Europe. There are different and diverging explanations for this, which differ between and even within countries. In general, in Western Europe it is assumed that farmers who are owners of their agricultural land are more willing to invest in and improve their land value. However, this argument is not applicable to Belgium, for instance, where tenants are highly protected by the national land rental policy (Swinnen and Vranken, 2009). Due to the favorable rental conditions in Belgium, farmers are more inclined to rent a portion of their utilized agricultural area since it would leave them more capital for investments. Nevertheless, unlike Western Europe, renting agricultural land is established mostly in Eastern Europe for numerous reasons: for instance, imperfectly working capital markets may mean that financing of land purchases is an issue. Renting land could also prevent capital from being tied up in land that cannot be freed for investments in farm-specific assets or new technologies, and transaction costs for land sales are high (Ciaian et al., 2012). Moreover, land reforms in Eastern Europe have involved land restitutions to individuals who are not active in agriculture. Therefore, land-owners may use land for reasons other than production, such as for storing wealth or for speculative purposes. Therefore, rental markets play a key role in the exchange of land from less to more productive land users, which explains the positive sign of the coefficient for Eastern Europe. With respect to soil type, gravel, silt and sandy soils tend to be slightly harmful in Western Europe, but beneficial in Eastern Europe. As expected, a location at a higher altitude has a positive impact on land values as well. Finally, with respect to the random effects, there are two sources of random variation: one between countries, and one for farms within a country (Larget, 2007). The variance for the random intercept is (1.150^2) 1.323 for Western Europe and (0.835^2) 0.697 for Eastern Europe. This explains how much variability there is between farms over all countries. This means that the average relationship can be shifted for each country by something that is normally distributed with a variance of 1.323 for Western Europe and 0.697 for Eastern Europe. When comparing the variance of Eastern and Western Europe, it can be seen that the differences between farms in Eastern European countries is smaller because their variance is smaller. On the other hand, the residual variance is (4.875^2) 23.763 for Western Europe and (5.027^2) 25.273 for Eastern Europe. This explains the amount of variability there is within the different countries. In this case, it can be seen that within distances between farmers are larger in Eastern European countries than in Western European countries.

2.4.2. Climate variables

The variables of key interest for this paper are the climate variables. It is clear from column D of Table 1 that it is fundamentally wrong to assume that farmers in Western Europe behave the same as farmers at the same latitude in Eastern Europe. Twenty-two of the 31 variables, 10 of which are climate variables, differ significantly between Eastern and Western Europe. The Wald chi-square test confirms that all the temperature variables (Chisq = 528.65), and all the precipitation values (Chisq = 371.89), and all the precipitation and temperature variables combined (Chisq = 880.91), jointly differ significantly each time at the 1 percent level between Eastern and Western Europe. Clearly, there is (currently) no such thing as a European response to climate change and it is crucial to acknowledge this when applying the Ricardian method to the model.

Therefore, we look in more detail below at the direction of the differences between the traditional Single Climate-Response Function, which does not sufficiently acknowledge differences between farmers at the same latitude, and the Double Climate-Response Function, which distinguishes clearly between regions at the same latitude. This means for Western Europe, comparing column A with column C, and for Eastern Europe comparing column A with column B from Table 1. Starting with Western Europe, it can be concluded that, when comparing the Single and the Double Climate-Response, there is no significant difference for the Western European region between the two models. For Eastern Europe, however, these conclusions cannot be drawn: comparing the Eastern European Single Climate-Response with its Double Climate-Response indicates that the Double Climate-Response is more volatile than the Single Climate-Response.

These two findings are confirmed when looking at Table 2 and Table 3. Table 2 presents the average regional marginal temperature and precipitation effects on land value for Eastern and Western Europe. It shows the percentage change in land value when temperature increases by 1°C, or when precipitation increases with 1 cm per season. Independent of the model chosen, both regions suffer from increases in summer temperatures. This is because warmer summers stress crops and livestock, while warmer springs are beneficial since they lengthen the growing seasons. However, even though the direction of the response is the same, it is clear that the Eastern European response is more volatile in the Double Climate-Response Model than in the Single Climate-Response Model, while for Western Europe both models give very similar results.

Table 2 – Marginal Effects at Median climate by region

		Marginal effect of temperature					Marginal effect of precipitation				
		Annual	Winter	Spring	Summer	Autumn	Annual	Winter	Spring	Summer	Autumn
Single Response	East	0.136***	0.079***	0.516***	-0.246***	-0.115***	0.079***	0.060***	-0.147***	0.125***	0.041***
	West	0.115***	0.054***	0.559***	-0.263***	-0.187***	0.054***	0.064***	-0.128***	0.126***	-0.009***
Double Response	East	0.129***	-0.434***	0.696***	-0.650***	0.518***	-0.236***	0.097***	-0.251***	-0.084***	0.001***
	West	0.122***	0.027***	0.541***	-0.193***	-0.252***	0.075***	0.105***	-0.126***	0.133***	-0.038***

Weighted T-test to test whether values significantly different from 0 (i.e., no impact): ***p<0.01,**p<0.05,*p<0.1. (%/ha per °C or cm/mo)

Table 3 – Marginal Effects at Median climate by country

	Double Climate-Response				Single Climate-Response			
	MEt	R	MEp	R	MEt	R	MEp	R
Austria	0.196	(11)	0.112	(14)	0.191	(13)	0.070	(13)
Belgium	0.187	(10)	0.080	(9)	0.173	(10)	0.055	(8)
Denmark	0.154	(7)	0.045	(3)	0.162	(7)	0.016	(3)
Finland	0.121	(5)	0.078	(8)	0.140	(6)	0.037	(6)
France	0.149	(6)	0.083	(12)	0.138	(5)	0.064	(10)
Germany	0.178	(9)	0.115	(15)	0.169	(9)	0.079	(15)
Greece	-0.038	(1)	0.080	(10)	-0.033	(1)	0.070	(12)
Ireland	0.307	(15)	0.015	(1)	0.276	(15)	0.006	(1)
Italy	0.010	(3)	0.050	(4)	0.015	(3)	0.036	(5)
Luxembourg	0.200	(13)	0.081	(11)	0.182	(11)	0.059	(9)
Netherlands	0.197	(12)	0.076	(7)	0.184	(12)	0.047	(7)
Portugal	0.027	(4)	0.063	(5)	0.021	(4)	0.065	(11)
Spain	-0.005	(2)	0.093	(13)	-0.006	(2)	0.078	(14)
Sweden	0.161	(8)	0.070	(6)	0.168	(8)	0.035	(4)
UK	0.270	(14)	0.027	(2)	0.251	(14)	0.013	(2)

	Double Climate Response				Single Climate Response			
	MEt	R	MEp	R	MEt	R	MEp	R
Bulgaria	-0.137	(2)	-0.314	(1)	0.032	(1)	0.100	(9)
Czech Rep.	0.119	(5)	-0.209	(8)	0.175	(9)	0.091	(8)
Estonia	0.714	(10)	-0.238	(5)	0.129	(4)	0.027	(2)
Hungary	-0.151	(1)	-0.282	(2)	0.110	(3)	0.090	(7)
Latvia	0.474	(8)	-0.225	(7)	0.143	(6)	0.044	(4)
Lithuania	0.571	(9)	-0.238	(6)	0.139	(5)	0.035	(3)
Poland	0.137	(6)	-0.245	(3)	0.159	(8)	0.076	(5)
Romania	0.019	(4)	-0.239	(4)	0.100	(2)	0.102	(10)
Slovakia	0.143	(7)	-0.131	(9)	0.176	(10)	0.079	(6)
Slovenia	-0.003	(3)	0.148	(10)	0.153	(7)	0.011	(1)

(R) The rank order indicates which countries have the lowest (1) and highest marginal effects. (%/ha per °C or cm/mo)

Table 4 – Percentage change in land value
(%/ha per scenario)

		NCPNAR	ECHOG
Single climate-response	East	0.029	0.214
	West	-0.012	-0.325
Double climate-response	East	-0.496	-0.472
	West	-0.017	-0.317

However, interpreting the average MEt (Table 2) does not provide a good view on the climate response of the different countries because it does not show the within differences (the high positive impacts of the Northern countries (Estonia, Latvia, and Lithuania) averages out the negative impacts of the Southern regions). In Table 3, on the other hand, both the MEt and MEp for the Double and the Single Climate-Response are presented, together with a ranking from the lowest marginal effect (1) to the highest marginal effect. These results are also visualized at NUTS3 level for the annual marginal effect of temperature in Figure 6a. With regard to Western Europe (both the Single and the Double Climate-Response Models), the marginal effects lie relatively close to each other. In the Double Climate-Response Model for Eastern Europe the Northern countries (Estonia, Latvia and Lithuania) enjoy significantly higher benefits from an increase in temperature than in the Single Climate-Response Model. These differences decrease in the Single Climate-Response Model and the impacts lie closer together.

Therefore, Table 3 and Figure 6a clearly confirm our findings from Table 1. Looking at the Single Climate-Response Model, the marginal impacts of climate in Eastern and Western Europe are very similar to each other. However, when looking at the Double Climate-Response Model, the two regions behave quite differently: Western Europe responds similar to climate change as in the Single model, while Eastern European countries face a more negative impact than in the Single Climate-Response Model.

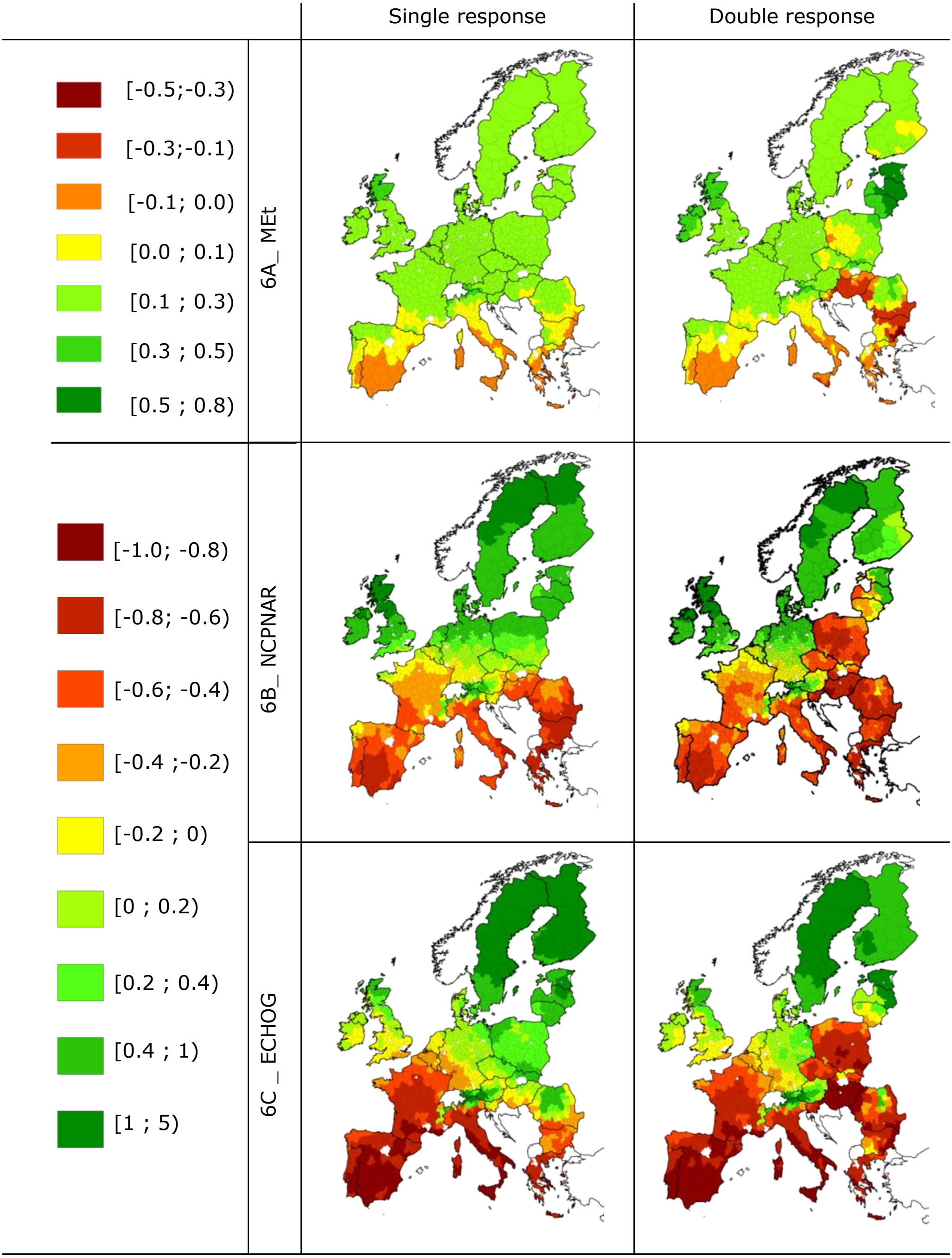

Figure 6 – Percentage change in land value: MEt, NCPNAR & ECHOG

Finally, the above results show that individual differences between countries need to be taken into account as well since marginal climate effects differ over Europe because of differing initial conditions. Therefore, we have verified that the base climate, which slightly differs in both regions, does not influence the marginal impacts. Using the Western European coefficients of the Double Climate-Response Model to predict what would happen in the Eastern European climate shows that Eastern Europe would react in a similar way to how Western Europe would. Both the marginal impact of temperature (14.05 percent) and precipitation (12 percent) increase in Eastern Europe when the Western European coefficients are used. For Western Europe, on the other hand, if the climate response of Eastern Europe (in the Double Climate-Response Model) is applied to the Western European climate, the marginal effect of temperature and precipitation both decrease. Comparing the marginal effect of Eastern Europe in the Single Climate-Response Model (13.6 percent) and the marginal effect of Eastern Europe when the climate response of Western Europe in the Double Climate-Response Model is used (14.05 percent) highlights the fact that the base climate is not causing significant bias to the previous conclusions.

2.4.3. Future welfare changes

Having proven that the Single and the Double Climate-Response Model differ significantly from each other and give different climate impacts under the same increase in temperature and precipitation, we now examine how these climate impacts change when GCM-based climate change scenarios are applied to the models. Using the NCAR PCM (mild climate change) and the ECHO-G (moderate climate change) scenario, this section determines for each of the regressions the new land value after climate change has taken place according to each scenario. Table 4 displays the percentage differences between the future land value estimates and the current climate estimates for each type of this paper's regressions. This is also visualized in Figures 6b and 6c.

In the NCAR PCM scenario, precipitation increases on average by 1.2 cm per year, and temperature increases by 3.1 °C per year in Eastern Europe. In Western Europe, temperature increases on average by 2.8 °C and precipitation decreases by 0.2 cm per year. Comparing the Single and the Double Climate-Response, it is clear that the same climate change scenario causes a more negative impact in Eastern Europe in the Double Climate-Response Model than in the Single Climate-Response Model. For Western Europe, decreases in land value are slightly under 0 percent depending on which regression is taken, but there is no significant difference between both models.

If the ECHOG scenario would occur, average increase in rainfall would be 0.6 cm less than in the NCAR PCM scenario, while the temperature increases by an additional 1.6 °C. For Western Europe, on the other hand, total rainfall decreases by 1.3 cm and temperature increases by 4.11 °C compared to the current climate. Land values in Western Europe would decrease by about 32 percent, independent of which regression is taken. For Eastern Europe, the same conclusions can be drawn as in the NCAR PCM scenario: if the Single Climate-Response is assumed to be the correct one, Eastern Europe benefits on average from climate. Otherwise, it faces decreases in land value of up to 47 percent.

Therefore, the same change in climate in Eastern Europe causes significantly different impacts under both models. As such, it can be concluded that under the Single Climate-Response Model, Eastern Europe is better off than under the Double Climate-Response Model.

2.5. Discussion

The impacts determined by the Single and the Double Climate-Response Model clearly differ significantly between Western and Eastern Europe. Therefore, there is (currently) no common European climate response. Firstly, this raises two questions: what explains the differences between the two models, and which of the two models should be used for further studies.

The difference between the Single and the Double Climate-Response Models is explained by the differences in datasets that they used. This is because the Ricardian technique only accounts for adaptation options that are observed in the dataset. For the Double Climate-Response Model, the paper allowed the model parameters to differ between Eastern and Western Europe. Therefore, the model looks independently at Eastern and Western Europe, which means that for each region there is one inventory of potential adaptation options, each with the technologies and knowledge of that region. Since the variation in Eastern European farms is smaller, and since agriculture is less developed, modernized, and capital-intensive than in Western Europe, the inventory of potential Eastern European adaptation options is smaller in the Double Climate-Response Model than in the Single Climate-Response Model. This is undoubtedly caused by institutional and societal differences that influence the development options of regional agriculture. Therefore, the negative impact of climate change is overestimated in the Double Climate-Response Model because multiple plausible adaptation options, which already exist in Western Europe, are not taken into account. Moreover, after unifying with the European Union, Eastern European countries are continuing to re-adjust their institutions according to Western European templates and Eastern European farmers have access to EU farm subsidies.

As such, looking at the Single Climate-Response Model, where all coefficients are assumed to be identical for Eastern and Western Europe, implies looking at a model that assumes the convergence of Eastern Europe to the Western European societal, economic, political and institutional model has been completed. Therefore, in the Single Climate-Response Model, the adaptive capacity of Eastern Europe is much larger because plausible adaptation options available in Western Europe are assumed to be as well available in the adaptation inventory of Eastern Europe. Consequently, the Single Climate-Response Model looks at one combined inventory of potential adaptation options of both Western and Eastern Europe together. However, this is overly optimistic at the moment because before Eastern Europe gains access to the same level and quantity of adaptation options as Western Europe, complex behavioral, technical, societal and institutional costs and adjustments at all levels of the society are required (Downing et al., 1997; Tol et al., 2004). Such a transformation cannot take place overnight and it is not clear how long the convergence process will take. Nevertheless, the Ricardian model, when taking adaptation into account, only assumes optimal autonomous adaptation at the local, farm-scale level, without looking at the broader contexts (such as agricultural and trade policies, policy intervention) or acknowledging the dynamic processes needed to go from the current equilibrium to the new equilibrium (Kelly et al., 2005; Lippert et al., 2009; Polsky and Easterling III, 2001). This observation is key to correctly interpreting and using the results of this study.

2.5.1. Policy implications

Ultimately, both models should be looked at simultaneously on a resilience scale from the current Double Climate-Response where Eastern Europe has a significantly lower adaptive capacity, to the most optimal Single Climate-Response where Eastern Europe benefits from the same adaptive capacity as Western Europe. As such, the Double Climate-Response Model represents the case in which there is no adaptation transfer from Western Europe to Eastern Europe and it is clearly the most pessimistic model on the resilience scale. Therefore, the adaptive capacity in the Double Climate-Response Model can be defined as independent and autonomous profit-maximizing farm behavior. On the other hand, the Single Climate-Response Model represents the most optimistic model on the resilience scale. This model represents the currently locked, potential adaptive capacity of Eastern Europe, which only becomes available if Eastern Europe is capable of implementing Western European adaptation technologies and the necessary accompanying institutional transformation.

One of the plausible reasons why adaptation is currently more difficult in Eastern Europe than in Western Europe can be found in the currently already existing adaptation deficit that most of these countries are facing regarding the current climate (Fay et al., 2010). Comparing gross value added or crop yield per farm across the EU-27 shows that most Eastern European farms are still not yet obtaining the yields they could potentially achieve (Giannakis and Bruggeman, 2015; Supit et al., 2010). This can be explained by the passed centralized input-focused over-specialization, which has "left the sector unprepared to adapt to knowledge-based farming better suited to a world of constrained resources" (p.110) (Fay et al., 2010). While market principles are now predominant all over the European Union, and while Eastern Europe made a lot of progress to close the gaps, the countries in this region continue to face significant socio-economic setbacks that decrease the countries' options to respond to the current and the future climate.

Nevertheless, yields, economic performance, competitiveness, and thus the adaptive capacity of agriculture can be increased by increasing levels of gross fixed capital formation (GFCF). The GFCF measurement indicates how much of the value added in agriculture is invested rather than consumed (European Commision, 2014). In 2011, 90 percent of the EU-28 gross value added was invested in the EU-15 and some of the lowest levels of agricultural investment could be found in Eastern European countries (European Commision, 2014). In addition, over the last years (although this is now changing with the 2013 CAP reform), CAP direct payments per farm holding and even per hectare were also significantly lower for Eastern European farms than for Western European farms. Therefore, it seems that there is also a gap between support needed and support received.

As a conclusion for policy measures, the results of this paper imply that the importance of a large adaptive capacity on all possible fields (crop variety, technological efficiency, institutional fundamentals, sustainable farm management, different farm types, etc.) in order to tackle climate change impacts cannot be overestimated. However, it takes time to increase adaptive capacity, while the effects of climate change are already becoming visible. Therefore, financial means and other institutional support with regard to knowledge transfer and implementation management are necessary in order to improve adaptive capacity. However, different farmers (big versus small, crop versus livestock, specialized versus mixed farms, location, etc.) are affected differently by climate change and require adapted support. Therefore, it is important to conduct further studies on the country or small region level to determine specifically which types of farms are the most vulnerable and to determine the exact type of support they each need. Currently, only a few studies have examined climate change on the individual country level in Eastern Europe.

Given the current development efforts of Eastern Europe, and if further significant institutional efforts are continued, we believe there is no reason to believe that the assumptions of the Double Climate-Response Model will hold in the future. However, before the Single Climate-Response Model becomes reality, significant transition costs are necessary before equal adjustment and adaptation conditions are achieved over all regions. These costs are not taken into account by the Ricardian Technique because it only measures long-term effects, ignoring the period between the short and the long term. The results of the Double Climate-Response Model provide an initial idea of the benefits of such transition costs and should encourage all stakeholders to make the effort to further increase adaptive capacity in Eastern Europe.

2.5.2. Methodology

Comparing the two models has provided a better understanding of the benefits of increasing adaptive capacity and an economic valuation for unlocking Eastern European potential adaptive capacity. Future Ricardian studies should examine how to further improve this two-model framework. First of all, not all regions have the situation where a developed region is located near a region in transition or in development. A research suggestion here could be to use traditional crop models or experimental simulations to test how more-developed technologies would behave in these less-developed environments. The results of these experimental simulations could be used to build a dataset with a higher adaptive capacity, which could be used to test how the climate response changes if a higher adaptive capacity is available. In a similar way, combining experimental simulations and cross-sectional methods could also be the solution to take into account future technological improvements. This paper has only been able to take into account existing technologies to model technological development in Eastern Europe. However, future technologies might increase adaptive capacity even more. By means of experimental simulations, the dataset could be enlarged with more technologies than are (currently) available in Europe alone, and so different Ricardian models can be estimated with different adaptive capacities. Further applications of this comparative Ricardian modeling should also elicit and visualize which adaptation options are included in the unused adaptive capacity. Finally, to further test the framework of the resilience scale from the Double to the Single Climate-Response Model presented in this paper, this study should be repeated after 5–10 years in order to identify the direction in which Eastern Europe is moving.

All of this is important because many climate change studies have already created before-and-after pictures of the impact of climate change. What is of interest for policy now is to picture the dynamic path in between those two stages (Mendelsohn, 2007). The present paper is a clear step towards comparing how different decisions with regard to adaptation options included in the dataset influence regional climate responsiveness. There is an urgent need to improve methods in this direction.

With regard to the correctness of these conclusions, a number of points reinforce this paper’s conclusion. First of all, the models are fairly robust.

This can be seen by looking at the Western European coefficients and marginal impacts over both models: the Western European climate response is almost the same in both the Single and the Double Climate-Response Models. In the Double Climate-Response Model, Western Europe relies on its own adaptive capacity (because the coefficients are determined only on the Western European dataset). Nevertheless, Western Europe responds approximately the same as it does in the Single Climate-Response model, where it can also rely on the adaptive capacity of Eastern Europe. This proves that the adaptive capacity of Western Europe is not significantly increased if the adaptive capacity of Eastern Europe is added. On the other hand, this is the case for Eastern Europe. If the adaptive capacity of Western Europe is added to the adaptive capacity of Eastern Europe, that region will respond more positively to changes in climate. This conclusion is also confirmed by looking at the variance for the random intercept of the LME Model, where it can be seen that there are fewer differences between Eastern European countries. With regard to their adaptive capacity, this means that farmers can rely less on adaptation knowledge and technologies from more Southern countries.

Secondly, as with all models, the correctness of the model depends on how well it can control for unmeasurable influences. This paper’s large dataset enables the LME Model to correct for national influences. One of the ways we tested this was by adding a national variable of which regional data were available (farm taxes- Results can be provided by the author on request). This brought no significant influence to the models, indicating that the national influence is well captured by the LME model. Also, in Appendix C, comparison with a standard country fixed effect model and an LME model estimated with ML estimation is shown for the Double model, indicating its robustness. However, in the event that there is an influence other than adaptive capacity that the paper does not control sufficiently for, it should be highlighted that the paper’s conclusions are only based on the comparison of two identical models. The only thing that differs between the models is the dataset upon which they are based. This also implies that potential bias is (at least partially) cancelled out when evaluating the differences. The best way to prove this would be to add (endogenous) variables that indicate differences in adaptive capacity. If this is successfully controlled for, the climate response of the Double and the Single Model should move together.

Thirdly, while we started by comparing the marginal effects of both models to examine the impact of the same increase in temperature and precipitation, we also verified that the base climate, which slightly differs in both regions, does not influence the conclusion.

Therefore, this paper offers a solution for one limitation of the Ricardian Method. However, when interpreting the results, readers should still keep in mind other limitations of the method. The method specifies climate as a combination of temperature and precipitation, while disregarding carbon dioxide concentrations and extreme weather events. Also, with regard to predictions for 2100, it assumes that apart from climate and adaptive capacity, all other factors remain constant. This is done in order to see the effect of change in climate and adaptive capacity, ceteris paribus, on climate change impacts. However, Eastern Europe, which is a transition economy, is likely to face changes in land value and prices as productivity increases and as Eastern Europe grows towards Western Europe. Transition costs, for instance, will probably be significant, even though they are also not taken into account by the methodology. Moreover, future predictions of benefits and damages from climate change may be overestimated because if production falls, prices will rise and vice versa. However, it is difficult to project how prices will behave in the European Union because of changing global and regional policies, increasing world population and changing food preferences.

2.6. Conclusion

This study traces back the concern of whether climate impact estimates are consistent and robust over space to the question whether policy, institutes, society, and behavior are capable of bringing forth equal and optimal adjustment conditions over the entire region studied. Using a comparative continental scale – Ricardian analysis – and acknowledging its assumption of autonomous farm adaptation behavior, we warn that underlying adaptation requirements are not necessarily realistically applicable to all regions in the dataset.

Therefore, with respect to the methodology and further applications, this paper shows the benefits of testing farm systems in developing regions or transition economies with reference to those of more developed regions with comparable climate variations. It does so by ameliorating the Ricardian methodology by restricting which farmers (and therefore which adaptation options) are allowed in the dataset. As such, we have modeled both a Single Climate-Response Model (implying that two regions have the same adaptive capacity) and a Double Climate-Response Model, which examines the adaptive capacity of two regions separately (without assuming there is a transfer in adaptation inventory and knowledge). The comparison between the two climate response functions identifies unused adaptive capacity enlargement options and provides insights into the economic value of these potential enlargement options. Further applications of this comparative Ricardian modeling should elicit and visualize which adaptation options are included in the unused adaptive capacity and how this translates to region- and farm-specific policy.

With respect to the European case study, this paper mostly improves understanding on the differences between Eastern and Western Europe in impacts and associated costs of climate change. It shows that the region with the lowest adaptive capacity, Eastern Europe, suffers the most from climate change. However, if Eastern Europe were to apply the same adaptation options as Western Europe, it would avoid a significant decrease in land value, or even benefit from climate change, depending on the climate scenario. Since it is unrealistic to assume that this will occur by counting on autonomous, profit-maximizing or market-driven farm behavior, we justify the need for planned adaptation in Eastern Europe.

The European Union, the CAP, national governments and regional policy must attempt to overcome the barriers to adaptation in Eastern Europe and increase Eastern European adaptive capacity by providing more information on adaptation opportunities and climate change, by enlarging the adaptation options and resource inventory and by creating a favorable implementation and management environment, by encouraging knowledge and skills transfer between all European farmers and by guiding farmers in making efficient adaptation decisions.

CHAPTER 3. THE EFFECT OF POLICY LEVERAGING CLIMATE CHANGE ADAPTIVE CAPACITY IN AGRICULTURE

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CHAPTER 3. The effect of policy leveraging climate change adaptive capacity in agriculture

"Climate change does not respect border; it does not respect who you are - rich and poor, small and big. Therefore, this is what we call 'global challenges,' which require global solidarity." - Ban Ki-moon

Abstract – Chapter 2 pointed out that 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 unrealistic as adaptation is facing numerous barriers such as low levels of adaptive capacity. Compared to the previous chapter, this chapter therefore captures and quantifies the impact of adaptive capacity explicitly in economic cross-sectional models, showing that those methods can be more policy-oriented. The results show that on average, once adaptive capacity is accounted for, the marginal effects of temperature decrease by 2.5–5 percentage points in Eastern and Southern European regions. Higher levels of adaptive capacity lead to more positive climate responses. If adaptive capacity increases from 0.4 to 0.8 on the ESPON index, the marginal effect of temperature increases by 0–10 percent on average. However, the relationship between marginal effects and adaptive capacity appeared to have a concave shape, leveling out at higher levels of adaptive capacity. This implies that adaptive capacity only increases marginal benefits from changes in climate up to a certain adaptive capacity level.

3.1. Accounting for adaptive capacity

Adaptation to climate change is unavoidable (Berrang-Ford et al., 2011) as substantial climate change is inevitable due to already unavoidable past emissions (IPCC, 2007b; Stern, 2007). 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) (Rosenzweig et al., 2014). 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 (Ciais et al., 2005). 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 (Ciais et al., 2005). Clearly, adaptability of farming systems is important and it will prove to be a key aspect of farm survival and food security (Darnhofer et al., 2010; Moore and Lobell, 2014). On average, adaptation leads to approximately 10% yield benefits compared with farmers that do not adapt, even though the benefits of adaptation differ between regions and farms (IPCC (2007b), WGII AR4 Section 5.5.1.). Adaptation has therefore become an important pillar for the response to climate change (Field et al., 2014).

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, 2007b). Historically, farmers responded autonomously to changes of climate (Wreford et al., 2010). As a result, studies examining the impact of climate change realized they had to account for these adaptive farm measurements instead of merely modeling the natural relationship between a crop and its surrounding climate. Farmers that adapt to climate change have a different climate response function than farmers who do not adapt. The most famous method addressing this point of taking into account adaptation, is the Ricardian Method (Mendelsohn et al., 1994).

Today, however, it appears that farmers are not responding quickly to recent climate changes anymore (Adger et al., 2007; Burke and Emerick, 2016). The Fourth Assessment Report (AR4) indicated that the level of adaptation was inadequate to reduce climate change vulnerability (IPCC, 2007b). Even though adaptation plans are being developed at different (sub)national levels, there is still limited evidence of adaptation implementation (IPCC, 2014a). 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 (Anwar et al., 2013). 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 (Berkhout et al., 2006; IPCC, 2014b; Kates, 2000). (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 (Brooks and Adger, 2005; IPCC, 2001). This is defined as adaptive capacity (IPCC, 2001). As described in the First Assessment Report (FAR), adaptive capacity is dynamic and influenced by social networks, institutions, governance, technology and other resources (Adger et al., 2007), 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) (Maranville, 1992). The theory of innovation economics says that economic growth is spurred by innovative capacity (Antonelli, 2014) 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 (de Assumpcao et al., 2017).

Given the fact that implementation of adaptation itself goes slowly, there is currently a larger focus on framing adaptation as capacity building (Smith et al., 2011). Individual adaptive capacities are being identified as critical for successful climate change adaptation (Wamsler and Brink, 2015). Methodologies modeling agricultural climate responses should therefore not merely account for adaptation. They should also 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), this leads to cross-sectional studies being too optimistic regarding autonomous profit-maximizing farm adaptation behavior because it makes adaptation unconditional, making it appear like a somewhat “easy” solution that does not need a lot of intervention (Lobell, 2014).

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 (Field et al., 2014). Nevertheless, within Europe, there are large differences in adaptive capacity distribution (ESPON, 2011; Fuentes, 2011) (see Figure 7A). 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 (Field et al., 2014) 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 (Field et al., 2014) and “there is a need to better monitor and evaluate local and national adaptation responses to climate change” (p.1304).

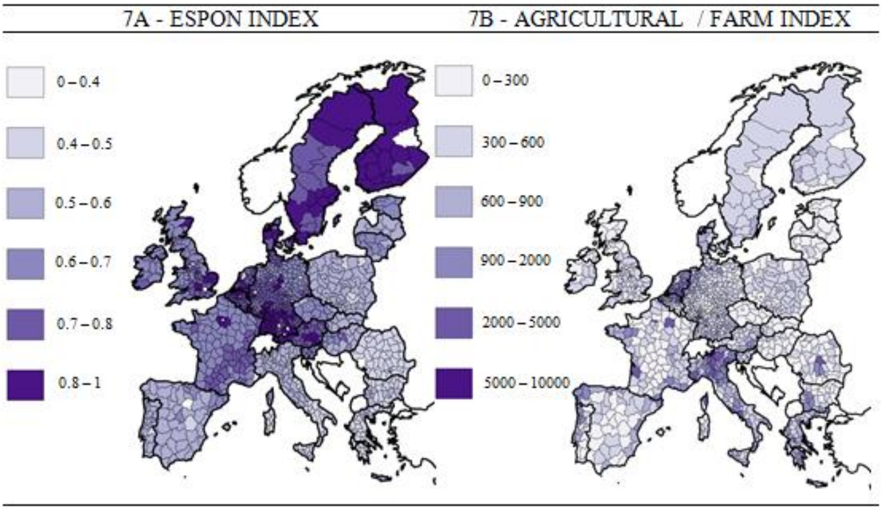

Figure 7 – ESPON and Agricultural Adaptive Capacity Index
7A: ESPON Adaptive Capacity Index (figure adapted from ESPON (2011)) – The higher the index, the better; 7B: Adaptive Capacity Index based on past yield fluctuations (own elaboration using FADN data 2008–2013) – The lower the index, the better.

3.2. 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 (Mendelsohn et al., 1994; Van Passel et al., 2017; Vanschoenwinkel et al., 2016). 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

(Ricardo, 1817; Seo and Mendelsohn, 2008b). 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) (Maharjan and Joshi, 2013; Mendelsohn et al., 1994). As such, the Ricardian model shows how only exogenous variables explain variations in land value (Mendelsohn et al., 2009). 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 (Mendelsohn et al., 2009). 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 (Mendelsohn et al., 1996). 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) (Lippert et al., 2009; Timmins, 2006). 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 (Marshall et al., 2013). 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 variables, the model can be summarized as follows:

$$LV^* = f(C, Z, \mathrm{M}, \mathbf{AC}) \qquad (1)$$

where future net value of net income or land value is presented by LV^*, 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 (Mendelsohn et al., 2009) since earlier field studies proved the non-linear nature of the net revenue function with climate (Mendelsohn and Dinar, 2003; Mendelsohn et al., 1994). 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 ($\mathrm{ME_i}$)), which is calculated as follows:

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

The annual average marginal effect (MEt and MEp) 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 MEt or an increase of 1cm/mo in precipitation for MEp.

Finally, the adaptive capacity explanatory group in equation (1) is presented by AC. We discuss this in more detail in subsection 3.2.1. The model is estimated through an ordinary least square regression and can be compared with previous peer-reviewed work (Van Passel et al., 2017; Vanschoenwinkel et al., 2016) because apart from the adaptive capacity index, similar data are used.

3.2.1. Adaptive Capacity

A good measure of adaptive capacity is needed. Adaptive capacity is a complex, multidimensional, and broad concept, consisting of several subcomponents (Below et al., 2012). Data from a wide range of factors such as financing, knowledge, nature, and technology should be captured when measuring adaptive capacity. Given this complexity, adaptive capacity is commonly synthesized in one term or index, making it more comprehensive and operational, and facilitating communication for both academic, political, and practical purposes (Gallopin, 1997). Nevertheless, 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 7A) (ESPON, 2011). 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 (ESPON, 2011; Jordan et al., 2010). 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 (IPCC, 2007b), 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 (Armitage, 2005).

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 (Adger et al., 2005; Smit and Wandel, 2006). In Germany for instance, inputs explain on average 49% of the total wheat yield volatility (Albers et al., 2017). The adaptive capacity index therefore must be specific enough to capture local variation (Vincent, 2007) and define farm systems more narrowly (Hinkel, 2011). Having a more specific agricultural index allows better understanding of fundamental processes underlying adaptation (Below et al., 2012). 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 (Grasso and Feola, 2012). In addition, scant guidance can be found regarding the selection of the indicator sub-determinants themselves, which causes some subjective interference of the researcher (Brooks et al., 2005). 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 (1) *current* farm performance and that current management characteristics are therefore good indicators of adaptive capacity (Reidsma et al., 2007). Other sources indicate that past experiences are good indicators of adaptive capacity. Regions build up a higher adaptive capacity to (2) *past* limiting factors and are therefore more prepared when these issues recur (Niles et al., 2015). As a result, more unfavorable agricultural areas do not necessarily suffer more as they adapt to the most limiting factors (Challinor et al., 2007; Reidsma et al., 2010). 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 (Reidsma and Ewert, 2008). Finally, there are authors such as Hinkel (2011) and Dilling et al. (2015) 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, (3) *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.

3.2.2. Data

In equation 1, we presented our data in four main groups. 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 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 (New et al., 2002). 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 (FAO/IIASA/ISRIC/ISSCAS/JRC, 2009). 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 (ESRI, 2014; EuroGeographics, 2014; Eurostat, 2016; National Geospatial-Intelligence Agency, 2014; Natural Earth, 2014). 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 D, 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) and Van Passel et al. (2017), although this paper uses more recent data from 2012.

3.3. Results

The regression results can be found back in table 5. 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 (Van Passel et al., 2017; Vanschoenwinkel et al., 2016)). In all cases, the coefficients on the adaptive capacity coefficients are highly significant, and the ANOVA tests show that adding adaptive capacity to the original 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), 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 8A 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 8A), with the marginal effects of temperature of the regression which does account for adaptive capacity by means of the ESPON index (Figure 8B), it becomes clear that apart from Finland, all countries show decreasing marginal effects of temperature when adding an AC index. In particular, countries scoring lowest on the ESPON index register the highest drops in MEts. Clear differences are also noted between Western (MEt = 10-15%) and Eastern (MEt = 7.5-10%) 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.

Table 5 – Linear regression results with and without adaptive capacity

	A - Original		B - ESPON only		C - Agri only	
	Coef	Std Er	Coef	St Er	Coef	St Er
(Intercept)	2.639***	0.428	2.525***	0.422	2.874***	0.422
P Winter	-0.041**	0.014	0.044**	0.014	-0.014	0.014
P Winter²	0.000	0.001	-0.001**	0.001	-0.001	0.001
P Spring	-0.041	0.026	-0.148***	0.026	0.005	0.026
P Spring²	0.003*	0.001	0.006***	0.001	-0.001	0.001
P Summer	0.151***	0.018	0.181***	0.018	0.110***	0.018
P Summer²	-0.001	0.001	-0.003***	0.001	0.000	0.001
P Autumn	0.067***	0.013	0.012	0.013	0.027**	0.013
P Autumn²	-0.005***	0.001	-0.004***	0.001	-0.003***	0.001
T Winter	0.184***	0.016	0.112***	0.016	0.192***	0.016
T Winter²	0.002**	0.001	0.010***	0.001	0.001	0.001
T Spring	0.126***	0.030	0.134***	0.029	0.071**	0.029
T Spring²	0.015***	0.002	0.011***	0.002	0.013***	0.002
T Summer	0.368***	0.055	-0.007	0.055	0.311***	0.054
T Summer²	-0.015***	0.001	-0.005***	0.001	-0.013***	0.001
T Autumn	-0.112*	0.057	0.290***	0.057	-0.128**	0.056
T Autumn²	-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
Ierland	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 index			3.205***	0.079		
Agricultural index					0.465***	0.011
ANOVA F-test			1,656.2***		1,745.1***	
Adjust R^2		0.709		0.718		0.718

A - Original = original regression; B - ESPON only = original regression with ESPON adaptive capacity; C - Agri only = original regression with NUTS 3 agricultural adaptive capacity

However, looking at Figure 9, 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 8B versus 8C), 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

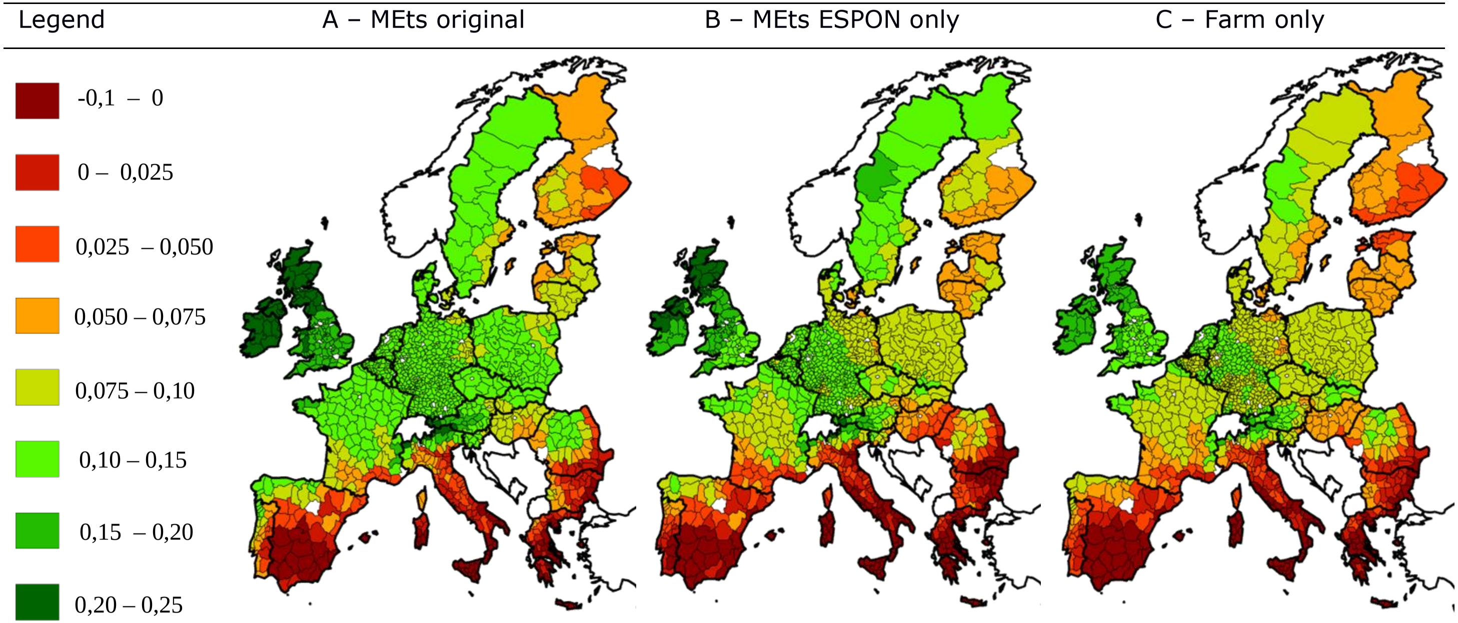

Figure 8 – Marginal effects of temperature per NUTS 3 region
Marginal effects plotted are weighted by a weight reflecting the total amount of farmland that each farm represents in its region. This implies that the marginal effects, as presented in this paper, can be interpreted as the percentage of change 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.

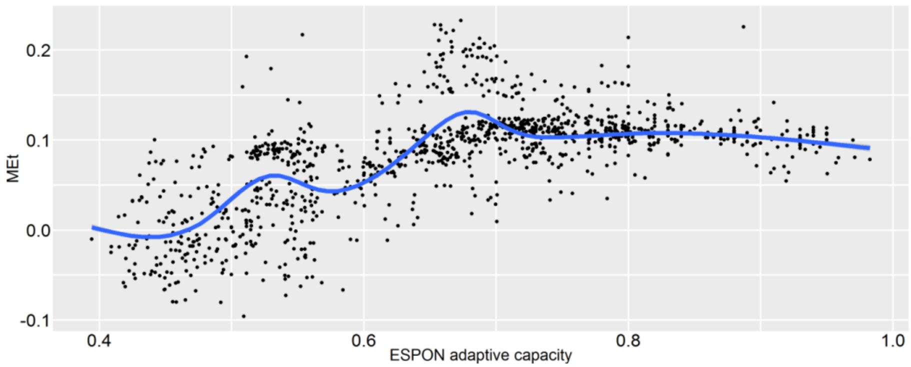

Figure 9 – Evolution of MEts compared to adaptive capacity

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 10). The higher the ESPON adaptive capacity index, the more MEts are adjusted downward when using a regional agricultural index.

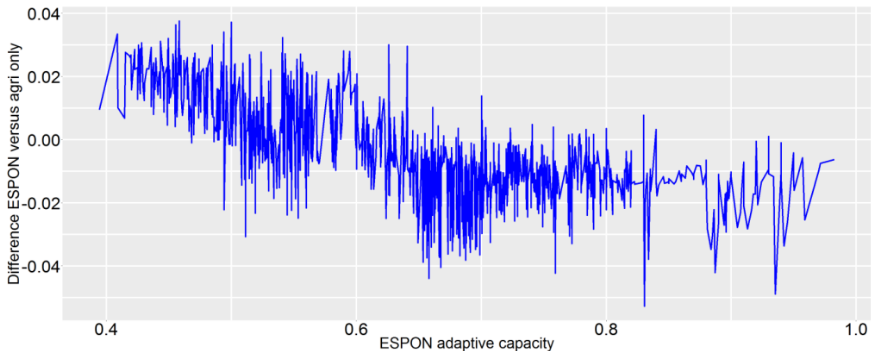

Figure 10 – Change in MEts using a farm index instead of ESPON index (y-axis), compared to the original ESPON adaptive capacity (x-axis)

Note, that Figure 9 and Figure 10 give different types of information as their y-axes are different. Northwestern European regions continue to perform better than other European regions (see Figure 8), and the relationship between MEts and adaptive capacity (Figure 9) is positive.

However, the point of Figure 10 is that the socioeconomic index favors more-developed regions. Looking at the 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.

3.4. Policy implications and discussion

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 (Jordan et al., 2012). 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, member states 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 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 (Ciais et al., 2005).

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 (Bureau and Mahé, 2015). Consequently, some measures counteract, instead of reinforce, one another, or are competing for the same funding (Swinnen, 2015). 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 measureable goals for progress towards improving agricultural responsiveness to climate change.

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 (Lenton et al., 2008)), even higher adaptive capacities cannot bring solutions (Reidsma and Ewert, 2008). 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, these questions must be put at the core of the adaptation paradigm.

3.5. 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.

CHAPTER 4.
CLIMATE RESPONSE OF RAINFED VERSUS IRRIGATED FARMS: THE BIAS OF FARM HETEROGENEITY IN IRRIGATION

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Chapter 4.
Climate response of rainfed versus irrigated farms: the bias of farm heterogeneity in irrigation

"It's too late to be studying Hebrew; it's more important to understand even the slang of today." — Henry David Thoreau

Abstract – Starting from this chapter, this dissertation focusses on one specific adaptation option: irrigation. This chapter serves as a preparatory chapter for chapter 5 in which the goal is to explicitly unravel the farm irrigation choice. In order to do this, it should however be noted that there is a lot of farm heterogeneity in implementing irrigation, or other specific climate change adaptation options. Researchers who do not take into account these within-adaptation differences, might significantly bias their findings. To prove this point, this chapter highlights the fact that there is no such thing as "irrigation". Instead, different farms consider water management options across a spectrum that ranges from purely rainfed farms to purely irrigated farms with in between the extremes practices such as supplemental irrigation, water conservation practices and different irrigation techniques.

Accounting for such differences is necessary, yet difficult due to a lack of farm specific data on water management and irrigation. This chapter uses unique Farm Accountancy Data Network data of Western European farmers on the proportion of farmland that each farm irrigates. Unlike previous work, this allows taking into account some within-irrigation heterogeneity instead of simply categorizing farms as being 'irrigated'.

We estimate and compare climate response models based on the Ricardian cross-sectional method for a large range of irrigation categories. The results give insights into how the farm irrigation climate response can be significantly different depending on how irrigation is defined. This proves that ignoring within-adaptation differences when comparing non-

adaptation with adaptation (in this case rainfed versus irrigated agriculture) might lead to biased conclusions with regard to effectiveness of adaptation strategies. Differences between farmers on both extremes of the irrigation spectrum can rise up to 30 percent, depending on the size of farmer. We therefore argue that it might be more relevant to understand at which point and under which circumstances irrigated agriculture is more or less beneficial than rainfed agriculture.

4.1. Introduction

Given the fact that irrigated agriculture is claimed to be less sensitive to changes in climate than rainfed agriculture (Kurukulasuriya et al., 2006), it should be an eye-opening fact to see that within irrigated agriculture marginal increases in temperature and precipitation have significantly different impacts all over the world. It is true that to a certain extent, this is explained by different levels of technological capacity, regional differences and crop choice (Vanschoenwinkel et al., 2016). However, it should also be questioned how much researchers unintentionally contribute to these differing regional conclusions by bluntly categorizing farmers in "rainfed" versus "irrigated" agriculture and comparing them as such. Nowadays, farmers consider water management options across a spectrum that ranges from purely rainfed farms to purely irrigated farms. In between the extremes, there are among others, farmers that use supplemental irrigation on only part of their field, farmers that apply conservation practices to store water in the soil, farmers that add more surface- or groundwater to their fields or farmers that irrigate on a very frequent basis (Molden, 2007). This implies that two farmers, who 'irrigate', can be significantly different from each other with regard to irrigation efficiency and effectiveness. This might explain differences in their climate responsiveness.

This paper therefore examines how farm categorization in rainfed versus irrigated farms influences research findings and conclusions. As such, we challenge the status quo by acknowledging that there is no such thing as 'irrigation'. The results of this paper have implications for numerous adaptation studies as they prove that heterogeneity in implementing adaptation options significantly influences results and therefore might be misleading.

4.2. State of the art

Agriculture is said to be "arguably the sector most affected by climate change" (p.1.) (Rosenzweig et al., 2014). Its production activity depends directly on climate inputs. However, agriculture is also partly a man-made system. This means that a response of a farm to climate is not a simple biophysical response. Instead it can be "manipulated" to become a more profitable or less climate sensitive response (Helms et al., 1996; Reilly, 1999). For instance, during periods of droughts or in water scarce regions, agriculture often relies on irrigation for its water requirements (Finger et al., 2011). Irrigated farms are less sensitive to climate change since irrigation has a moderating effect (Kurukulasuriya et al., 2006). It reduces dependency on and uncertainty of rainfall patterns and decreases interannual variability of production (Tubiello, 2005).

It therefore seems that under unfavorable climate circumstances, irrigated agriculture is less sensitive than rainfed agriculture. However, looking at cross-sectional studies that compared irrigated versus rainfed agriculture, it appears to be hard to draw a line between the conclusions of different studies. Indeed, in Europe and China, on average irrigated agriculture appears to be less sensitive than rainfed agriculture (Van Passel et al., 2017; Wang et al., 2009). Yet, in Mexico, the Marginal effect of temperature (MEt) and the Marginal effect of Precipitation (MEp) are more optimistic for rainfed agriculture than for irrigated agriculture (Mendelsohn et al., 2009). In Africa, irrigated farms seem to benefit from marginal increases in temperature, while they suffer from marginal increases in precipitation (Seo and Mendelsohn, 2008c). Kurukulasuriya et al. (2006) show less supportive evidence of this negative MEp for irrigated farms. Finally, in Southern-America, the impacts of marginal increases in temperature and precipitation are the opposite of the impacts in Africa (Seo and Mendelsohn, 2008a).

Clearly, even though under the same conditions irrigated agriculture is assumed to be less sensitive to changes in climate than rainfed agriculture (Kurukulasuriya et al., 2006), it seems that there are signficant differences between different study findings. Some of these inconsistent and contradicting findings are likely explained by differences in technology, knowledge, experience and other factors inside and outside the farm (Reidsma et al., 2010). Yet, we believe a large proportion of these differences is also explained due to the fact that it is rarely specified 'what' irrigated agriculture entails. Two farmers who irrigate might be completely different with regard to their frequency or intensity of irrigation. They might use different irrigation techniques or extract the irrigation water from different resources which might influence the quality. Some farmers irrigate all their fields, while others only apply irrigation to part of their fields. As such, farmers can be assigned to a continuum of categories in between the extremes of purely rainfed agriculture to purely irrigated agriculture. Farmers in one of these categories (even though all categories are one form of irrigation) might respond differently to changes in climate than farmers in another irrigation category. It is therefore important to examine whether it is necessary to distinguish between different farm irrigation practices when comparing rainfed and irrigated agriculture.

To objectively compare different types of irrigated farms, one should have data on the quality, intensity and frequency of irrigation, and the resulting investment and operational costs. In addition, it is important to know where the irrigation water comes from (e.g. surface- or groundwater) and whether this water resource is renewable. There are also significant differences in irrigation technologies with regard to efficiency and effectiveness. Ideally, all these data should be available on a within-seasonal basis because irrigation requirements, costs and applicability highly vary from season to season. All these data can influence a farmer's decision to irrigate and the resulting profitability of his decision.

4.3. Data

Unfortunately, data on specific farm irrigation characteristics only rarely exist on a detailed, farm scale level. Data that can be found through for instance Eurostat and FAO (2017), are mostly on an aggregated (e.g. country) scale and do not give sufficient information on farm differences in irrigation application, requirements, water usage and related costs.

The data that we use are FADN (Farm Accountancy Data Network) data. FADN provides farm-specific measures of approximately 80,000 farm holdings in the European Union, which represent nearly 14 million farms with a total utilized agricultural area of about 216 million hectares. Their irrigation data register for each farm "the area of crops which have actually been irrigated at least once during the year" (p17) (European Commission, 2014). Irrigation data on such a large scale are unique and give a more detailed picture of irrigation on farm level than most other datasets do. With these data we can distinguish farmers based on their long-term irrigation investments regarding the percentage of UAA (utilized agricultural area) that they can irrigate. In a lot of cases this is a fixed investment which puts a limit on the percentage of area that can be irrigated (for instance the length of hoses and pipes, or the radius the sprinkler installation can reach). These data are therefore highly suited to examine the influence of climatic conditions on the farm long term irrigation investments. Note however that these data are less suited to measure short term farm specific irrigation management strategies in response to weather conditions (such as the frequency of usage, and the amount and the quality of water used in the irrigation installations). This is outside the scope of this paper as we only research whether it is necessary to distinguish farm-irrigation heterogeneity in response to climatic changes.

These farm-level irrigation data will be used to prepare different irrigation sub-samples (see section 4.4) to estimate different climate response functions. For the climate response functions themselves, we use the cross-sectional Ricardian method of Mendelsohn et al. (1994) and therefore use the same variables as previously peer-reviewed work did. That is, we link farm land values to specific socio-economic, geographic, climatic, biological and farm influences. These variables are described and summarized in Appendix E (see also Van Passel et al. (2017) and Vanschoenwinkel et al. (2016)). Farm land values are used because they are assumed to be proxies for the net present value of farm revenues and therefore more robust and stable than yearly revenues. In addition, the FADN data are collected uniformly and consistenly over Europe which is important to correctly compare different regions. To describe climate, temperature and precipitation variables are used. These climate data are averaged into four seasons because there is a high correlation in climate data from month to month. Linear and quadric terms are introduced for both temperature and precipitation since earlier field studies proved the non-linear nature of the net revenue function (Mendelsohn and Dinar, 2003; Mendelsohn et al., 1994).

Apart from the farm specific variables, all variables are on a NUTS3 geographical scale as for privacy reasons it is not posible to link the farm holdings to unique locational coordinates. With regard to the sample of farmers taken, we dropped out all mixed and livestock farms to obtain better estimations with regard to irrigation. Finally, it should be noted that for this study, looking at the data of one year is enough because we only examine the farm response to climatic conditions. Using data of 2007, 2008… or 2012 therefore should not change the results if data are sampled in the same way. However, we do show the findings of the period before 2008 (namely 2007) and after 2008 (namely 2012) because, as will be discussed in section 4.5, starting from 2008 there were changes in the way farms are sampled.

4.4. Method

The method consists of three parts: (1) determining how the sample will be divided in rainfed versus irrigated farms depending on the percentage of UAA a farmer irrigates, (2) determining the climate response function per sample, and (3) deriving the marginal effects of temperature and precipitation per function. These three steps are repeated 1000 times so that different climate responses of different categorizations can be compared with one another. We now explain these three steps in more detail before showing the results.

The climate response itself is estimated by means of the cross-sectional Ricardian method as presented by Mendelsohn et al. (1994). The method uses data on farm land values, assuming that these are proxies for the net present value of farm revenues. Each farmer is assumed to maximize his profits (and thus his land value) by optimizing endogenous variables such as inputs, crop choices and other management decisions. As such, such variables cannot explain changes in land value or revenues and only exogenous variables outside the control of the farmer are taken into account. The cross-sectional data used by the method allow comparing regions with different climatic, geographic, biophysical and socio-economic characteristics to understand their influences on the farm climate response. For the purpose of this paper, we run the model with an Ordinary Least Squares Regression but we split the full sample of farmers in an irrigated and a rainfed sample to determine the climate response function for each of these samples separately. This is also done by Kurukulasuriya et al. (2006), Mendelsohn and Dinar (2003), Schlenker et al. (2006), Seo and Mendelsohn (2008b) and Van Passel et al. (2017) who estimated separate response functions for rainfed and irrigated crops.

This irrigated and rainfed climate response is estimated 1000 times, for 1000 different farm categorizations in rainfed versus irrigated crops. The farm categorization in rainfed versus irrigated crops is done based on the percentage of UAA farmers irrigate. We call this percentage the *irrigation* *threshold*. If a farm irrigates at least x% of its UAA, it is categorized as an irrigated farm. We allow to change this threshold x from 0,1% to 100% with steps of 0,1 throughout the analysis. As such we make a different irrigation and rainfed categories for each irrigation threshold. In total we use 1000 irrigation thresholds and as such we determine 1000 rainfed and irrigation climate responses that can be compared with one another. This will help us to better understand whether a farmer that irrigates for instance only 1% of his UAA, should be categorized as a true irrigated farm or not.

For each of these subsamples, based on one specific irrigation threshold, we compare the irrigated and rainfed agricultural climate response with regard to their annual marginal effect of temperature (MEt) and their annual marginal effect of precipitation (MEp) by checking whether they were significantly different from each other (Weighted Welch's t-test) and by comparing their absolute values. The marginal effects are necessary to determine because we both use linear and quadratic climate terms per season in the climate response functions (see Vanschoenwinkel et al. (2016)). Calculating the marginal effects per season is done as follows (determined separately for precipitation (p) and temperature (t)) for season i ($\mathrm{ME_i}$)):

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

The annual average marginal effect (MEt and MEp) is derived from the previous by taking the sum of the average seasonal marginal effects. The marginal effects can be interpreted as the percentage change in 1 hectare land value associated with an increase of 1°C in temperature for MEt or an increase of 1 cm in precipitation for MEp. Note that *each* marginal effect goes along with only *one* irrigation threshold as it is determined for each climate response function separately. Each marginal effect on each of the graphs is determined by a unique climate response function per irrigation-threshold. The entire three-step procedure is repeated per year (in this case 2007 and 2012) and per additional subsampling (small versus large farms).

These results are visualized in the graphs in the next section. The marginal effects of irrigation are presented by a blue line and the marginal effects of rainfed agriculture by a green line. The significance of the t-test is visualized by means of a red background. If there is no significant difference between rainfed and irrigated agriculture, these points will have a red background. However, with regard to the significance of the Welch's t-test, it should be noted that we only executed the t-test for discrete points ranging from 0.1-100%. That means that there might still be points in between that we did not test for and that might yet be insignificantly different from each other. This can for instance be seen in figure 12f where the irrigated-line suddenly drops below the rainfed line. In the point where the two lines intersect, there is obviously no significant difference between rainfed and irrigated agriculture. Yet, no red background is visible because the intersection must be somewhere between 95.2 and 95,3%. We only tested for 95.2% and 95.3%. Not for the values in between.

Furthermore, we also indicate with a bar chart included in each graph, the size of the sample of irrigated farms. This is because, the higher the threshold, the lower the sample of irrigated farms that remains. To keep track of this evolution, the bar chart in the graph indicates how many farmers remain and at what percentage they irrigate. In case the categorization of farmers in irrigated or rainfed farmers does not matter, the blue line should be horizontal, meaning that each irrigation-threshold results in a similar marginal effect or climate response.

4.5. Results

We determined for 1000 different categorizations of irrigation (that is 1000 irrigation-thresholds), a climate response function for rainfed and irrigated agriculture. This implies that we have a total of 2000 regressions per analysis (1000 irrigated and 1000 rainfed climate responses) that have to be compared with one another. As this would be very cumbersome, we focus our analysis on the visualization of the marginal effects of climate of all these regressions. These can be found in the graphs below. In the Appendix F, an example of the paper's linear regressions of the 50%-threshold can be consulted for 2007 and 2012.

Figure 11 shows the marginal effects of temperature for 2007 and 2012, distinguishing the results of the entire sample compared to samples of large and small farms. Looking at the full sample in 2007 (figure 11a), there is clearly a positive relationship between the MEt and the percentage of UAA that a farmer irrigates. That is, farmers who irrigate a higher percentage of their UAA have a more positive MEt than rainfed farmers. Clearly, when no distinction is made between farmers that irrigate at least 73,1% of their UAA and farmers that irrigate a smaller part of their UAA, the analysis shows that the MEts of rainfed agriculture are more beneficial than the MEts of irrigated agriculture. The decision of the researcher to categorize farmers in one category or another therefore influences the final conclusion with regard to the effect of a marginal increase in temperature on irrigated versus rainfed agriculture.

Farm categorization is, less of an issue when using data of 2012 (Figure 11b). The MEts of 2012 are different from those in 2007 with regard to the fact that irrigated agriculture on average responds more beneficial than rainfed agriculture to marginal increases in temperature. No threshold with regard to the percentage of UAA irrigated must be exceeded although there are points on the graph where the differences between rainfed and irrigated agriculture are not significant or where the MEts of irrigated agriculture sometimes become less beneficial than those of rainfed agriculture (in between the threshold of 40.7-83.4%).

These results, however, slightly change if other farm differences are also taken into account. Farmers are very heterogeneous and different farm types (defined by characteristics such as farm size and crop choice) might respond differently to climate change and irrigation practices. It is therefore important to understand farm differences. In this paper, we compare small and large farms with each other and it can be seen that this explains the differences between 2007 and 2012. Looking at 11c and 11d, it can be seen that large farms in general have lower MEts when opting for irrigation, while small farms (11e and 11f) have more beneficial MEts in case they irrigate. Only in 2007, small farms first have to irrigate a minimum percentage of their UAA before the MEt of irrigation becomes more beneficial than the MEt of rainfed agriculture. This threshold to be exceeded before the MEts of small irrigated farms become more beneficial than those of rainfed agriculture needs to be smaller than when compared to the results of the full sample (~40.0% instead of ~73.1%). As such, there are differences between 2007 and 2012 with regard to the proportion of large and small farms that influence the conclusion when looking at the results of the full sample.

With regard to the MEp, comparison between rainfed and irrigated farms is more straightforward. In both 2007 and 2012, independent of the percentage UAA irrigated, irrigated agriculture benefits more from decreases in precipitation than rainfed agriculture. Furthermore, the relationship between MEp and the percentage of UAA irrigated is negative, indicating that farms that irrigate a higher percentage of UAA are less vulnerable to decreases in precipitation. This negative relationship is mostly visible for large farms that irrigate as they use irrigation in particular to avoid the negative impacts of decreases in precipitation (figure 12c and 12d). Small irrigated farmers (figure 12e and 12f) benefit from additional precipitation or respond more neutral.

4.6. Discussion

The results prove our point of criticism: differences between long term farm irrigation practices might influence the researcher’s conclusion of whether rainfed or irrigated agriculture is more or less responsive to

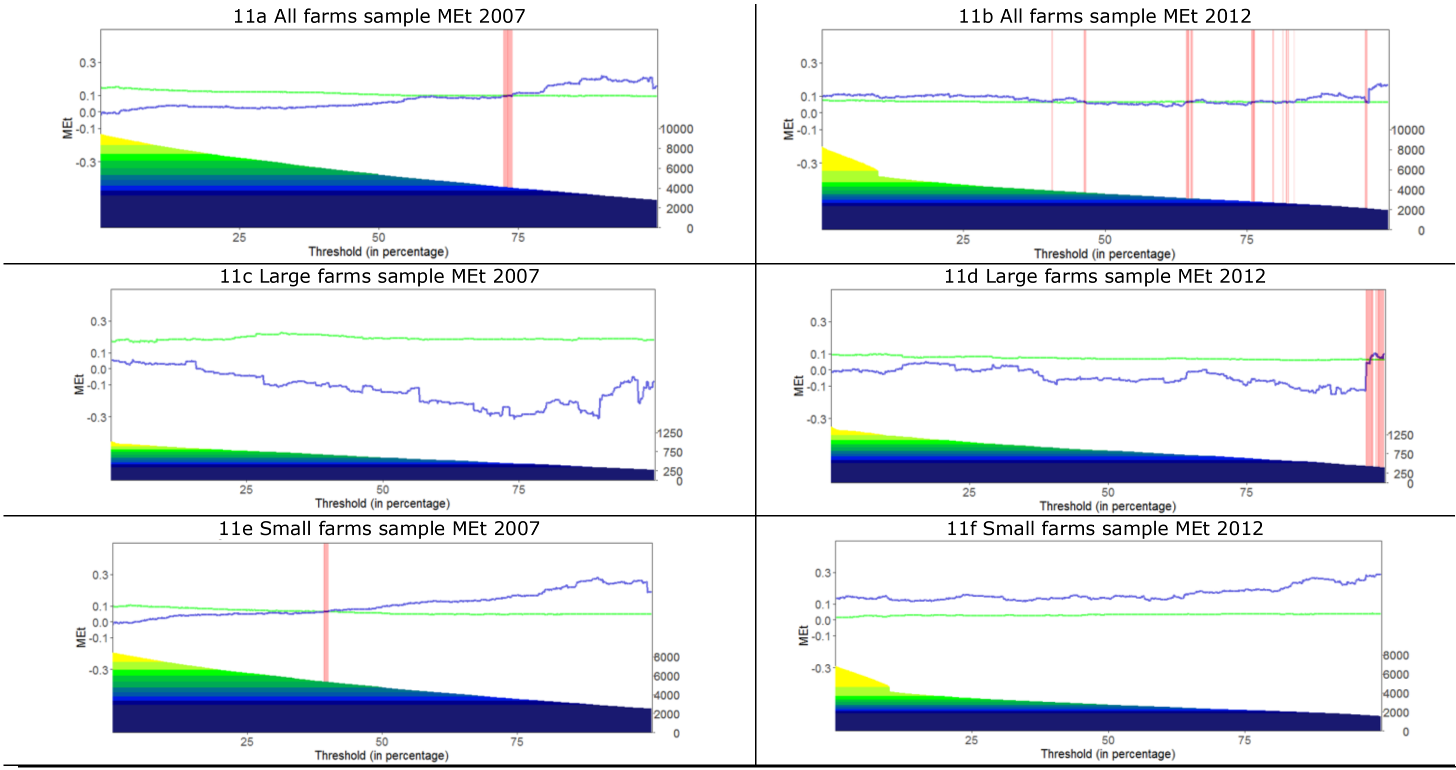

Figure 11 – Marginal effects of temperature

Number of irrigated farms

0-10% irrigation
10-20% irrigation
20-30% irrigation
30-40% irrigation
40-50% irrigation
50-60% irrigation
60-70% irrigation
70-80% irrigation
80-90% irrigation
90-100% irrigation

Significantly different at 1%

No Yes

MEt

Irrigation Rainfed

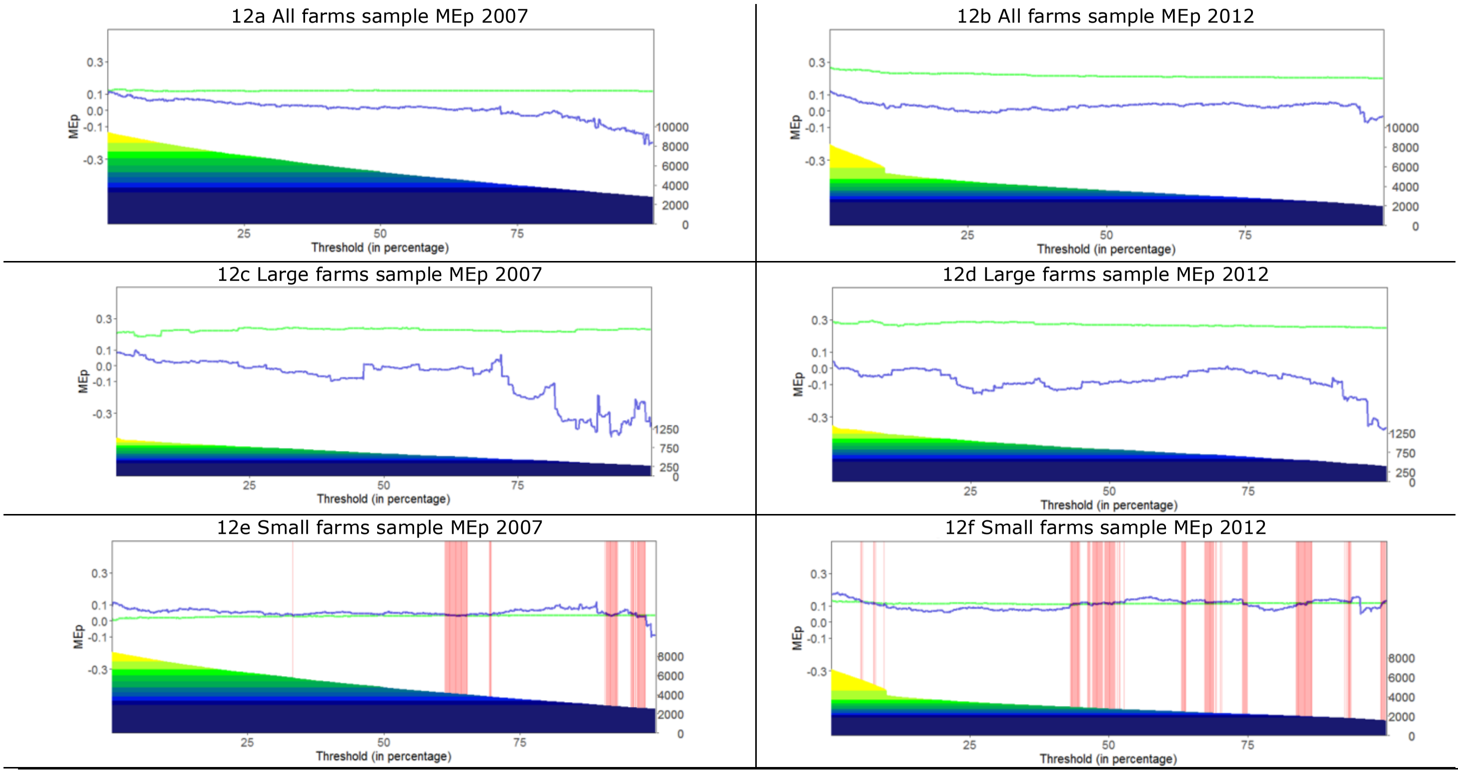

Figure 12 – Marginal effects of precipitation

Number of irrigated farms: 0-10% irrigation, 10-20% irrigation, 20-30% irrigation, 30-40% irrigation, 40-50% irrigation, 50-60% irrigation, 60-70% irrigation, 70-80% irrigation, 80-90% irrigation, 90-100% irrigation

Significantly different at 1%: No, Yes

MEp: Irrigation, Rainfed

changes in climate. Farms that irrigate larger proportions of their UAA respond significantly different than farms that irrigate only occasionally. Researchers should therefore clearly define irrigated agriculture and not assume that all irrigated farms are the same.

Given the differences between farmers and their different irrigation strategies and customs, it is however not straightforward to say which threshold a researcher should take to analyze rainfed versus irrigated farmers. In addition, regarding the sampling of the data in small versus large farmers, it should be noted that comparison between large and small farmers in Europa might be hard due to the fact that large farms in Europe are located mostly in North-Western regions where more rainfed agriculture is present. The results of large farmers should therefore not simply be generalized to all European farmers. Furthermore, Southern regions mostly have small farmers, and these farmers seem to prefer increases in precipitation (2007) or do not face serious consequences when precipitation increases (2012). This might indicate that they have less constant access to water resources and need additional precipitation to maintain their water reserves.

Further research is therefore needed to better understand how differences in irrigation influence farm climate responses. In this respect it is important to understand that there is a difference between long term responses to climate and short term responses to weather. This study only measures the impact of climate change on the farm and not the impact of weather itself. To study the impact of weather changes, researchers should look more at short term irrigation responses such as the intensity and frequency of irrigation, and the type of water used.

However, in case research further examines short term irrigation management variables, it is important to understand that such variables increase endogeneity issues. This is due to the fact that short term farm management is much more flexible and in control of the farmer than long term irrigation investments. In this regard, it is important to improve methods in order to take into account such endogeneity issues. For the method and data used in this study, it is therefore more robust and correct to apply climatic data. In addition, the sample size of our data is large, minimizing possible biases. However, in case more flexible management variables are examined, endogeneity issues have to be accounted for. As such, even though frequently used (see Kurukulasuriya et al. (2006), Mendelsohn and Dinar (2003), Schlenker et al. (2006), Seo and Mendelsohn (2008b) and Van Passel et al. (2017)), it should be noted that the methodology of subsampling irrigated and rainfed farms is less accurate. This is a frequently cited problem which requires more research attention (see for instance Kurukulasuriya et al. (2011) and Chatzopoulos and Lippert (2016)). Chapter 5 addresses this issue in more detail and shows that endogeneity indeed leads to less robust model estimates, but that due to the large dataset used in this dissertation this does not influence research conclusions. Chapter 4 therefore provides useful insights into how we will define irrigation in chapter 5 (given the fact that irrigation is a continuous variable). The graphs of 2012 show that the direction of the conclusion in general stays the same over all the threshold and we therefore chose to maximize the number of farmers in our irrigation subsample. As such for chapter 5, we use a threshold of 0.1% to define irrigation.

Thirdly, before it is possible to account for farm irrigation management heterogeneity, more farm irrigation data are needed. Given the fact that more institutions and researchers are aiming to collect more irrigation data, a peculiar finding of how sample characteristics can further influence differences between irrigated and rainfed farms of this paper should be highlighted regarding the FADN. With regard to the MEts, the climate responses of 2007 and 2012 differ significantly from another. However, given the fact that we use climatic control variables, it is unlikely that in such a short period of time, a region’s climate response would change this drastically. Instead, these differences are caused by changes in the data sampling of large and small farmers in Italy between these years. Before 2007, the full Italian FADN sample contained about 17,000 farms. After 2007, only about 12,000 farms remained (Cisilino et al., 2011). This is possible because the data collection of the FADN occurs at country level and Member States have their own selection plans (FADN, 2016). Starting from the 2008 accounting year, the Italian survey system introduced a new software with related changes in data collection (Bodini and Marongiu, 2009). One of the sampling differences in the Italian sample appears to be the exclusion of very large farm holdings. This has two implications for our analysis: (1) we weight based on farm size as measured by UAA, (2) most Italian irrigated farms are large and are as a result dropped from the sample. The later means that there is a decrease of more than 40% in Italian irrigated farms in our sample (from 4588 irrigated and 3019 rainfed farms in 2007, to 2652 irrigated and 2370 rainfed farms in 2012). Given the fact that most irrigated farms in Europe are situated in Italy, this is a very important change for our analysis. We tested the years 2008, 2009, 2010 and 2011 and concluded that our results of these 4 years are (as expected) similar to the results of 2012. Results only differ between the period before and the period starting from 2008 due to the sampling differences.

4.7. Conclusion

The climate response of irrigated versus rainfed agriculture highly differs depending on long term farm irrigation decisions. As such, conclusions with regard to differences between the benefits of rainfed versus irrigated agriculture can highly differ depending on how irrigation is defined. Reseachers should be aware of this and not blunty generalize their research conclusions to all irrigated farm types. There are certainly irrigation strategies that are more effective and efficient than others.

Research therefore needs to use more farm-specific irrigation and water management data. Given the fact that these data are not always available, it might also be relevant to understand better at which point and under which circumstances irrigated agriculture is more or less beneficial than rainfed agriculture. Finally, the criticism brought up by this paper should be taken further to other adaptation practices to understand how farm heterogeneity in implementing one adaptation option influences research findings. This should also be coupled to the adaptation decision process of the farm itself to tackle endogeneity issues.

CHAPTER 5.
HOW DO WESTERN EUROPEAN FARMS BEHAVE AND RESPOND TO CLIMATE CHANGE? A SIMULTANEOUS IRRIGATION-CROP DECISION MODEL

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Chapter 5
How do Western European farms behave and respond to climate change? A simultaneous irrigation-crop decision model

"If we don't […] deepen our fundamental understanding of the world, we won't provide a basis for the next generation of innovations." – Bill Gates

Abstract – Famers trying to adapt to climate change face a wide range of adaptation options which are simultaneously determined. Adaptation decision models do not capture such real-life complexity and only examine adaptation options individually. This chapter therefore models a simultaneous irrigation-crop farm decision model by using spatially detailed farm level data of over 18,000 farms on irrigation and seven different crop choices. In doing so, it adds to the recurring discussion about whether cross-sectional models properly capture irrigation in the climate response function and concludes that explicitly modeling farm decisions leads to more robust estimation results than when compared to their exogenous counterparts. Furthermore, the simultaneous decision model leads to a variety of results with regard to rain-fed and irrigated agriculture of European farmers. Some of the main results show that Southern European regions show significantly negative irrigation probabilities when temperature marginally increases (-5 to -7% in summer). This shows that those regions adapt through other means than irrigation to higher temperatures (for instance through crop choice). Yet, marginal increases in precipitation do increase Southern European small farmers' irrigation probability (up to 4.5%), showing that precipitation is needed before irrigation can take place. These results imply that irrigation, as an adaptation tool to climate change, is often hampered due to climate constraints.

5.1. Introduction

"Clever humans" have always adapted agriculture to new growing conditions (Burke and Lobell, 2010; Wreford et al., 2010). Yet, it appears that today's farmers are not responding quickly to recent climate changes (Adger et al., 2007; Burke and Emerick, 2016), despite the fact that climate change is undoubtedly happening and causing significant agricultural losses (Rosenzweig et al., 2014). Therefore, immediate guidance on adaptation decisions and implementation is indispensable (IPCC, 2014a). However, unless we *"begin to understand all the complex processes and reasons by which farmers make decisions, our efforts to help improve decisions will fail" (p. 288) (Öhlmér et al., 1998)*. It is therefore important to examine how a farmer choses an adaptation option.

This article takes a closer look at one type of adaptation, namely irrigation, as it is one of the primary mechanisms for agriculture to respond and adapt to climate (Howden et al., 2007). Remarkably, however, only few studies examine farm irrigation decisions explicitly. An interesting irrigation decision model was developed by Kurukulasuriya et al. (2011). However, the article considers the farm irrigation choice only as a response to climate and other exogenous variables such as subsidies, geographical characteristics and socio-economic factors. More recent work of Olen et al. (2016) showed that (1) irrigation management contains not only making changes in the size of irrigated land, but also allows for adoption of different irrigation technologies, adjustments in water application rates for specific crops, and allocation of land to different crops. Secondly, (2) an irrigation decision is crop-specific, implying that, thirdly, (3) a farm's irrigation decision and final climate response are also dependent on other farm decisions that have to be modelled jointly to properly understand the irrigation decision process.

Olen et al. (2016) brought contributions to point (1) and (2) by estimating separately crop-specific irrigation decisions regarding the share of irrigated land (IS_{ij}), technology adoption per crop (TA_{ij}) and water application rates (AR_{ij}). However, they did not estimate all these decisions jointly and therefore call for improvements regarding estimation methods to estimate a mixed structural model that simultaneously estimates all decisions together. This article builds further on their work and suggestions by structuring their separate decisions in one framework and by estimating a mixed simultaneous decision model.

We start with the case of Europe because, on a European scale, no quantitative analysis on farms’ irrigation decisions exists, even though Europe is facing significant changes in its irrigated agriculture. In Europe, approximately 85 percent of the European irrigated land is concentrated in the lower latitude Mediterranean area (Giannakis et al., 2016), showing the importance of irrigation to reduce dependency on and uncertainty of rainfall patterns (Tubiello, 2005). Nevertheless, Kahil et al. (2015) have shown that climate change will have sizeable negative impacts on irrigated agriculture in Southern Europe, implying that irrigation might be a questionable adaptation tool in some circumstances. In addition, irrigated agriculture is now also spreading to regions at higher latitude due to climate-driven drought and water scarcity, meaning that investments in irrigation and water infrastructure are needed in a significant part of the European Union. Therefore, a quantitative analysis to gain insights into which factors influence the irrigation decision is indispensable to support policy decisions in Europe, but also in many other regions where the irrigated area is expanding due to climate-driven stimuli. It is therefore important to examine which variables influence the European irrigation decision. We start by briefly reviewing past irrigation modeling issues and capture these for the purpose of this article in one framework. We explain how to estimate the model and present the data we use. In the final sections we present and discuss the results and draw conclusions.

5.2. Irrigation Decision Model

This article uses a method that has its roots in statistical cross-sectional methods (as also used by Olen et al. (2016)). Such methods can gain insights into irrigation or other adaptation choices by looking at farmers’ actual irrigation or adaptation responses to the ongoing climate.

Experimental cross simulation models[1] are less appropriate for this purpose as they do not capture the behavior of the farmer himself. The cross-sectional method used is the Ricardian method, which is established by Mendelsohn et al. (1994). The Ricardian method explains variations in land value (as a proxy for the net present value of farm revenues) by means of exogenous variables such as climate, soil, and socio-economic determinants. Endogenous variables such as inputs, crop choices and other management (adaptation) decisions are not explicitly examined by the method because these variables are assumed to be optimized by the profit-maximizing farmer himself. As such, the method takes adaptation into account because all farmers are expected to be adapted to the environment in which they live.

5.2.1. Past modeling issues

However, when using this methodology, adaptation options (whom are endogenous) are not explicitly modeled because they are assumed to be optimized. Look for instance at figure 13 in which you can see that different adaptation choices (rainfed versus irrigation) have different climate responses. With the traditional Ricardian method, only *one* climate response function is estimated, aggregating the coefficients for all the different adaptation options. The traditional Ricardian method is therefore also called 'the black box' as it does not reveal the exact nature of the adaptation choice chosen by the farmers (Seo and Mendelsohn, 2008c). This leads to a number of disadvantages: first of all it is not possible to distinguish between and compare rainfed and irrigated agriculture if only one aggregated climate response function is estimated. Yet, irrigation "breaks the link between the growth of a plant and the climate" (p. 396) (Schlenker et al., 2005), implying that the climate coefficients should be

[1] Crop simulation models are based on a deep understanding of agronomic science and are one of the most popular methods for estimating agricultural climate change impacts (Mendelsohn and Dinar, 2009).

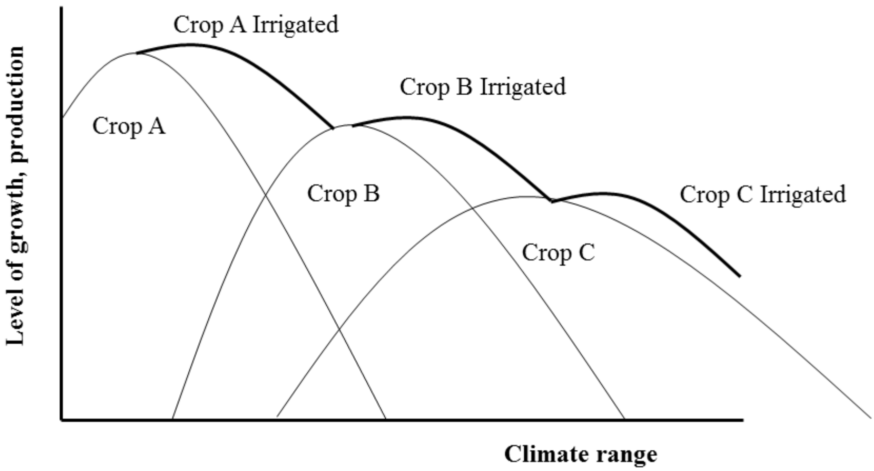

Figure 13 – Adaptation via cropping pattern shift and irrigation (source Mendelsohn and Dinar (2003))

allowed to differ between irrigated and rain-fed farms. Conclusions based on aggregated coefficients for irrigated and rain-fed farming combined might be biased and give less accurate information. Several studies have attempted to model irrigation by estimating separate response functions for rain-fed and irrigated farms by splitting the full sample based on irrigation (Kurukulasuriya et al., 2006; Mendelsohn and Dinar, 2003; Schlenker et al., 2007; Seo and Mendelsohn, 2008b; Van Passel et al., 2017). In doing so, however, they consider irrigation to be an exogenous variable and do not allow the farmer to switch between rain-fed and irrigated crops. This could lead to endogenous treatment bias if one only observes whether farms use rain-fed or irrigated land (Kurukulasuriya and Mendelsohn, 2007). The sample is a non-random sample in the sense that the farmer self-selects himself in either the sample of irrigated farms or the sample of rain-fed farms (Heckman, 1979). This endogenous treatment bias also seems to be an issue in the article of Olen et al. (2016), as they do not look at the crop choice decision and therefore assume erroneously that crop choice is an exogenous variable. To solve this endogenous treatment bias, the irrigation choice itself should be modeled explicitly as it is influenced by numerous other variables.

Due to the above issues, there have been recurring discussions on the accuracy of representing and capturing irrigation in cross-sectional models (Cline, 1996; Darwin, 1999; Schlenker et al., 2007). A better understanding of the farm irrigation decision process will therefore not only give more insights for policy regarding how farmers adapt, but it will also help comparing adaptation options and improve climate change impact estimates (Vincent, 2007).

5.2.2. Framework

The irrigation decision itself is influenced by numerous variables such as water availability and supply, climate parameters, farm characteristics, soil characteristics and topography, specific irrigation investment or variable costs, institutional influences, and market conditions (Bowman and Zilberman, 2013; Brouwer et al., 1992; Culas and Mahendrarajah, 2005; Elliott et al., 2014; Evans et al., 1996; Greig, 2009; Jamagani and Bivan, 2013; Knapp and Huang, 2017; Koundouri et al., 2006; Ley et al., 1994; Matti et al., 2010; Olen et al., 2016; Scherer et al., 2013; Schewe et al., 2014; Schlenker et al., 2007; USDA, 1997; Zilberman et al., 2012).

On top of these variables, one variable that is often not included in the irrigation decision model but that has a very high influence on the irrigation decision is the farm crop choice. The decision to irrigate is highly dependent on the crop choice of the farm because different crops have different water requirements (Fisher-Vanden et al., 2014). As such, depending on the crop choice, climate and water scarcity have a different effect on irrigation decisions, as crop choice is a tool for adapting to climate change. This is due to differences in root density, root depth, crop water use rate, critical growth period, crop evapotranspiration and pest resilience of different crops. It is important to make the irrigation decision crop-specific as otherwise aggregation mixes up crop-specific effects of different factors on the irrigation decision (Green and Sunding, 1997; Olen et al., 2016; Pfeiffer and Lin, 2014).

However, the crop a farmer cultivates is also a farm decision. A farmer will not decide to irrigate if he does not know yet whether the crop he will chose will or will not need additional water. Crop choice should therefore be modelled jointly with the irrigation decision and cannot simply be added as an additional variable to the irrigation model. But, on the other hand, the farm crop decision is also dependent on the farm's irrigation decision. This is because in some regions crops cannot be cultivated with the local amount of precipitation and additional artificial water supplies are needed. If the farmer does choose such a crop, it means that he also immediately decides upon whether to irrigate or not. This implies that the farmer simultaneously has to decide on both the crop and irrigation choice. As such, an irrigation decision model needs to be estimated simultaneously with the farm crop decision model.

Finally, as indicated by Olen et al. (2016), the irrigation decision is not only a 'yes' or 'no' decision determining whether to irrigate or not. Instead, it consists of a number of decisions concerning irrigation management (such as technology, water application rate, share of irrigated land).

In our irrigation decision framework, we put all the above components together as shown in figure 14. We split the irrigation decision in two parts: equation (2) shows the decision whether the farmer decides to irrigate or not (this is a binary decision model). This decision is taken simultaneously with the crop decision (equation 1, which is a multinomial decision model). Once a farmer has decided upon this crop and irrigation choice, a number of subsequent irrigation (or rain-fed) decisions (a-d) follow that further explain 'how' the farmer will irrigate (or apply rain-fed agriculture[2]). Eventually, for each combination of decisions (1), (2) and (a-d), the farmer will face a unique climate response function (measured by land value as this is a proxy for the net present value of farm revenues). Olen et al. (2016) estimated equations (a-c) separately. Our article will estimate equations 1-3 simultaneously, but will not explicitly model the within irrigation-heterogeneity (equations a-d).

(1) $\Pr[Crop_i = j] = f(Z_i, C, IRR_i) \qquad j \in k$

$\updownarrow$

(2) $IRR_i = f(Z_i, C, crop_{ij}) \qquad IRR_i = 0 - 1$

Yes, the farm irrigates — $IRR_i = 1\,;\, Crop_i = j$

No, the farm does not irrigate — $IRR_i = 0\,;\, Crop_i = j$

(a) $IS_{ij} = f(Z_{ij}, C)$

(b) $AR_{ij} = f(Z_{ij}, C)$

(c) $TA_{ij} = f(Z_{ij}, C)$

(d) ...   ...

(3) $LANDV_{ij}(IRR_i = 1) = f(Z_{ij}, C_R) \qquad LANDV_{ij}(IRR_i = 0) = f(Z_{ij}, C_R)$

$Crop_i = farm\ crop\ decision\,;\ IRR_i = farm\ irrigation\ decision;\ TA_{ij} = Farm\ Technology\ Adoption\ per\ crop;\ AR_{ij} = Farm\ Water\ Application\ Rate\ per\ crop\,;\ IS_{ij} = Farm\ share\ of\ cropland\ irrigated\ per\ crop\,;\ Z_i = control\ variables,\ C = climate$

Figure 14 – Farm irrigation decision framework
Framework consists of simultaneous decisions (1) and (2), and subsequent decisions (a-d) once (1) and (2) are decided upon. This leads to (3) the conditional climate response function. Abbreviations used in Olen et al. (2016) are used as a basis.

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[2] Note that we did not add subsequent decision equations under the IRR=0 (rainfed) decision. We left this space open because rainfed farmers decide upon different elements than irrigated farmers. Olen et al. (2016) did not examine these decisions and further research is therefore needed in this area. This is outside the scope of this article.

5.2.3. Empirical Model

Our irrigation decision model therefore consists of a unique system of three equations. The farmer is assumed to make a decision that maximizes the conditional income (equation 3) resulting from the simultaneous irrigation-crop decision (equation 1-2). Therefore, the farmer will only irrigate if irrigation is more beneficial than rain-fed agriculture. We implement a binary logit model that captures the decision to irrigate (IRR_i where IRR_i=0 is a rain-fed farm, while IRR_i=1 is an irrigated farm) (equation 2). This decision to irrigate is simultaneously determined with the farm crop choice ($crop_i$ where crop is divided into seven crop categories: olives, rice, cereals, field crops, fruits, root crops, and wine), which is a multinomial model that evaluates the probability that a certain crop will be cultivated (equation 1). Finally, equation 3 explains the value of land ($LANDV_i$), conditional on the previous farm choices. The system is therefore complicated given its mix between non-linear and linear models. The system can be written for each farm *i* as:

$$\Pr\left[crop_i = j\right] = \frac{\exp(x\boldsymbol{b'}_{ij})}{1+\sum_{j=1}^{k}\exp(x\boldsymbol{b'}_{ij})} \qquad j \in k \quad (1)$$

$$x'\boldsymbol{b}_{ij} = \beta_{0j} + \beta_{1j}IRR_i + \beta'_{2j}Z_i + \beta'_{3j}C_R + \eta_i + \xi_i\beta_{4j}$$

$$IRR_i = \alpha_0 + \alpha'_1 Z_i + \alpha'_2 C_R + crop_{ij} + \eta_i + \epsilon_i \qquad i = 1 \dots N\ ;\ IRR_i = 0-1 \quad (2)$$

$$LANDV_i = IRR_i * (\gamma_0 + \gamma'_1 Z_i + \gamma'_2 C_R + \lambda_i + \zeta_i) \quad (3)$$

in which the errors in the equations are denoted as ϵ_i, ξ_i (which differs per crop type) and ζ_i. C_R represents the linear and quadratic regional NUTS3 climatic influences in terms of seasonal temperature and precipitation and Z_i represents all other exogenous variables that influence the farm choice.

The model involves simultaneous endogeneity and endogenous treatment selection which are both solved through the error terms λ_i and η_i. This method is also known as the control function approach and is more robust in this case as it explicitly models omitted relevant variables (Heckman and Navarro-Lozano, 2004). More specifically, λ_i and η_i are the unobserved random components that solve the endogenous treatment bias and the simultaneous endogeneity, respectively. The inherent causal endogeneity issue is solved by applying a generalized structural equation model (GSEM) consisting of the two equations (IRR_i and $crop_i$), both of which include the same unobserved farm heterogeneity component (η_i) (Drukker, 2014). In GSEM, these unobserved components can solve for omitted variable bias when included in both equations. As such it corrects for causal endogeneity. The residual error (ϵ_i) represents the noise which includes possible measurement errors and variables such as knowhow and other potential farm-specific variables that influence irrigation choice and not crop choice. This model is estimated by means of full-information maximum likelihood (FIML) estimates. As such, it determines the probability of being in a specific treatment group (rain-fed or irrigated agriculture) by simultaneously taking crop choice into account. In the second stage, to solve the endogenous treatment problem (which is basically a correlation between the error term of the irrigation choice model (ϵ_i) and the land value model (ζ_i)), we include only the part of irrigation that is not correlated with specific, unobserved factors that also determine land value. This is expressed as the λ_i in the second stage. In theory, this model of three equations should be estimated at once; however, due to computational difficulties[3], the model was estimated in two steps (a simultaneous irrigation-crop choice model and the conditional land value equation) (see also Wooldridge (2005)). With regard to the λ_i in the last step of the model, this implies that we had to approach this λ_i by including the predicted residuals from the first-stage probit model ($\hat{\epsilon}_i$) in the second stage (inverse Mills would also have been a similar possibility) (Fernández-Val and Vella, 2011).

[3] The model converges for significantly restricted samples. However, when increasing the number of explanatory variables and observations it is not possible to estimate the full model at once.

With regard to the interpretation of the results, it should be noted that not all coefficients can be interpreted directly. The climate coefficients have a linear and a quadratic term, which makes calculating their marginal effects, as explained by Mendelsohn et al. (1994), a more straightforward way of analyzing the climate effects. For the linear regression model of land value, the marginal effects of temperature (MEt) and the marginal effects of precipitation (MEp) are calculated for each season i ($\mathrm{ME_i}$) as follows:

$$ME_i = \frac{\partial V}{\partial C_i} = \beta_{1,i} + 2\beta_{2,i} C_i \qquad (4)$$

The annual average marginal effect (MEt and MEp) is derived from the previous equation by taking the sum of the average seasonal marginal effects. Marginal effects are interpreted as the percentage change in 1 hectare land value associated with an increase of 1°C in temperature or an increase of 1 cm in precipitation. The marginal effects of the non-linear logit model in the simultaneous irrigation-crop model can be determined similarly after having taken a logit transformation. The MEs of the logit model are interpreted as the increase in the probability of irrigation when temperature increases by 1°C or when precipitation increases by 1 cm.

The marginal effects for the conditional land value are divided up into the marginal effects for rain-fed and irrigated farms. In order to compare these split-up results with the traditional cross-sectional model, which does not distinguish between rain-fed and irrigated farms (the no-first-stage choice model), we determine the expected marginal effects of the sample by summing the probability of each farm choice (irrigation versus rain-fed) multiplied by the marginal effects of that farm choice (see Seo and Mendelsohn (2008) for more details). That is:

$ME(C) = \sum_{IRR=0}^{1} P_{IRR}(C) * ME_{IRR}(C)$ with IRR=0(rain-fed) & IRR=1(irrigation) (5)

The exogenous full-sample marginal effects are determined directly as in Mendelsohn et al. (1994) because they do not explicitly take adaptation choices into account. The model itself was run in Stata (StataCorp, 2015) within the infrastructure of the Flemish Supercomputer Center (VSC, 2017) for additional computational resources.

5.3. Data

The different types of crop categories included in the analysis are summarized by country in Appendix G. However, irrigation is also non-linearly influenced by climatic parameters such as temperature and precipitation that we capture per seasonal influence. Given that extreme events are assumed to be important stimuli for irrigation adaptation (Berrang-Ford et al., 2011), we also control for drought severity from 1901 to 2008 as measured by Sheffield and Wood (2008) and drought frequency as indicated by the drought hazard frequency typology (ESPON, 2011). The drought severity variable measures the average length of drought times the dryness of the drought (as measured by soil moisture remaining below the 20th percentile). The drought frequency indicator contains five categories indicating the degrees of drought frequencies. However, adaptation measures are not only taken in response to climate (Runhaar et al., 2012). Soils can also increase or decrease the probability of irrigation, although this depends on their combination with the inclination of the soil. Steep soils are generally less attractive for irrigation (Kurukulasuriya et al., 2011). Therefore, we account for geographical characteristics such as elevation mean and range. We also capture farm-specific subsidies that might influence the irrigation decision. Finally, the decision to irrigate depends on the water flow on which irrigation depends. Water availability is one of the most constraining factors for food security (Kang et al., 2009). As such, work that considers irrigation adaptation needs to pay close attention to the particular hydrological systems and the property rights regimes. With regard to irrigation water property rights, the Ricardian method has been criticized in the U.S. due to the fact that Western and Eastern U.S. farmers have different water rights. This implies that the infinitely-elastic-supply-of-irrigation-water assumption of the method (Cline, 1996) is wrong if different farmers have access to water in a different way. With regard to water rights, however, Europe differs from the U.S. in the sense that it has an established framework for community action in the field of water policy since 2000. The Water Framework Directive (WFD) (Directive 2000/60/EC) was adopted exactly to make the patchwork of existing policies and legislations more coherent over the European Union (European Court of Auditors, 2014). However, given the fact that the implementation of the water resource plans of the WFD is based on river basins, it is also important to capture water stress and other water supply indicators. The present study captures water stress in the region, accounting for both water supply and demand. This competition for water between different sectors (municipal, industrial, and agricultural sectors) is called the baseline water stress and is measured by the total annual water withdrawals of all sectors, expressed as a percentage of the total annual available flow (Gassert et al., 2013). Therefore, the baseline water stress variable might also help control for potential water regulations or water costs that we cannot control for explicitly. This is important because the demand for water is likely to also depend on the price of water (Mendelsohn and Dinar, 2003). For additional water supply indicators, we also rely on the return flow ratio, which measures the percentage of available water previously used and discharged upstream as wastewater. As such, it indicates availability and dependence on wastewater treatment plants (Gassert et al., 2013). We do not take groundwater into account, as this is already predicted in large part by the local climate and demand for water sources (Mendelsohn and Dinar, 2003). In addition, it is highly correlated with precipitation. With the current EU policy setting and above water control variables, it is reasonable to assume that property rights and hydrology in Europe are better suited to empirical modeling of adaptive irrigation behavior than in the U.S.

Like irrigation, *crop choice* is influenced by extreme weather events, climatic variables, soil, and geography and subsidies. Unlike irrigation, we also include flood occurrences to control for other extreme events that impact crop choice specifically. Flood occurrence data measure the number of floods recorded in each catchment between 1985 and 2011 (Gassert et al., 2013). We also aim to control for market conditions such as supply of specific inputs and demand for the specific crop types by controlling for distance from cities and ports, length of motorways per 1000 km², population density, and GDP per capita.

Finally, the *conditional value of land* is determined by similar variables to those used in Vanschoenwinkel et al. (2016) and Van Passel et al. (2017). We include distance from cities and ports, as these might influence land value, account for soil type and elevation characteristics, and control for farm and socio-economic characteristics such as subsidies and percentage of rented land. Finally, we control for country-specific characteristics by including country-fixed effects.

All of the resources used to obtain these data are summarized in Appendix H. For all farm-specific data (agricultural land value, subsidies, and land rented), we relied on unique farm accountancy data collected in 2012 by the FADN (Farm Accountancy Data Network) (FADN, 2014). We opted for 2012 data because these were the most recent data available at the time. FADN provides farm-specific measures of approximately 80,000 farm holdings in the European Union, which represent nearly 14 million farms with a total utilized agricultural area of about 216 million hectares. For privacy reasons, it is not possible to link these farm holdings to unique locational coordinates, but they can be linked to the different NUTS3s (Nomenclature of Territorial Units for Statistics regions), which are homogenous geographic units across all European countries that are identified by the EU. As a result, all non-farm specific control variables are at NUTS3 level. The variables of drought severity, upstream water storage, return flow ratio, flood occurrence and baseline water stress were originally obtained through the World Resources Institute, which provides global water risk maps through the Aqueduct interactive platform (Gassert et al., 2013). We obtained data on NUTS3 level from these maps by intersecting them with NUTS3 maps using the rgeos (Bivand et al., 2017) and raster (Hijmans et al., 2016) packages in R. Finally, the baseline climate should be representative for the recent average climate in the study region and should be of a sufficient duration to encompass a range of climatic variations (Carter and La Rovere, 2001). The present study uses the 30-year normal period for temperature and precipitation from 1961–1990 from the Climatic Research Unit (CRU) CL 2.0 (New et al., 2002). These long-run climate estimates are stable and the monthly climate data are aggregated into seasons because the correlation between climate data of neighboring months was too high (Mendelsohn et al., 2001). With regard to the other data and sources, we refer to Appendix H. Our data do not include the most northern countries (Sweden, Finland, and Denmark) because they rely mostly on livestock and mixed farming (and these farms are not included in our analysis given our focus on irrigation).

5.4. Results

We start by discussing the GSEM simultaneous irrigation and crop choice model, before examining the conditional land values and discussing the robustness of our results. For each of these steps, we also analyze whether there are differences between large and small farms. This is because by 2050, there are likely to be fewer but larger farms and it is therefore also important to examine differences in adaptation behavior and consequences between larger and smaller farmers (Reidsma et al., 2015). The division of the sample into large and small farms is based on the economic farm size (ESU, see Appendix H). Farms with an economic farm size larger than 120 ESU are categorized as large farmers. In total, we have 4269 large farms (of which 2972 rain-fed and 1297 irrigated) and 13,767 small farms (of which 7301 rain-fed, and 6466 irrigated). We analyzed a total of 18,036 farms, of which 10,273 were rain-fed and 7763 were irrigated.

5.4.1. Simultaneous irrigation-crop decision model

As table 6 shows, in all models, irrigation is highly dependent on crop choice as all the crop dummies are significant. Crops such as root crops, field crops, fruits, and rice have a highly positive influence on the probability of adopting irrigation, while crops such as wine and olives are more likely to occur without irrigation compared to cereals. The other way around, this crop choice (as can be seen in table 7[4]) was also highly dependent on the decision to irrigate.

Furthermore, given the significance of most of the climate coefficients in the choice model, it is clear that temperature and precipitation have an influence on farm choice. The marginal effects of temperature and precipitation (table 8) show that on an annual basis, higher temperatures and more precipitation have a positive effect on the probability to irrigate.

However, there are both regional, seasonal and farm differences in the relationship between climate and irrigation probability. In Figure 15, we estimated the quadratic relationship between annual climate (in terms of temperature or precipitation) and the probability that irrigation is chosen as an adaptation option. Figure 15A clearly shows the effect of higher temperatures on the probability to irrigate. However, for precipitation there are significant regional differences. Figure 15C (higher latitude farms) shows that the relationship between the probability to irrigate and

[4] Given that we are mostly interested in the results of the irrigation choice model, Table 7 does not elaborate on the distinctions between large and small farms. The crop choice model in this article is mostly of interest for improving the irrigation model and solving endogeneity issues. However, results of the crop model for large and small farms can be obtained by contacting the authors.

Table 6 – GSEM model part irrigation choice

	Small Farms			Large Farms			All Farms		
	Coef	**St Er**	**Sig**	**Coef**	**St Er**	**Sig**	**Coef**	**St Er**	**Sig**
Irrigaton Prob									
Olives	-0.466	0.080	***	-1.335	0.240	***	-0.614	0.074	***
Fieldcrops	0.720	0.055	***	0.924	0.109	***	0.795	0.048	***
Roots	3.221	0.107	***	2.356	0.116	***	2.951	0.069	***
Wine	-0.730	0.066	***	-0.570	0.128	***	-0.647	0.056	***
Fruit	3.937	0.102	***	4.127	0.145	***	4.102	0.080	***
Rice	6.033	1.018	***	3.420	0.495	***	4.104	0.380	***
Cereals		NA			NA			NA	
Drought freq									
Very low (<12.1%)									
Low (12.1-14%)	1.542	0.459	***	1.012	0.154	***	0.672	0.128	***
Medium (14-16%)	2.293	0.461	***	0.647	0.176	***	1.024	0.135	***
High (16-18%)	2.769	0.464	***	1.904	0.215	***	1.800	0.144	***
Very high (>18%)	2.060	0.466	***	1.339	0.217	***	1.096	0.147	***
Drought severity	-0.070	0.006	***	-0.062	0.010	***	-0.069	0.005	***
Water Return	-1.680	0.165	***	-2.158	0.388	***	-1.844	0.138	***
Water stress	0.820	0.098	***	1.280	0.262	***	0.952	0.084	***
Tem Winter	-0.625	0.112	***	-0.004	0.177		-0.126	0.087	
Tem Winter²	0.036	0.012	***	-0.157	0.019	***	-0.025	0.009	***
Tem Spring	-4.787	0.346	***	1.133	0.502	**	-2.297	0.253	***
Tem Spring²	0.213	0.015	***	-0.027	0.024		0.118	0.011	***
Tem Summer	4.132	0.422	***	-2.834	0.651	***	1.756	0.308	***
Tem Summer²	-0.100	0.010	***	0.043	0.016	***	-0.049	0.007	***
Tem Autumn	4.013	0.543	***	-0.012	0.676		1.497	0.386	***
Tem Autumn²	-0.135	0.021	***	0.088	0.027	***	-0.041	0.015	***
Prec Winter	0.058	0.071		-1.075	0.168	***	-0.126	0.061	**
Prec Winter²	-0.011	0.003	***	0.057	0.009	***	-0.002	0.003	
Prec Spring	-0.864	0.171	***	0.140	0.284		-0.268	0.136	**
Prec Spring²	0.113	0.011	***	0.052	0.018	***	0.070	0.009	***
Prec Summer	0.138	0.091		-1.175	0.186	***	-0.244	0.076	***
Prec Summer²	-0.020	0.005	***	0.068	0.010	***	0.004	0.004	
Prec Autumn	0.732	0.109	***	0.895	0.216	***	0.750	0.085	***
Prec Autumn²	-0.065	0.007	***	-0.073	0.012	***	-0.055	0.005	***
Gravel soil	0.077	0.016	***	0.349	0.026	***	0.172	0.013	***
Silt soil	-0.150	0.011	***	0.007	0.017		-0.138	0.009	***
Sand soil	-0.086	0.006	***	0.053	0.011	***	-0.064	0.005	***
pH	0.526	0.075	***	0.835	0.116	***	0.829	0.059	***
Subsidies	0.635	0.056	***	0.380	0.124	***	0.544	0.050	***
Intercept	-41.16	2.853	***	9.615	2.998	***	-18.069	1.763	***
Log likelihood full GSEM	-47706			-30051			-82597		

the amount of precipitation is actually concave; this implies that at a certain point, there is enough precipitation in the region and no irrigation is necessary. As such, it is clear that precipitation is a substitute for irrigation, even though in non-Mediterranean regions the probability to irrigate is quite low (lower than 20%). In Mediterranean regions (figure 15B) – that is, Portugal, Spain, Italy, and Greece – this relationship is less clear because most regions did not yet reach the 'tipping' point of having

Table 7 – GSEM model part crop choice
(crop category "Fruit" is the base category)

	Root crops		Rice		Wine		Olives		Cereals		Field crops	
	Coef	Sg	Coef	Sg	Coef	Sg	Coef	Sg	Coef	Sg	Coef	Sg
Irrigation	-1.80	***	0.54		-4.68	***	-4.54	***	-4.33	***	-3.54	***
Tem Winter	-0.91	***	3.45	***	-0.07		2.48	***	0.78	***	-0.47	***
Tem Winter²	0.02		-0.07		0.05	***	-0.11	***	-0.07	***	-0.04	***
Tem Spring	3.66	***	-4.03		-0.53		-0.31		-2.08	***	-0.10	
Tem Spring²	-0.21	***	0.34		0.06	***	-0.00		0.11	***	0.01	
Tem Summer	-4.53	***	11.14	*	1.09	*	5.27	***	2.62	***	-1.21	**
Tem Summer²	0.12	***	-0.19		-0.00		-0.08	***	-0.06	***	0.02	*
Tem Autumn	0.01		-6.38		0.88		-5.38	***	-2.22	***	0.48	
Tem Autumn²	0.05	**	0.02		-0.10	***	0.14	***	0.06	**	0.03	
Prec Winter	0.96	***	-2.52	***	0.96	***	1.56	***	1.16	***	1.00	***
Prec Winter²	-0.05	***	0.07	**	-0.05	***	-0.07	***	-0.07	***	-0.05	***
Prec Spring	2.57	***	1.99		-0.63	***	2.25	***	0.52	***	0.61	***
Prec Spring²	-0.18	***	0.08		0.10	***	-0.12	***	-0.03	*	-0.04	***
Prec Summer	0.22		1.00		0.64	***	1.45	***	0.48	***	0.47	***
Prec Summer²	-0.03	***	-0.08		-0.07	***	-0.10	***	-0.05	***	-0.05	***
Prec Autumn	-3.06	***	-0.35		-0.55	***	-3.51	***	-2.71	***	-2.26	***
Prec Autumn²	0.18	***	0.08	**	0.04	***	0.22	***	0.17	***	0.14	***
Flood occur	0.01		0.1		-0.1	***	-0.06	***	0.00		0.01	
Motorw leng	0.01	***	-0.15	***	0.00		0.02	***	-0.02	***	-0.01	***
Gravel soil	0.03		0.14		0.17	***	0.16	***	-0.06	***	0.05	**
Silt soil	-0.15	***	0.30	***	-0.06	***	-0.08	***	-0.11	***	-0.08	***
Sand soil	-0.01		0.29	***	-0.02	**	-0.11	***	-0.04	***	0.01	
pH	1.27	***	0.59		0.69	***	0.16		0.16	*	0.75	***
Distance city	0.91		-15.2	***	-12.1	***	-12.4	***	-8.76	***	-4.51	***
Distance port	-2.15	***	-9.81	***	5.50	***	2.70	***	-0.90	**	2.04	***
GDP / capita	0.03	***	-0.13	**	-0.03	***	-0.11	***	-0.01		-0.01	
Eleva mean	1.307	***	-3.65	*	1.98	***	0.77	*	1.76	***	1.55	***
Eleva range	-0.96	***	2.35	***	-0.75	***	0.65	***	-0.27	***	-0.48	***
Pop density	-1.24	***	0.28		-1.64	***	-2.08	***	-0.91	***	-0.91	***
Subsidies	0.72	***	1.24	***	-0.87	***	0.64	***	-0.79	***	-0.02	
Organ carb	0.21	***	0.14		-0.26	***	-0.47	**	0.05	*	0.12	***
Intercept	19.80	***	-114	**	-17.5	***	-31.8	***	10.30	***	9.47	***
Log likelihood full GSEM	-82597											

enough precipitation. These regions are more dependent on irrigation and probabilities to irrigate exceed 60% when sufficient precipitation is present. As figure 15B shows, they can only irrigate if there has been enough precipitation for them to have sufficient water to use for irrigation (for instance, precipitation refills groundwater layers). As such, the more precipitation falls, the more they can irrigate. In Southern regions,

Table 8 – Marginal effect on probability to irrigate

Marginal effect on the probability to irrigate for large farms

	MEts1	MEts2	MEts3	MEts4	MEt	MEps1	MEps2	MEps3	MEps4	MEp
Austria	0.009	0.020	-0.039	0.048	0.038	-0.017	0.024	0.004	0.000	0.010
Belgium	-0.060	0.046	-0.096	0.126	0.016	-0.023	0.056	-0.012	-0.008	0.013
Germany	-0.002	0.007	-0.014	0.017	0.007	-0.005	0.007	-0.002	0.001	0.001
Spain	-0.288	0.068	-0.133	0.358	0.006	-0.056	0.094	-0.116	0.016	-0.062
France	-0.133	0.053	-0.110	0.195	0.004	-0.026	0.077	-0.039	-0.017	-0.005
Greece	-0.085	0.040	-0.076	0.171	0.051	-0.020	0.050	-0.055	0.007	-0.017
Ireland	-0.047	0.021	-0.049	0.052	-0.023	-0.001	0.026	-0.010	-0.012	0.003
Italy	-0.251	0.084	-0.167	0.385	0.052	-0.038	0.137	-0.060	-0.066	-0.027
Luxembourg	-0.003	0.005	-0.010	0.011	0.004	-0.001	0.006	-0.001	-0.002	0.002
The Netherlands	-0.118	0.098	-0.206	0.248	0.023	-0.052	0.099	-0.033	-0.023	-0.009
Portugal	-0.630	0.064	-0.169	0.579	-0.155	0.002	0.130	-0.192	-0.008	-0.068
United Kingdom	-0.036	0.022	-0.048	0.055	-0.007	-0.011	0.022	-0.012	-0.002	-0.004
Total	-0.09	0.04	-0.08	0.14	0.01	-0.02	0.05	-0.03	-0.01	-0.01

Marginal effect on the probability to irrigate for small farms

	MEts1	MEts2	MEts3	MEts4	MEt	MEps1	MEps2	MEps3	MEps4	MEp
Austria	-0.028	-0.041	0.023	0.060	0.015	-0.002	0.021	-0.009	-0.001	0.009
Belgium	-0.013	-0.033	0.025	0.037	0.015	-0.003	0.018	-0.005	-0.006	0.004
Germany	-0.013	-0.032	0.018	0.034	0.007	-0.001	0.010	-0.004	-0.001	0.004
Spain	-0.031	0.002	-0.020	0.033	-0.015	-0.008	0.039	0.005	0.009	0.045
France	-0.036	-0.051	0.044	0.079	0.037	-0.013	0.100	-0.012	-0.034	0.041
Greece	-0.026	0.091	-0.059	-0.022	-0.016	-0.019	0.031	0.008	-0.005	0.016
Ireland	0.000	-0.001	0.001	0.001	0.001	0.000	0.001	0.000	0.000	0.000
Italy	-0.039	0.012	-0.010	0.031	-0.006	-0.017	0.097	-0.010	-0.062	0.007
Luxembourg	-0.014	-0.033	0.021	0.039	0.013	-0.003	0.019	-0.004	-0.007	0.005
The Netherlands	-0.014	-0.042	0.030	0.041	0.015	-0.003	0.012	-0.005	-0.007	-0.002
Portugal	-0.007	0.088	0.001	-0.015	0.067	-0.031	0.114	0.008	-0.046	0.045
United Kingdom	-0.003	-0.010	0.008	0.009	0.004	0.000	0.002	-0.001	0.000	0.001
Total	-0.03	0.01	-0.01	0.03	-0.02	-0.01	0.05	0.00	-0.01	0.03

Marginal effect on the probability to irrigate for all farms

	MEts1	MEts2	MEts3	MEts4	MEt	MEps1	MEps2	MEps3	MEps4	MEp
Austria	-0.002	-0.008	0.001	0.024	0.014	-0.005	0.020	-0.006	0.002	0.012
Belgium	-0.020	-0.015	0.007	0.048	0.020	-0.011	0.048	-0.014	-0.001	0.021
Germany	-0.003	-0.008	0.002	0.014	0.005	-0.003	0.010	-0.004	0.003	0.006
Spain	-0.070	0.070	-0.059	0.052	-0.007	-0.023	0.068	-0.036	0.030	0.039
France	-0.041	0.016	-0.011	0.052	0.017	-0.017	0.081	-0.023	-0.009	0.032
Greece	-0.066	0.103	-0.070	0.036	0.003	-0.024	0.060	-0.035	0.017	0.019
Ireland	-0.004	-0.004	0.004	0.007	0.003	-0.002	0.007	-0.002	-0.002	0.001
Italy	-0.066	0.066	-0.050	0.059	0.009	-0.026	0.113	-0.035	-0.035	0.017
Luxembourg	-0.007	-0.012	0.004	0.026	0.012	-0.006	0.026	-0.007	-0.003	0.010
The Netherlands	-0.033	-0.048	0.023	0.085	0.027	-0.019	0.062	-0.025	-0.006	0.012
Portugal	-0.093	0.134	-0.054	0.031	0.018	-0.027	0.105	-0.038	-0.010	0.030
United Kingdom	-0.008	-0.010	0.006	0.017	0.005	-0.004	0.012	-0.005	0.002	0.005
Total	-0.04	0.04	-0.03	0.04	0.00	-0.02	0.05	-0.02	0.00	0.02

Marginal effects are derived from coefficients in Table 6. MEts/ps1: marginal effect temperature/precipitation winter, MEts/ps2: marginal effect temperature/precipitation spring, MEts/ps3: marginal effect temperature/precipitation summer, MEts/ps4: marginal effect temperature/precipitation winter.

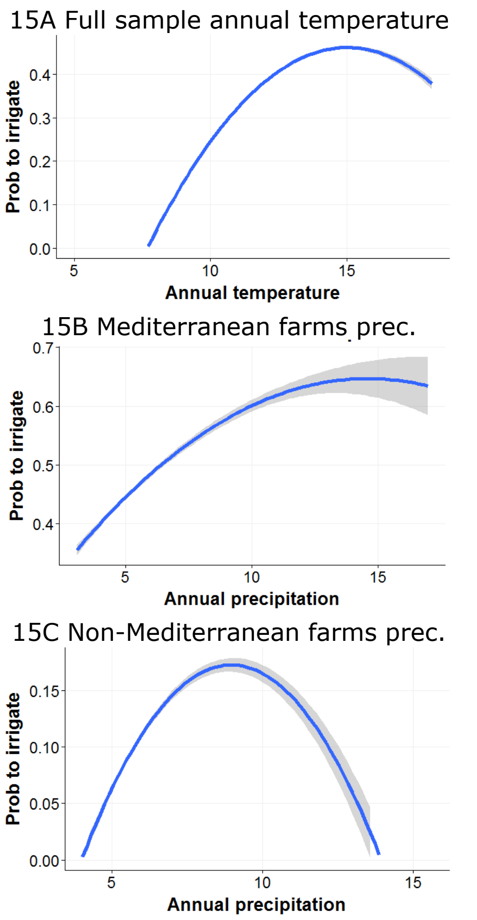


Figure 15 – Irrigation probability versus annual climate
(grey areas are 95% confidence intervals)

therefore, irrigation is somehow dependent on precipitation. With regard to the seasonal differences, table 8 shows that less rain in winter and summer gives rise to a higher probability to irrigate (a decrease of 1 cm precipitation leads to a 2% increase in irrigation probability). This makes sense, as winter and summer crops are in their critical growth stages during these seasons, implying that they need enough water. Irrigation is a clear substitute for precipitation in these seasons. With regard to temperature, higher temperatures in winter and summer lead to lower probabilities of irrigation (a decrease in probability of up to 4% if temperature increases with one degree). Higher temperatures in winter imply that irrigation as a frost protection is less needed. With regard to higher temperatures in summer, however, it can be seen that the low average irrigation probability is highly influenced by Southern European regions such as Spain (-5.2%), Greece (-7%), Italy (-5%), and Portugal (-5.4%). This implies that these regions adapt to high temperatures by means of their crop choice (for example, cotton and olives are less sensitive to higher temperatures and are less likely to need additional irrigation). These conclusions should not be generalized to all farms. Large and small farmers make different choices in response to temperature and precipitation. For instance, large farmers seem to irrigate more when there is less precipitation, indicating that they use irrigation as a substitute for precipitation. Those large farmers respond less to changes in temperature (for instance, when summer temperature increases with one degree, the probability to irrigate decreases on average with 8%). Instead, small farmers seem to irrigate more when there is more precipitation (on average, an increase in precipitation of one cm leads to a 3% increase in the probability to irrigate), which again points out their dependency on precipitation before they can irrigate. This is especially the case in Southern European regions (see for instance Spain and Portugal which record increases of on average 4.5% in their probability to irrigate when precipitation increases with one cm). With regard to annual temperature, it seems that small farms in Southern regions are less likely to irrigate if temperature increases, indicating that they might rather adapt through more drought resistant crop choices.

With regard to the influence of drought on irrigation probability (see table 6), we controlled both for drought frequency and drought severity. Drought frequency has a positive influence on irrigation probability. However, if drought occurs with a very high frequency, the probability of irrigation is lower than when drought occurs with a high frequency. Moreover, the higher the severity of the drought, the less likely it is that irrigation will occur. These two last findings can be explained by the fact that periods of severe drought lead to severe pressures on irrigation water capacity. In addition, there might be additional regulations that prioritize water use for sanitary or drinking water purposes. In case of very severe periods of droughts, irrigation costs might no longer be economically justifiable or the crops might already be damaged too much. More competition for water resources seems to be in line with higher farm irrigation probabilities. This could be explained by the fact that regions with more competition for water resources are more likely to have a water policy or more renewable water sources to solve their water scarcity issues. While small and large farms react similarly to drought events, it seems that small farmers are more responsive.

5.4.2. Conditional land value

Depending on the choices the farmer makes in the irrigation-crop decision model, the farmer will have a different climate response or conditional land value. This article focusses on the difference in climate response between farmers that opt for irrigation and farmers that opt for rain-fed agriculture. When comparing such climate responses properly, the model should account for endogeneity. As can be seen in table 9, in the endogenous model, endogenous treatment (λ_i) is in both cases highly significant. This indicates that irrigation is indeed endogenous and therefore within the control of the farmer. As such, it is an important adaptation strategy as long as enough water is available. For the cross-sectional climate change impact models, this means that we have proven that models that fail to account for endogenous irrigation are biased. For comparative purposes, we also include the model that does not correct for endogeneity (that is, the exogenous model or the original cross-sectional model).

Looking at the endogenous model in table 9, it can be seen that both rain-fed and irrigated farms are sensitive to climate as most of the climate coefficients are significant in both climate response functions. On an annual basis and looking at the full dataset (without distinguishing between rain-fed and irrigated farms), for most member states, both temperature and precipitation do not have a negative effect on land value as negative seasonal effects are offset. However, irrigated farms responded significantly differently than rain-fed farms to 11 of the 16 climate variables. This becomes clearer in table 10 and figures 16 and 17 who present the marginal effects of temperature and precipitation. It can be seen that irrigated crops are more resistant and less sensitive to higher temperatures than rain-fed crops in southern regions. Nevertheless, irrigation seems to be less beneficial in response to higher temperature in northern regions than in more southern regions. Spain for instance has on average a 7% increase in rain-fed land value if annual temperature increases with one degree, while irrigated land has an increase of 17%. On the other hand, in Belgium rain-fed agriculture has a higher benefit (34.6%) than irrigated agriculture (11.3%) when temperature increases with one degree. This shows the adaptive effect irrigation has in Southern Europe. An examination of increases in precipitation suggests that rain-fed crops benefit significantly more than irrigated crops (on average they benefit from an increase of 25% in their land value if annual precipitation increases with 1 cm, while irrigated crops benefit a smaller increase of 16%). This makes sense because irrigation is a substitute for precipitation. Especially Northern Italy, where a lot of rice is cultivated and where significant irrigation investments have been done, would suffer from increases in precipitation.

Finally, the conditional climate response of large and small farms (figure 16 and 17) shows that in between irrigated farms, there can still be differences in climate responses. For instance, most small farms that irrigate are located in southern regions and face highly positive marginal effects of temperature. Large irrigated farms face quite negative marginal

Table 9 – Conditional Land Value per farm choice

For each sample, rain-fed and irrigated farms are compared (Diff) to measure their significant differences.

	Large					Small				
	Rain-fed Endo		Irrigation Endo		Diff	Rain-fed Endo		Irrigation Endo		Diff
Log Land Value	Coef	Sig	Coef	Sig	Sig	Coef	Sig	Coef	Sig	Sig
T Winter	0.13	***	-0.19	***	***	0.01		-0.29	***	***
T Winter²	-0.04	***	-0.00		***	0.01	***	0.02	***	***
T Spring	-1.92	***	0.24		***	-0.49	***	0.60	***	***
T Spring²	0.14	***	-0.01	*	***	0.04	***	0.00		***
T Summer	0.92	***	-0.82	***	***	-0.18		-1.38	***	***
T Summer²	-0.05	***	0.02	***	***	0.00		0.03	***	***
T Autumn	1.08	***	0.29		***	0.75	***	0.92	***	
T Autumn²	-0.03	***	0.01		***	-0.04	***	-0.04	***	
P Winter	0.09	***	-0.67	***	***	0.07	***	-0.10	***	***
P Winter²	-0.00	**	0.03	***	***	0.00	***	0.01	***	**
P Spring	0.37	***	1.40	***	***	0.04		0.06		
P Spring²	-0.04	***	-0.09	***	***	0.00		-0.02	***	***
P Summer	0.01		-0.60	***	***	0.03		0.15	***	**
P Summer²	0.02	***	0.05	***	***	0.00	***	0.01	**	
P Autumn	0.01		0.28	***	***	0.04		0.36	***	***
P Autumn²	0.00		-0.01	***	**	-0.01	***	-0.02	***	*
Pop density	0.03		0.13	**		0.35	***	0.35	***	
Subsidies	0.01		0.19	***	***	0.21	***	0.20	***	
Distance ports	1.81	***	-1.21	***	***	-0.60	***	-1.32	***	***
Distance cities	-2.50	***	-2.80	***		-0.22	*	-1.25	***	***
Rent land	0.14	***	0.38	***	***	-0.02		0.04		*
Elev mean	-0.22	**	0.04		*	-0.45	***	0.16	**	***
Elev range	0.17	***	-0.05	***	***	0.11	***	0.02		***
Gravel soil	0.02	***	-0.02	***	***	-0.04	***	0.06	***	***
pH	0.86	***	1.98	***	***	-0.24		-0.63	**	
pH squared	-0.06	***	-0.14	***	***	0.04	***	0.04	*	
Silt soil	-0.01	**	-0.02	***	***	-0.02	***	-0.02	***	
Sand soil	-0.01	***	-0.01	***		-0.03	***	-0.04	***	*
Austria	-2.53	***	-3.04	***	***	-2.21	***	-2.76	***	
Belgium	-0.66	***	0.00		*	0.06		0.00		
Germany	-0.67	***	0.00			0.20	*	0.00		
Greece	-1.66	***	-0.96	***	**	-0.57	***	-0.07		
Spain	-1.08	***	-2.12	***	***	-1.12	***	-0.43		
France	-2.07	**	-2.26	***	***	-1.33	***	-1.19	***	
Ireland	-0.76	***	0.00			-0.00		0.00		
Italy	-0.05		-0.69	**	***	0.52	***	0.53	*	
The Netherlands	0.22		0.48	*	*	1.31	***	1.38	***	
Portugal	-4.63	***	-2.84	***	***	-1.93	***	-2.16	***	
United Kingdom	-0.86	***	-0.75	***		-0.23	**	0.00		
λ_i	-0.21	***	-0.30	***		-0.23	***	-0.13	***	*
Intercept	1.47		8.69	***	***	11.05	***	17.38	***	***
Adj R-squared	0.63		0.74			0.66		0.64		

Table 9 Continued – Conditional Land Value per farm choice

For each sample, rain-fed and irrigated farms are compared (Diff) to measure their significant differences.

	Full											
	Rain-fed Endo		Irrigation Endo		Diff	Rain-fed Exo		Irrigation Exo		Diff	Fulldata Exo	
Log Land Value	Coef	Sig	Coef	Sig	Sig	Coef	Sig	Coef	Sig	Sig	Coef	Sig
T Winter	0.06	***	-0.32	***	***	0.05	**	-0.31	***	***	-0.11	***
T Winter²	-0.02	***	0.02	***	***	-0.02	***	0.02	***	***	-0.00	**
T Spring	-0.29	***	0.44	***	***	-0.30	***	0.48	***	***	-0.08	*
T Spring²	0.04	***	0.00		***	0.04	***	-0.00		***	0.03	***
T Summer	-0.58	***	-1.32	***	***	-0.60	***	-1.35	***	***	-0.94	***
T Summer²	0.00	**	0.02	***	***	0.00	**	0.03	***	***	0.01	***
T Autumn	0.85	***	1.01	***		0.88	***	1.03	***		1.06	***
T Autumn²	-0.03	***	-0.03	***		-0.03	***	-0.03	***		-0.04	***
P Winter	0.03	**	-0.27	***	***	0.03	*	-0.25	***	***	-0.09	***
P Winter²	0.00	***	0.01	***	***	0.00	***	0.01	***	***	0.01	***
P Spring	0.31	***	0.41	***	*	0.31	***	0.40	***		0.33	***
P Spring²	-0.02	***	-0.04	***	***	-0.02	***	-0.04	***	***	-0.02	***
P Summer	-0.00		-0.03			-0.01		-0.01			-0.03	
P Summer²	0.01	***	0.02	***	**	0.01	***	0.02	***	**	0.01	***
P Autumn	0.07	***	0.30	***	***	0.08	***	0.29	***	***	0.14	***
P Autumn²	-0.01	***	-0.01	***		-0.01	***	-0.01	***		-0.01	***
Pop density	0.12	***	0.25	***	***	0.12	***	0.26	***	***	0.18	***
Subsidies	0.15	***	0.22	***	***	0.16	***	0.20	***	**	0.24	***
Distance ports	0.63	***	-1.03	***	***	0.63	***	-1.04	***	***	0.05	
Distance cities	-1.72	***	-1.74	***		-1.71	***	-1.78	***		-2.04	***
Rent land	0.00		0.12	***	***	0.01		0.13	***	***	0.06	***
Elev mean	-0.12	**	0.16	**	***	-0.11	**	0.20	***	***	0.01	
Elev range	0.04	***	0.00		**	0.04	***	0.00		**	0.06	***
Gravel soil	-0.02	***	0.04	***	***	-0.02	***	0.04	***	***	-0.00	
pH	-0.80	***	0.17		***	-0.84	***	0.20		***	-0.52	***
pH squared	0.08	***	-0.01		***	0.09	***	-0.01		***	0.06	***
Silt soil	-0.02	***	-0.03	***	***	-0.02	***	-0.03	***	***	-0.02	***
Sand soil	-0.02	***	-0.03	***	***	-0.02	***	-0.03	***	***	-0.02	***
Austria	-2.16	***	-3.45	***	***	-2.16	***	-3.48	***	***	-2.51	***
Belgium	-0.12		0.00		**	-0.10		0.00		**	-0.06	
Germany	-0.05		0.00			-0.04		0.00			-0.16	*
Greece	-0.61	***	-0.97	***		-0.52	***	-1.02	***		-0.15	
Spain	-1.13	***	-1.53	***		-1.10	***	-1.59	***		-0.90	***
France	-1.54	***	-2.14	***		-1.53	***	-2.17	***		-1.45	***
Ireland	-0.36	***	0.00			-0.35	***	0.00			-0.34	***
Italy	0.30	***	-0.48		***	0.33	***	-0.53	*	**	0.44	***
The Netherlands	0.90	***	0.08		***	0.92	***	0.02		***	0.86	***
Portugal	-2.48	***	-2.88	***		-2.46	***	-2.94	***		-2.31	***
United Kingdom	-0.35		-0.85	***		-0.34	***	-0.93	***		-0.34	***
λ_i	-0.19	***	0.18	***	***							
Intercept	13.69	***	14.56	***		13.48	***	14.73	***		14.39	***
Adj R-squared	0.64		0.67			0.64		0.67			0.63	

Table 10 – Marginal effects of temperature per season

	Full sample Rainfed Endogenous					Full sample Irrigation Endogenous					Full sample Full Endogenous				
	MEts1	MEts2	MEts3	MEts4	MEt	MEts1	MEts2	MEts3	MEts4	MEt	MEts1	MEts2	MEts3	MEts4	MEt
Austria	0.085	0.363	-0.421	0.318	0.346	-0.323	0.438	-0.433	0.431	0.113	0.055	0.373	-0.423	0.325	0.330
Belgium	-0.024	0.351	-0.430	0.257	0.154	-0.232	0.438	-0.514	0.394	0.087	-0.042	0.358	-0.438	0.269	0.147
Germany	0.049	0.291	-0.430	0.319	0.229	.	.	.	.	.	0.042	0.294	-0.432	0.322	0.226
Spain	-0.142	0.575	-0.383	0.022	0.072	-0.131	0.438	-0.295	0.164	0.176	-0.136	0.520	-0.348	0.078	0.114
France	-0.073	0.438	-0.418	0.178	0.125	-0.180	0.438	-0.427	0.284	0.115	-0.104	0.440	-0.421	0.205	0.121
Greece	-0.157	0.651	-0.378	-0.042	0.075	-0.156	0.438	-0.256	0.141	0.166	-0.151	0.492	-0.288	0.091	0.144
Ireland	-0.087	0.280	-0.455	0.308	0.046	.	.	.	.	.	-0.088	0.282	-0.457	0.309	0.047
Italy	-0.124	0.551	-0.392	0.035	0.070	-0.179	0.438	-0.345	0.216	0.129	-0.149	0.498	-0.370	0.119	0.098
Luxembourg	0.023	0.317	-0.432	0.315	0.223	.	.	.	.	.	0.014	0.321	-0.435	0.320	0.219
Netherlands	-0.022	0.304	-0.437	0.274	0.119	-0.241	0.439	-0.558	0.422	0.062	-0.088	0.346	-0.475	0.320	0.103
Portugal	-0.235	0.701	-0.389	-0.077	0.001	-0.061	0.438	-0.333	0.093	0.137	-0.151	0.581	-0.362	-0.006	0.061
U. Kingdom	-0.050	0.270	-0.448	0.297	0.069	-0.213	0.439	-0.598	0.422	0.050	-0.067	0.288	-0.464	0.310	0.067
Total	-0.05	0.41	-0.42	0.19	0.13	-0.16	0.44	-0.34	0.21	0.14	-0.08	0.42	-0.39	0.19	0.13

	Full sample Rainfed Exogenous					Full sample Irrigation Exogenous					Full sample Full Exogenous				
	MEts1	MEts2	MEts3	MEts4	MEt	MEts1	MEts2	MEts3	MEts4	MEt	MEts1	MEts2	MEts3	MEts4	MEt
Austria	0.075	0.370	-0.434	0.339	0.350	-0.321	0.442	-0.420	0.404	0.106	-0.105	0.497	-0.526	0.400	0.266
Belgium	-0.036	0.358	-0.443	0.276	0.155	-0.217	0.445	-0.505	0.365	0.089	-0.131	0.482	-0.553	0.328	0.126
Germany	0.038	0.297	-0.443	0.340	0.231	.	.	.	.	.	-0.113	0.430	-0.553	0.405	0.168
Spain	-0.154	0.588	-0.395	0.035	0.073	-0.103	0.434	-0.274	0.120	0.177	-0.158	0.674	-0.436	0.041	0.120
France	-0.085	0.447	-0.431	0.194	0.126	-0.158	0.440	-0.413	0.247	0.117	-0.143	0.562	-0.517	0.216	0.119
Greece	-0.169	0.665	-0.390	-0.030	0.076	-0.131	0.432	-0.234	0.095	0.162	-0.154	0.717	-0.423	0.005	0.144
Ireland	-0.099	0.286	-0.469	0.328	0.046	.	.	.	.	.	-0.145	0.420	-0.617	0.390	0.048
Italy	-0.136	0.563	-0.405	0.049	0.071	-0.157	0.437	-0.327	0.175	0.127	-0.150	0.643	-0.461	0.080	0.111
Luxembourg	0.012	0.323	-0.445	0.335	0.226	.	.	.	.	.	-0.119	0.452	-0.557	0.399	0.175
Netherlands	-0.033	0.310	-0.451	0.293	0.119	-0.227	0.448	-0.550	0.395	0.066	-0.130	0.442	-0.571	0.351	0.092
Portugal	-0.248	0.716	-0.401	-0.066	0.001	-0.023	0.429	-0.314	0.045	0.137	-0.179	0.770	-0.453	-0.064	0.075
U. Kingdom	-0.062	0.275	-0.462	0.317	0.068	-0.195	0.450	-0.592	0.395	0.057	-0.137	0.412	-0.597	0.374	0.052
Total	-0.06	0.42	-0.43	0.21	0.13	-0.14	0.44	-0.33	0.17	0.14	-0.14	0.56	-0.50	0.20	0.12

(1 = winter, 2 = spring, 3 = summer, 4 = autumn) or on average per year (MEt) on conditional land value.

Table 11 – Marginal effects of precipitation per season

	Full sample Rainfed Endogenous					Full sample Irrigation Endogenous					Full sample Full Endogenous				
	MEps1	MEps2	MEps3	MEps4	MEp	MEps1	MEps2	MEps3	MEps4	MEp	MEps1	MEps2	MEps3	MEps4	MEp
Austria	0.057	0.114	0.195	-0.040	0.325	-0.158	0.048	0.210	0.182	0.282	0.043	0.108	0.196	-0.025	0.322
Belgium	0.071	0.085	0.167	-0.082	0.241	-0.086	-0.028	0.204	0.133	0.223	0.059	0.074	0.170	-0.064	0.238
Germany	0.059	0.140	0.150	-0.034	0.315	.	.	.	.	.	0.056	0.138	0.151	-0.030	0.314
Spain	0.064	0.148	0.047	-0.033	0.226	-0.118	0.061	0.057	0.170	0.171	-0.008	0.114	0.051	0.047	0.204
France	0.071	0.087	0.129	-0.078	0.209	-0.065	-0.093	0.155	0.109	0.106	0.035	0.036	0.136	-0.028	0.179
Greece	0.085	0.146	0.040	-0.059	0.211	-0.057	0.077	0.049	0.163	0.232	-0.016	0.096	0.046	0.102	0.228
Ireland	0.090	0.055	0.155	-0.144	0.156	.	.	.	.	.	0.089	0.053	0.156	-0.142	0.156
Italy	0.075	0.097	0.105	-0.110	0.167	-0.056	-0.087	0.168	0.080	0.106	0.014	0.011	0.135	-0.022	0.138
Luxembourg	0.079	0.067	0.168	-0.093	0.221	.	.	.	.	.	0.076	0.062	0.170	-0.087	0.220
Netherlands	0.069	0.126	0.157	-0.084	0.268	-0.094	0.033	0.193	0.127	0.259	0.019	0.098	0.168	-0.019	0.266
Portugal	0.094	0.096	0.037	-0.083	0.143	0.056	-0.072	0.036	0.108	0.129	0.078	0.027	0.036	-0.004	0.137
U. Kingdom	0.073	0.111	0.137	-0.082	0.239	-0.102	0.044	0.153	0.144	0.239	0.054	0.104	0.139	-0.058	0.239
Total	0.07	0.13	0.12	-0.06	0.25	-0.08	0.01	0.11	0.13	0.16	0.03	0.09	0.11	-0.00	0.22

	Full sample Rainfed Exogenous					Full sample Irrigation Exogenous					Full sample Full Exogenous				
	MEps1	MEps2	MEps3	MEps4	MEp	MEps1	MEps2	MEps3	MEps4	MEp	MEps1	MEps2	MEps3	MEps4	MEp
Austria	0.054	0.120	0.193	-0.038	0.329	-0.143	0.026	0.223	0.178	0.284	-0.027	0.066	0.215	0.024	0.278
Belgium	0.069	0.092	0.164	-0.081	0.245	-0.073	-0.050	0.216	0.132	0.224	0.011	0.024	0.183	-0.019	0.198
Germany	0.056	0.145	0.148	-0.031	0.318	.	.	.	.	.	-0.021	0.099	0.162	0.030	0.270
Spain	0.061	0.153	0.044	-0.030	0.229	-0.104	0.040	0.072	0.166	0.174	-0.009	0.104	0.041	0.028	0.164
France	0.069	0.094	0.127	-0.077	0.213	-0.053	-0.117	0.169	0.109	0.107	0.013	0.017	0.137	-0.021	0.146
Greece	0.084	0.151	0.037	-0.057	0.214	-0.045	0.056	0.063	0.160	0.235	0.028	0.107	0.039	0.013	0.187
Ireland	0.089	0.063	0.153	-0.147	0.159	.	.	.	.	.	0.059	-0.017	0.169	-0.084	0.127
Italy	0.073	0.105	0.103	-0.112	0.168	-0.044	-0.111	0.182	0.082	0.109	0.021	0.022	0.127	-0.053	0.116
Luxembourg	0.078	0.075	0.166	-0.094	0.225	.	.	.	.	.	0.031	0.000	0.185	-0.032	0.184
Netherlands	0.066	0.132	0.155	-0.083	0.270	-0.081	0.011	0.206	0.126	0.262	0.003	0.079	0.171	-0.019	0.234
Portugal	0.093	0.103	0.034	-0.082	0.148	0.065	-0.096	0.051	0.108	0.128	0.073	0.026	0.027	-0.026	0.100
U. Kingdom	0.071	0.117	0.135	-0.082	0.241	-0.088	0.022	0.166	0.142	0.242	0.012	0.062	0.145	-0.017	0.203

(1 = winter, 2 = spring, 3 = summer, 4 = autumn) or on average per year (MEp) on conditional land value. Land value = agricultural land value per hectare based on the regression models' estimates.

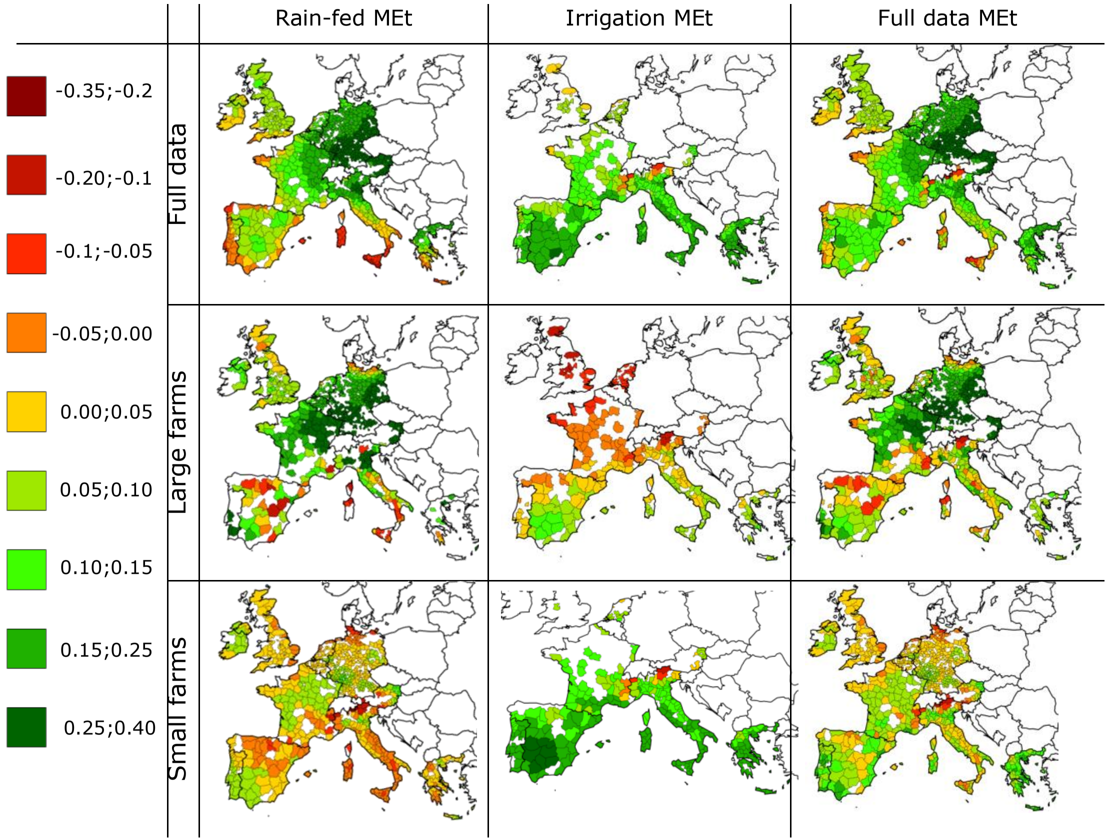


Figure 16 – Conditional marginal effect of temperature on land value

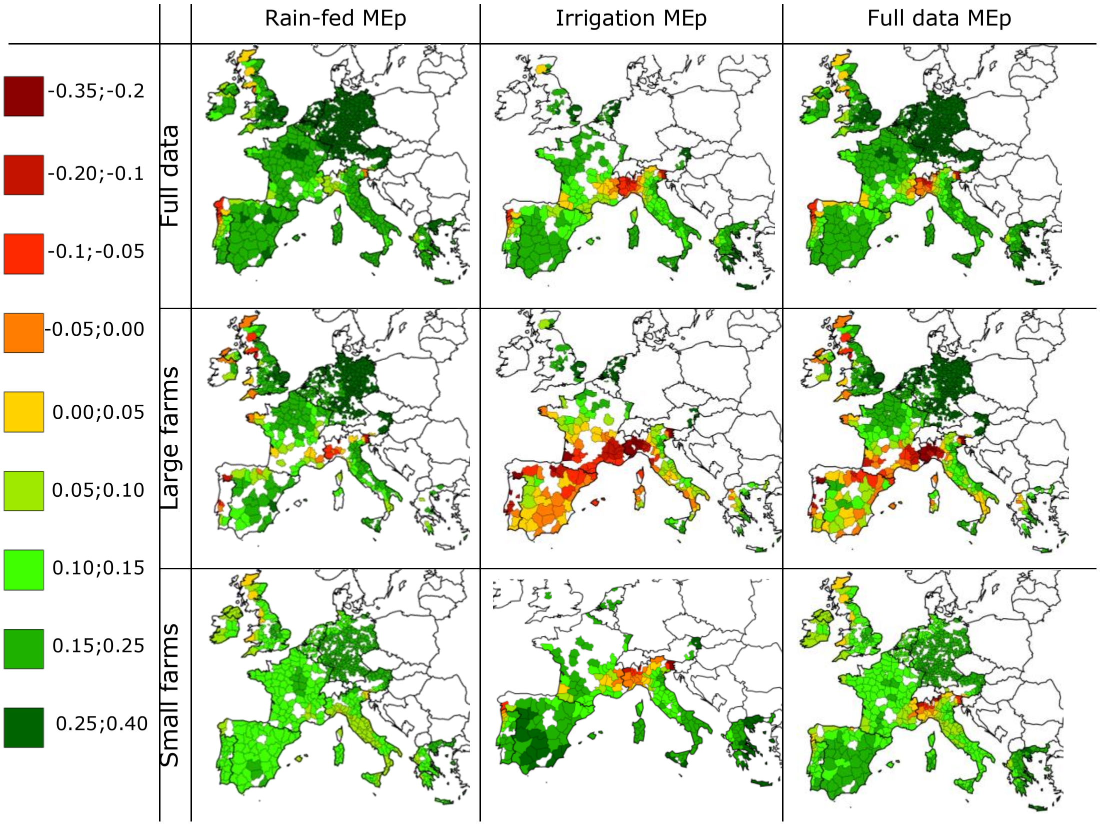


Figure 17 – Conditional marginal effect of precipitation on land value

effects of temperature in northern regions. Therefore, it appears that small farmers are more adapted to the climate in terms of temperature increases. Large farmers might irrigate more as a way to intensify their farm and might therefore be less adapted to the temperature of the climate they live in. Instead, large irrigated farms seem to respond positively to decreases in precipitation, most likely because they have made significant investments in irrigation. Small irrigated farms suffer from decreases in precipitation, even though irrigation is assumed to be a substitute for precipitation.

5.4.3. Model robustness

A traditional Ricardian climate response function determines the marginal effects of climate conform the formula in equation 4. That is, it determines a marginal effect for the full sample, not distinguishing between different types of adaptation. However, as can be seen in figure 13, different adaptation options do have different climate responses and therefore marginal effects. The structural endogenous Ricardian climate response function estimated in this article determines the marginal effects of climate conform the formula in equation 5. That is, it determines the marginal effects per adaptation option and multiplies them with the probability this adaptation option takes place. Finally, the sum of these multiplications is taken. In table 10 and 11, all the marginal effects for temperature and precipitation are presented for both the endogenous and the exogenous model. When comparing only the rainfed estimates when determined with the exogenous and the endogenous model, it can be seen that differences are very small between the exogenous and endogenous land value estimates and between the exogenous and endogenous irrigation estimates. However, looking at the full climate response function (see final column of table 10 and 11), it can be seen that there are significant differences between the endogenous estimates (equation 5) and the exogenous estimates (equation 4). Comparing the rainfed estimates with the full sample estimates shows that the structural endogenous Ricardian model that explicitly models adaptation is more robust than the traditional Ricardian estimates. This can be seen by looking at countries that do not contain irrigated farmers in the sample. In this case, we do not have observations of German, Irish and Luxembourgian farmers that irrigate. This means that our marginal effect estimates of the Rainfed German, Irish and Luxembourgian farmers, should be the same as the marginal effect estimates of the German, Irish and Luxembourgian full sample farmers because there is no difference between the full and the rain-fed dataset for these countries. For our endogenous GSEM model that accounts explicitly for adaptation, this is indeed the case. See for instance table 10 where the MEts1 for the Rainfed Endogenous model in Germany equals 0.049. This is very close to the estimate of MEts1 for the full Endogenous model which equals 0.042. However, when adaptation is not explicitly modeled, the full data estimates are biased by the adaptation options in other regions. See for instance table 10 where the MEts1 for the Rainfed Exogenous model in Germany equals 0.038. This is quite different from the estimate of MEts1 for the full Endogenous model which equals -0.113. Clearly, the aggregated effect of irrigation biases the estimates of the original Ricardian model. As such, our endogenous estimates are more robust than the original Ricardian ones when looking at a seasonal basis.

Furthermore, the analysis goes to great lengths to adjust for unwanted variation. The analysis is particularly robust because it accounts for crop choice in the irrigation decision, but also because it includes additional data on water resources and consumption. In addition, the simultaneous estimation of crop and irrigation choice also implies that all unobserved farm characteristics that influence both irrigation and crop choice are captured by unobserved components. Nevertheless, it is likely that there are still variables on a national level, such as agricultural policy, taxes, technology and trade, that vary across farms and member states. We capture these in the land value regression by including country fixed effects. Even though we also have access to data regarding evapotranspiration, percentage of clouds, and solar radiation, we did not add these variables, in order to avoid correlation between such control variables and our climate variables. Given the significance of most of our coefficients, further correlation does not seem to be a problem in our analysis. Finally, with regard to the large-small farm categorization, we analyzed whether different categorizations based on different thresholds of economic farm size influenced the results. This had only limited influence on the results. Additional tests with different categorizations were done and our main results hold across all of these specifications. The descriptive statistics in Appendix G also show that there is a reasonable spread of large and small farms all over Western Europe.

5.5. Policy and future research implications

This article shows that even with cross-sectional data, it is possible to gain insights into complicated real-life farm decisions and it even increases the robustness of impact estimates. Gaining insights in adaptation is important because adaptation to new climatic events leads, in the short (and medium) term, to transition and adjustment costs (Kelly et al., 2005), which often leads to reluctance to implement adaptation plans[5] immediately. More studies on the economic impact of adaptation therefore should be conducted to guide policy.

5.5.1. Article findings

The article shows that irrigation is an endogenous farm choice that is influenced by climatic influences. As such, it can be an important adaptation strategy in Europe to make crops less vulnerable to climatic changes. For instance, results show that, in southern regions (where

[5] For instance, the EU agreed to spend at least 20 percent of its 2014–2020 budget on climate-related action (ECA, 2016). Given that almost 40 percent of the EU budget is spent on agriculture and rural development (E.C., 2015), one of the major EU spending programs where climate actions should be undertaken is the Common Agricultural Policy (CAP) (E.C., 2017). However, according to the ECA (2016), there is no significant change in common agricultural policy, or in rural development spending, and business as usual prevails.

climate is most unfavorable), irrigated crops are more resistant to increases in temperature or decreases in precipitation than rain-fed crops.

However, many of the article's results also point out that water availability might be an important restraint, indicating the risk of maladaptation when irrigation investments are made in regions that only have limited water availability. Overly high summer temperatures decrease the irrigation probability, while very severe or frequent periods of droughts decrease the probability that farmers will irrigate. On the other hand, the article also shows that large farms that irrigate and that do have access to sufficient water, might not always adapt properly to climate in terms of temperature. This proves that over-specialization in irrigation equipment while ignoring adaptation through other means might not always be appropriate. In this context, the article shows that irrigation as an adaptation option can be substituted by means of different farm crop choices as the farm irrigation choice is highly influenced by the farm crop choice. As such, crop choice can reduce farm water requirements. For policy makers, this implies that, given the significance of crop choice in the irrigation decision, policy can guide the irrigation decision of water scarce areas towards crops that require less water and thus less irrigation. For those crops where irrigation remains, and given the significance of water availability in the irrigation decision model, water management (such as capture and storage) will likely be an important working point for Europe.

5.5.2. Method

The model presented in this article is unique in the sense that it models two farm adaptation decisions simultaneously instead of modeling no, or only one, adaptation option explicitly. This is more realistic, as farmers in real-life also have to make decisions that simultaneously influence one another. In addition, the model's estimates are more robust than those of the traditional cross-sectional model which does not explicitly consider adaptation; this increases the model's value for climate impact estimates.

The disadvantage of such a model is that it requires significant computational efforts and data, making it less accessible to be implemented everywhere.

Furthermore, the model presents numerous opportunities for further research. First of all, future research should consider the estimation of an even larger simultaneous equation model in which more adaptation options are considered explicitly, or in which linkages with other related fields are examined (such as the interactions between climate and water availability). Furthermore, when studying adaptation behavior, the time frame that the farmer considers might have a great influence on his/her decisions (Knapp and Huang, 2017). The present study looked at long-term climate, ignoring short-term fluctuations. However, many farm decisions are related to daily changes in management in response to short-term changes in various exogenous variables. Therefore, panel data studies on decision behavior are also needed in order to further improve adaptation understanding. For instance, it would be interesting to examine adaptation switchers over time (that is, farmers who switch from one adaptation option to another over the years). In this regard, it should also be noted that the role of information exchange is very important in terms of making and executing adaptation decisions. Evidence shows that word of mouth information between farmers represents roughly half of the information that farmers use to make economic decisions (Zilberman et al., 2012). Also, farmers prefer to 'wait and see' in order to learn from the early adopters. Therefore, adoption might be slow at the beginning, but can speed up fast at later stages (Zhao, 2007), which reduces the likelihood of making bad investments. Consequently, alternative decision modeling will also be important to model the dynamic multistage process (awareness, interest, evaluation, trial, and the final adaptation) (Rogers, 1962). To increase further understanding on a farmers' decision to adapt to climate change, data modeling can be combined with economic decision models. The data and results of the data models can form input to a decision tree analysis or an application of the real options theory. Such analyses define the optimal timing for a farmer to adopt a specific adaptation strategy under climate change uncertainty. For instance, Regan et al. (2015) studied the conversion of land from agriculture to biomass. Sanderson et al. (2016) defined the threshold at which a farmer switches from a wheat-dominated system to alternative systems. Based on these analyses, different adaptation scenarios can be compared.

5.6. Conclusion

The present article shows that the combination of specific farm types (large versus small farms) and adaptation options (crop and irrigation choice) leads to very heterogeneous regional farm responses to climate change. Appropriate farm adaptation decisions lead to less sensitive farm responses to changes in climate. As such, Southern European regions do not always suffer from climate change, even though on average, this is the case. Nevertheless, the article also shows that adaptation decisions and implementations might be hampered by climate constraints. Therefore, it is important to model correctly farm adaptation decisions to understand potential threats of maladaptation or to reveal good practices. This article focused on making adaptation models more realistic in the sense that farmers make simultaneous adaptation decisions. This helps to gain more insights in the irrigation decision itself, and leads to more robust climate change estimates than when compared to their exogenous counterparts.

CHAPTER 6. CONCLUSION

Chapter 6. Conclusion and discussion

"We basically have three choices: mitigation, adaptation and suffering. We're going to do some of each. The question is what the mix is going to be. The more mitigation we do, the less adaptation will be required and the less suffering there will be." David Roberts (2012)

6.1. Methodological improvements

Agriculture is the most studied sector with regard to the impact of climate change, due to the assumption that it is the sector most affected *by* climate change (Rosenzweig et al., 2014). However, surprisingly few studies have explicitly reported on adaptive actions the sector can take to improve its climate response or to become less climate-sensitive (Berrang-Ford et al., 2011; Berrang-Ford et al., 2015). Knowledge on how to adapt is limited, even though there is pressing evidence of climate change losses that show that adaptation to climate change is an "increasingly urgent concern" (Smith et al., 2011).

Consequently, it is no longer sufficient to estimate the impact of climate change on agriculture while simply taking adaptation 'into account'. Instead, the sciences must bring adaptation to the forefront of climate change impact studies by explicitly modeling adaptation or its components. As such, the results will be more useful for policy as they provide direct insights to adaptation. Therefore, this dissertation focused on **how one of the most frequently used climate change impact estimation methods, the Ricardian cross-sectional method, can be improved to make its results regarding adaptation more defined and explicit for policy use**.

The operational definition of this question focuses on four methodological weaknesses in the Ricardian method that cause barriers with regard to its understanding regarding adaptation: (1) ignorance of adaptive capacity and adaptation requirements, (2) ignorance of technological development,

(3) disregarding within-adaptation-heterogeneity, and (4) not revealing the adaptation decision process. The first and the second set of research questions, presented in Chapters 2 and 3, relate to the weakness that the Ricardian method does not verify whether all the adaptation strategies available in the dataset are accessible to all farmers. The method controls for adaptation conditions such as base climate, soil, and some socio-economic variables. However, these control variables are not sufficient to check whether all farmers have the means to acquire and implement the most optimal, profit-maximizing adaptation options that the Ricardian method assumes they will chose. In practice, farmers might opt or be forced to choose less optimal adaptation strategies. As such, the Ricardian method is too optimistic regarding the agricultural climate response. It gives a false feeling of certainty that farmers will adapt in the most optimal way, making the role of policy less important. Therefore, when using a large dataset, it is highly possible that the dataset contains adaptation strategies that the farmer in practice would not be able to use, so this must be controlled for. Chapters 2 and 3 both resolve this weakness in different ways.

Chapter 2 suggests clustering farmers or regions based on pre-existing historical conditions that are assumed to influence farm ability to adapt. As such, it offers a solution for researchers who only have limited access to additional variables that reveal farm adaptive capacity. Of course, this only works on the condition that the researcher is aware of such regional differences (as in our case with Eastern versus Western Europe). In this way, if other variables are well controlled for, it is possible in many regions to implicitly measure the effect of adaptive capacity. The theory behind such clustering of regions is that one limits the number of adaptation options available to those that are already within the region. Therefore, broadening the dataset with adaptation options from other regions expands the range of adaptation options the farm can chose from, and will improve the climate response of the first region. As such, it takes into account technological development based on existing technologies in other regions. Given that the Ricardian method assumes that each farmer has access to the most optimal adaptation strategies available in the dataset, this would lead to a climate response that takes into account adaptation strategies that are currently unavailable. To take technological development into account even further, it should be possible to use traditional crop models or experimental simulations to test how more-developed technologies would behave in these regions. The results of these experimental simulations could be used to build a dataset with more technological development, which could be used to test how the climate response would change if such technological development were taken into account. In a similar way, combining experimental simulations and cross-sectional methods could also be the solution to take future technological improvements into account. In the interests of unlocking their potential for increased adaptive capacity to lessen the harm and increase the possible benefits of climate change, it is important to look at more developed regions when examining farm systems in other developing regions. Therefore, Chapter 2 also suggests a solution for the methodological weakness whereby the traditional Ricardian method cannot take technological development into account.

Chapter 3 offers a second solution that takes differences in farmers' abilities to adapt into account by explicitly capturing adaptive capacity as an additional explanatory variable in the model. Adaptive capacity is influenced by characteristics such as information and skills, institutions, equity, technology, and economic wealth (IPCC, 2007a), and therefore measures whether the requirements to be able to adapt are present. Where possible (that is, if the researcher has access to these data), this should be the preferred solution for solving this weakness because it leads to more accurate and regional specific estimates on the impact of adaptive capacity. Researchers who ignore adaptive capacity must be aware that their results are overly optimistic in the sense that farmers are unlikely to have full adaptive capacity. In addition, when translating their research findings to policy, researchers must point out that adaptation is unlikely to occur autonomously if adaptation requirements are not fulfilled.

Chapters 2 and 3 provide solutions to the failure of the traditional Ricardian method to sufficiently capture adaptation requirements. While this is done for adaptation in general and not for specific adaptation options, it is also, ultimately, necessary to properly understand which adaptation options need to be prioritized in which contexts. In this regard, it is important to be able to compare adaptation options with one another in order to properly select which adaptation options are most appropriate in which context. Unfortunately, a major weakness of the Ricardian method is that it does not show adaptation itself explicitly, which means it does not reveal the adaptation decision process that leads to a conditional climate response per adaptation choice. As a result, the Ricardian method is often compared to a 'black box'. A number of studies have attempted to model adaptation by estimating separate response functions for different types of adaptation (Kurukulasuriya et al., 2006; Mendelsohn and Dinar, 2003; Schlenker et al., 2007; Seo and Mendelsohn, 2008b; Van Passel et al., 2017). However, in doing so, those studies consider adaptation to be an exogenous variable. This could lead to endogenous treatment bias if one only observes whether or not farms choose a specific adaptation option (Kurukulasuriya and Mendelsohn, 2007). A further weakness of the Ricardian method is that a farmer does not simply make *one* adaptation decision; instead, he or she can choose from a number of implementation decisions related to the main decision. These decisions generate a range of adaptation options that give rise to a wide range of climate responses depending on the degree of adaptation. This within-adaptation heterogeneity might lead to incorrect conclusions about the overall successfulness of the adaptation category. Chapters 4 and 5 provide solutions for the two abovementioned weaknesses by taking a closer look at one important adaptation strategy: irrigation.

Chapter 4 focuses on the weakness whereby within-adaptation heterogeneity might cause individual farm climate responses to differ significantly from the overall climate response. Therefore, that chapter suggests that researchers should understand the extremes between which an adaptation option can vary, and then assess how the farm climate response changes when moving from one adaptation extreme to the other. This can be done by making subsamples of all the within-adaptation differences to identify how their climate responses change when the adaptation option is taken to the next level. Alternatively, a continuous variable can be used as an interaction term with the climate response to measure the degree of adaptation on a scale from "not choosing for this adaptation option" (for example, rain-fed agriculture in this case) to "using the most extreme form of this adaptation option" (for example, irrigating 100 percent of the UAA).

Finally, Chapter 5 models the adaptation decision process explicitly and resolves the 'black box' weakness of the Ricardian method. It first advises researchers to first make an overview of adaptation decisions linked to the adaptation decision the researcher aims to model. As such, the researcher can clearly define the scope of his adaptation decision model as farmers often take numerous decisions jointly. The decision model within this scope can then be estimated. This dissertation focuses on the binary irrigation decision process (not the subsequent irrigation decisions) and its conditional (rain-fed versus irrigated) climate response function. However, the irrigation decision itself is crop-specific. Crop choice is a farm management decision and should therefore be modeled jointly with the irrigation choice. Given that both crop and irrigation choice influence each other simultaneously, this dissertation is the first to present a mixed simultaneous irrigation-crop choice model. Thus, Chapter 5 provides solutions for the endogeneity issues that the Ricardian model faces when aiming to reveal adaptation options explicitly. Chapter 5 also proves that the Ricardian estimates become more robust when adaptation is modeled explicitly. The chapter also provides adaptation insights regarding both the farm choice and the effectiveness of the adaptation option compared to alternative adaptation strategies. Finally, Chapter 5 shows that it is possible, and of added value, to illicit more complex adaptation decision models from the Ricardian method.

6.2. Adaptation insights

While improving the Ricardian framework to capture adaptation and its components more explicitly, this dissertation provides answers to the research questions (*RQ*) introduced in Chapter 1.

In Chapter 2, this dissertation proved that *Western and Eastern Europe have a different agricultural climate response (RQ 2.1).* The results show that when both regions rely independently on autonomous profit-maximizing farm behavior, this leads – depending on the climate change scenario – to an almost 50 percent loss in Eastern European land values compared to a 2–32 percent loss for Western Europe. This is because the two regions do not have the same means to adapt to climate change. However, it is possible to *improve the agricultural climate response function of Eastern Europe by broadening its range of adaptation options up to the same level as Western Europe (RQ 2.2)*. If Eastern Europe were to apply and implement the same adaptation options as Western Europe by 2100, it could avoid a 50–69 percentage points decrease in land value depending on the climate scenario. Indeed, the climate response of Western and Eastern Europe could be similar, as long as policy, society, and behavior are devoted to bringing forth equal and optimal adjustment and adaptation conditions over both regions.

In reality, however, it is unlikely that all European regions have a 100 percent adaptive capacity to immediately respond properly to the emerging climatic changes. Indeed, *there are large differences in adaptive capacity within the entire European Union (RQ 3.1)*. Not only Eastern European regions, but also Southern European regions have an adaptive capacity that is significantly lower than the adaptive capacity of North-Western European regions (Figure 7 in Chapter 3 presents this clearly). As such, it is necessary to account for differences in adaptive capacity on a smaller regional scale than when broadly clustering regions in East versus West. This dissertation determines that *the effect of taking into account adaptive capacity when modeling the impact of climate change on European agriculture is negative (RQ 3.2). C*limate responses that do not take into account adaptive capacity are overly optimistic because they assume that regions have all the necessary means to adapt. On average, the marginal effects of temperature decrease by 2.5–5 percentage points in Eastern and Southern European regions once adaptive capacity is accounted for. Yet, even in Western Europe, the results clearly showed that regions with a lower adaptive capacity suffer more from marginal changes in climate than their neighboring regions (such as Eastern versus Western Germany). As such, this dissertation quantitatively confirms the findings of other researchers who believed that it is important to focus on increasing societies capability to deal with climate change (Van Bree and van der Sluijs, 2014). There is clearly a positive *relationship between adaptive capacity and the agricultural climate response (RQ 3.3)*. If adaptive capacity increases from 0.4 to 0.8 on the ESPON index, the marginal effect of temperature increases by 0–10 percent on average. However, the relationship between marginal effects and adaptive capacity appeared to have a concave shape, leveling out at higher levels of adaptive capacity. This implies that adaptive capacity only increases marginal benefits from changes in climate up to a certain adaptive capacity level.

With regard to this dissertation's focus on irrigation as a climate change adaptation strategy, it was highlighted that farmers can consider water management options across a spectrum that ranges from purely rain-fed farms to purely irrigated farms with in between the extremes practices such as supplemental irrigation, water conservation practices, and different irrigation techniques. The graphs in Chapter 4 (Figures 11 and 12) prove that *ignoring this continuous spectrum from purely rain-fed to purely irrigated agricultural farms influences climate change impact results (RQ 4.1)*. Differences between farmers on both extremes of the irrigation spectrum can reach 30 percent, depending on the size of farmer.

Finally, when eliciting the irrigation decision process, this dissertation proved that *crop choice has a significant influence on the farm's irrigation choice (RQ 5.1)*. All crop dummies are significant in the irrigation model, implying that farm irrigation decision models should always be crop-specific and account for the farm crop choice. Currently, however, crop choice is hardly ever taken into account when examining the farm irrigation decision. Furthermore, the farm irrigation decision is also influenced by *climatic influences that increase a farm's probability to opt for irrigated farming (RQ 5.2)*. Some of the main results show that Southern European regions show significantly negative irrigation probabilities when temperature marginally increases (-5 to -7 percent in summer). This shows that those regions adapt through other means than irrigation to higher temperatures (for instance through crop choice). However, marginal increases in precipitation do increase Southern European small farmers' irrigation probability (by up to 4.5 percent), showing that precipitation is needed before irrigation can take place. These results imply that irrigation, as an adaptation tool to climate change, is often hampered due to climate and water constraints. This conclusion could also be derived from the fact that very high drought frequencies also had a lower positive influence on the irrigation probability. Climate clearly has a significant influence on a farm's irrigation probability.

Having determined the farm's irrigation decision model, this dissertation examined whether *irrigated and rain-fed farms have a different climate response function (RQ 5.3)*. Indeed, there is a clear difference between irrigated and rain-fed agriculture as irrigated farms responded significantly differently than rain-fed farms to 11 of the 16 climate variables. It can be seen that irrigated crops are more resistant and less sensitive to higher temperatures than rain-fed crops in southern regions. Nevertheless, irrigation seems to be less beneficial in response to higher temperature in northern regions than in more southern regions. For instance, Spain has, on average, a 7 percent increase in rain-fed land value if annual temperature increases by one degree, while irrigated land has an increase of 17 percent. In Belgium, on the other hand, rain-fed agriculture has a higher benefit (34.6 percent) than irrigated agriculture (11.3 percent) when temperature increases by one degree. This shows the adaptive effect of irrigation in Southern Europe. An examination of increases in precipitation suggests that rain-fed crops benefit significantly more than irrigated crops (on average, they benefit from an increase of 25 percent in their land value if annual precipitation increases by one cm, while irrigated crops benefit a smaller increase of 16 percent). This makes sense because irrigation is a substitute for precipitation. Nevertheless, this relationship does not account for small farms because they suffer from decreases in precipitation due to their greater dependence on water access before they can irrigate.

In order to answer the research questions regarding the irrigation decision model, this dissertation developed a unique but complicated simultaneous irrigation-crop decision model. This model was compared with the traditional cross-sectional model to determine *whether traditional cross-sectional models properly capture irrigation (RQ 5.4)*. The answer is that the estimates of the traditional model are biased by the adaptation options in the other regions. Therefore, explicitly modeling these adaptation options leads to more robust results.

6.3. Implications for policy

Based on the contents of this dissertation, more specific policy suggestions can be formulated with regard to triggering climate change adaptation than would have been the case with the traditional Ricardian method (Figure 18).

First of all, given that cross-sectional studies are frequently used when modeling climate change impacts, it is important for policy to realize that

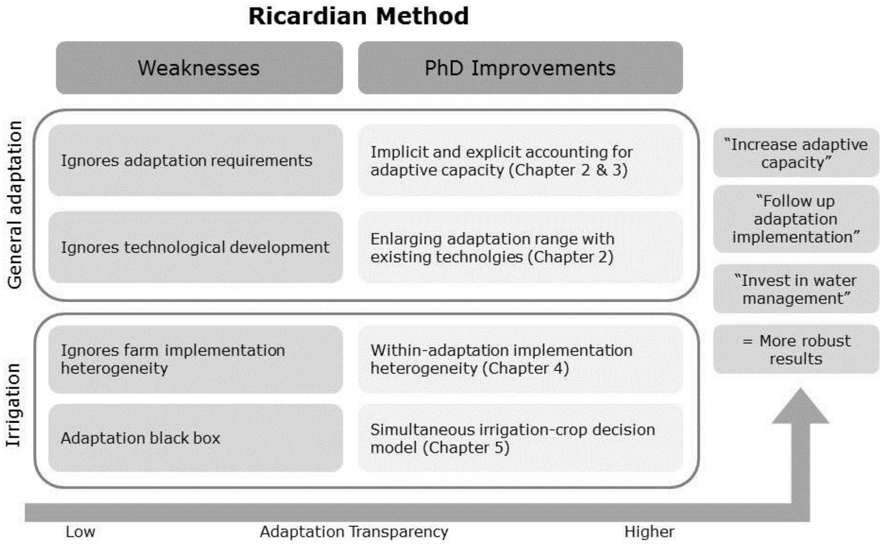


Figure 18 – Dissertation conclusions.

such studies might overestimate farm autonomous adaptation capabilities. The degree of adaptation depends heavily on adaptive capacity levels and only takes place if the appropriate adaptation requirements are present. Therefore, policy makers should intervene and stimulate adaptive capacity development as increases in adaptive capacity lead to significant improvements in agricultural responses to climate change. Moreover, increases in adaptive capacity can also increase current farm productivity and will lead to both benefits now and in the future. In addition, increasing adaptive capacity takes time and should therefore be started as soon as possible.

Secondly, given that there are clear differences in the way different adaptation options are implemented, implementation and execution of adaptation options should be followed up. Adaptation does not have the same cross-national characteristics as mitigation policy where photovoltaics can more easily be placed in a similar way in different countries. Scaling-up adaptation policy is not easy as sufficient attention to local conditions is necessary. Therefore, it is important to ensure that maladaptation does not occur due to the fact that similar adaptation options are implemented in different regions without modifications to local circumstances. Simply copying adaptation tools from one region to another might not always be appropriate and local research is necessary to tailor adaptation to specific farm needs.

Thirdly, the EU should ensure sufficient investments in water management infrastructure and water regulations. Water will clearly be an issue for agriculture, which means that adaptation through irrigation might be an issue in case of water scarcity. This dissertation shows that if insufficient water is available in certain regions, adaptation through more drought-resilient crops is possible. Therefore, it is important to properly understand farm adaptation choices. Apart from this, investing in more water-efficient irrigation technologies or strategies will also help reduce water scarcity issues.

In summary, adaptation is a necessary activity in 21^{st}-century agriculture. This dissertation highlights the points that policy should increase adaptive capacity, that water management policies are highly necessary to overcome water shortages, and that it is necessary to make sure adaptation is implemented in locally appropriate ways. Arguably, the best place to increase adaptive capacity is the European Common Agricultural Policy (CAP). Therefore, for the 2020-CAP reform it is important to increase funding for Pillar II, not allowing funds to be transferred from this pillar to Pillar I. Furthermore, given the clear differences in adaptive capacity in the European Union, policy should ensure that there is enough room for flexibility when implementing common regulations and when obtaining goals. While this flexibility is currently provided, it undermines the common objectives and goals. Therefore, the CAP should set clearer non-voluntarily and measurable targets for climate action, against which member states must deliver in order to receive funding.

6.4. Further research suggestions based on comments on data and methodology

The results presented in this dissertation are based on diverse assumptions and model limitations. These had to be imposed in order to keep the execution of the research realistic within the given timeframe. This dissertation only addresses four weaknesses of the Ricardian method and hereby zooms in on adaptation itself. However, there are other limitations that must be identified.

First of all, because the method is a cross-sectional analysis, it cannot take into account variables that do not vary over time. For instance, the effect of CO_2 fertilization, which is globally almost identical, cannot be taken into account. Nevertheless, CO_2 fertilization is assumed to increase crops yields significantly and should be accounted for. In this dissertation, mostly comparative analyses between different regions (Eastern versus Western Europe) or between different adaptation options (irrigation versus rain-fed) were conducted, due to which the bias is not expected to influence conclusions significantly. Nevertheless, if absolute values of the analysis are interpreted, the results are generally expected to overestimate damages due to the expected positive effect of CO_2 fertilization.

In a similar manner, the Ricardian model also assumes that the prices of inputs and outputs remain constant over time (Cline, 1996). It is hard to find data on such variables and prices might not always differ between farmers within one country or market. In reality, however, prices do differ over years and failure to account for this creates bias. For instance, if agriculture is not beneficial enough, farmers would shift to other activities, although this could lead to insufficient amounts of food (Cline, 1996). Mendelsohn and Nordhaus (1999) noted that it is possible to determine the direction of this bias: if climate change decreases yields, and therefore supply, and this leads to increases in prices, the method overestimates damages. However, food prices depend on the global response to climate change and these prices are not expected to change a lot with climate change (Mendelsohn et al., 2009). All depends on the balance between how climate change leads to increases of food in one region and losses in another region (Reilly et al., 1994). As such, if prices do not change easily, the bias in the Ricardian method is assumed to be small. With regard to Europe, it should also be recognized that its policies are rather protective and that influences with regard to prices can be assumed to be limited.

Another important variable that the Ricardian method cannot easily account for is the influence of agricultural or trade policies. These policies can influence endogenous variables such as inputs and crop choice, so a change in such policies could lead to totally different adaptation choices which the Ricardian model did not account for (Mendelsohn et al., 2009). As explained in Chapter 2, individual farm subsidies are used as a proxy to account for such policies. However, this is not a perfect solution and further research should focus specifically on the influence that current policy has on adaptation itself. As indicated above, this has not been studied previously as the influence of European adaptation policy is not clear.

Compared to other Ricardian studies, the present dissertation used a large dataset with detailed farm-level data. It is important to have such detailed data for the Ricardian method because they provide rich results and give meaningful policy implications (Wang et al., 2009). A minor weakness of these data is that, 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. Numerous data are available on NUTS3 level, so the data are accurate to obtain robust results. However, as explained in Chapters 4 and 5, more control variables regarding water management could further improve the analysis. However, these data are not available on a detailed farm scale or even the NUTS3 scale. Nevertheless, Mendelsohn and Dinar (2003) showed that adding, for instance, surface water to the analysis does not change the results significantly, so its omission possibly only leads to a limited bias. The potential omitted variable bias issue can be solved by means of a panel approach that focuses on variations over time to see how a region reacts to hotter and warmer conditions (see, for instance, Deschenes and Greenstone (2007)).

A major weakness of the data, however, is that the results cannot easily be compared over different years; this is because, starting in 2008, some countries (such as Poland and Italy) changed their sampling collection method or some variable definitions. Given that these FADN data are used as a basis to establish the Common Agricultural Policy, it is important to clearly understand these weaknesses.

With regard to further data collection, it is important that data are collected in an even more uniform way. The FADN data are already a good example of this, but there are still limitations, as indicated above. Furthermore, additional information should be collected from the farmer itself regarding specific technologies (for instance, regarding irrigation), water use, innovation, and farm knowledge. Such detailed farm data are necessary to further examine local adaptation as adaptation demands more spatially and temporally detailed information (Füssel and Hildén, 2014).

Finally, it should be highlighted that this dissertation focused on the Ricardian method because it is one of the most frequently used methods with regard to climate change impact estimations. Therefore, it is important to ensure that its results are valuable for policy decision making. We do not argue that the method produces superior results to crop simulation or other models. Instead, the weaknesses of the Ricardian method are the strengths of the crop simulation models and vice versa

(Mendelsohn, 2007). Both methods should be used simultaneously in order to fill up weakness of both methods. For instance, crop simulation models are strong in isolating the impact of climate change because they are executed in controlled environments. They obtain detailed understanding about different processes. However, this also makes it harder for them to extrapolate the results to higher scales and to the real world. The cross-sectional method, on the other hand, cannot as easily control for different influences as the crop simulation models do and they model a lot of the processes as a black box without giving insights into them. Nevertheless, the method can give a good presentation of large regions. In addition, the cross-sectional method captures adaptation because it measures what farmers have done. Crop simulation models cannot easily include adaptation and the researcher must bring them in through simulations (Mendelsohn, 2007). As a result, the adaptation options that these models examine are arbitrary and not necessarily targeted at climate change or motivated by profit maximization (Mendelsohn and Dinar, 2009). Therefore, the researcher exogenously includes adaptation in crop simulation models. Nevertheless, some of the better crop simulation models give a better idea of the benefits of some limited adaptation options (see, for instance, Easterling et al. (2003), Rosenzweig and Parry (1994), Parry et al. (2004), and Parry et al. (2005)). Some models even examine possible real-life responses of farmers to climate change (such as Iglesias and Minguez (1997)) and as such provide even more detailed and correct results regarding one type of adaptation option. I am in favor of combining both the cross-sectional method and the crop simulation models when interpreting their results. It may even be possible to increase and enlarge the dataset used for the cross-sectional method by more advanced adaptation methods, in which data are simulated through crop simulation models.

APPENDICES

Appendix A – Overview variables and descriptive statistics (FADN 2007)

	Variable	Description	Units	Mean East	Mean West	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	1419.5	15,817.7	50.0	621,900	22.94	FADN
	Land owned	Land in the owner's occupation and land in share-cropping	ha	40.58	37.37	1.00	4739.00	94.43	FADN
	UAA	Utilized agricultural area consists of land in owner occupation, rented land, land in share-cropping.	ha	118.47	78.20	1.00	9808.00	262.5	FADN
	Farms represented	Sum of weighting coefficients of individual holdings in the sample.	number	89.43	56.77	1.00	10550	243.8	FADN
	Subsidies	Subsidies on current operations linked to production (not investments) per UAA	€/ha	227.80	430.70	0.00	4981.00	390.6	FADN
	Share rented land	Total leased land out of the total utilized agricultural land.	ha/ha	0.30	0.33	0.00	1.00	0.33	FADN
Soil	Gravel	Volume % gravel (materials in a soil larger than 2mm) in the topsoil	%vol	6.51	9.19	2.44	18.35	2.77	World Soil database
	Sand	Weight % sand content in the topsoil	%wt	27.64	31.53	10.83	45.93	6.45	World Soil database
	Silt	Weight % silt content in the topsoil	%wt	52.39	46.28	18.19	83.02	10.54	World Soil database
	Clay	Weight % clay content in the topsoil	%wt	19.93	21.3	5.80	44.53	5.00	World Soil database
	pH	pH measured in a soil-water solution		5.99	6.28	4.18	7.88	0.65	World Soil database

Appendix A – continued

Geographic and socio-economic	Distance to cities	Distance from cities with population > 500,000	km	101.73	115.23	0.00	843.00	73.8	Natural Earth data
	Distance to ports	Distance from medium and large ports	km	268.59	162.67	0.00	636.20	130	World port index
	Elevation mean	Elevation mean	m	199.50	382.54	0.00	2092.0	301	ESRI
	Elevation range	Elevation range	m	441.63	1145.45	1.00	4255.0	870	ESRI
	GDP	Gross domestic product per capita	€/cap	7068	24654	2.10	78.00	11.2	Eurostat
	Freight transport	National annual road freight transport by regions of loading (1000 tonnes – total transported goods)	tonnes	2628	5508	0.00	162.10	7.12	Eurostat
	Population density	Population density in 2010	cap/km²	98.50	156.13	2.00	2883.0	190	ESRI, MBR, and Euro-Geographic

Summary of climate variables

	Winter			Spring			Summer			Autumn			Annual		
	CUR-RENT	NCAR PCM	ECHO-G	CUR-RENT	NCAR PCM	ECHO-G	CUR-RENT	NCAR PCM	ECHO-G	CUR-RENT	NCAR PCM	ECHO-G	CUR-RENT	NCAR PCM	ECHO-G
Precipitation West	6.9	7.2	7.4	6	6.4	5.6	5.6	5.2	4.4	7.2	6.7	6.9	25.7	25.5	24.4
Precipitation East	3.7	4.4	4.4	4.7	5.8	5.1	7.4	7.2	6.9	4.8	4.5	4.9	20.7	21.9	21.3
Temperature West	3.5	6.4	7.1	9.3	11.7	12.8	18	20.6	22.7	11.4	14.5	15.9	10.5	13.3	14.6
Temperature East	-1.8	2.3	3.6	8.1	10.6	12.4	17.5	20.2	21.8	8.9	12.2	13.8	8.2	11.3	12.9

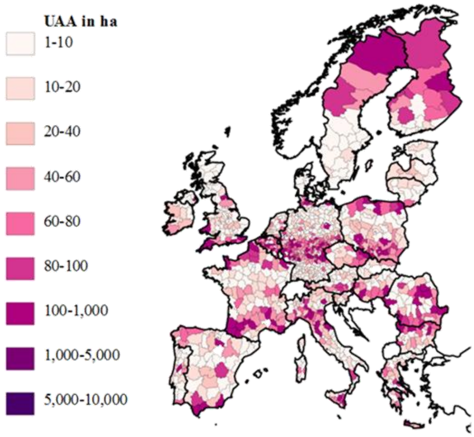
Temperature in °C and Precipitation in cm

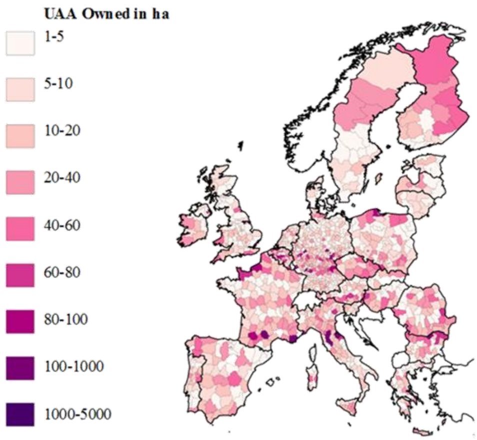
Appendix B – Descriptive statistics per country (in ha) (FADN 2007)

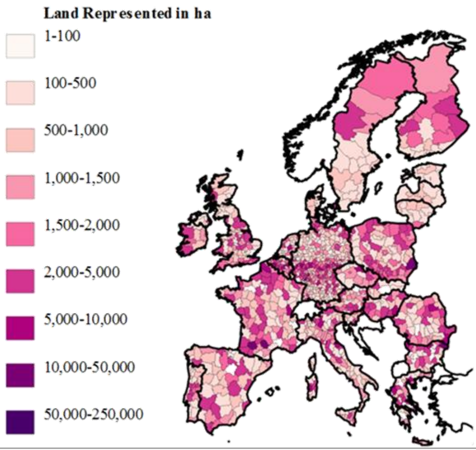
Country	UAA	UAA owned	Land represented
Bulgaria	111,200	14,477	1,322,985
Czech Republic	643,471	58,183	2,936,164
Estonia	118,143	42,211	851,698
Hungary	162,639	75,703	2,563,471
Lithuania	175,466	49,330	1,951,138
Latvia	192,106	82,295	1,300,086
Poland	435,538	284,297	12,404,944
Romania	192,326	130,987	6,210,678
Slovenia	14,617	7,673	465,960
Slovakia	155,401	8,777	599,898
East	2,200,908	753,932	30,607,023

Country	UAA	UAA owned	Land represented
Austria	77,906	50,797	2,423,340
Belgium	47,478	13,714	1,163,564
Denmark	1,164,091	256,210	13,832,557
Finland	213,474	150,156	2,291,069
France	345,511	250,590	18,026,483
Germany	54,296	34,471	1,977,304
Greece	273,808	73,850	12,596,828
Ireland	37,625	17,070	2,851,355
Italy	63,316	51,414	4,722,952
Luxembourg	412,512	275,067	10,286,832
Netherlands	42,346	20,448	129,084
Portugal	49,136	30,429	1,730,903
Spain	40,428	33,208	1,615,103
Sweden	82,051	47,104	1,938,570
United Kingdom	365,603	256,132	10,150,824
West	3,269,582	1,560,658	85,736,765

Appendix B – continued: distribution of sampled farm land







Appendix C – Alternative estimation methods

	OLS Double Climate-Response Model						**LMEM with ML estimator**					
	East			West			East			West		
	Coef	**Sig**	**St Er**	**Coef**	**Sig**	**St Er**	**Coef**	**Sig**	**St Er**	**Coef**	**Sig**	**St Er**
(Intercept)	-2.210		2.299	2.938	***	2.350	-0.977		2.327	2.956		2.394
T Winter	-0.513	***	0.049	-0.018		0.021	-0.511	***	0.049	-0.017		0.021
T Winter²	-0.021	**	0.009	0.006	***	0.001	-0.021	**	0.009	0.006	***	0.001
T Spring	1.572	***	0.142	0.082	*	0.044	1.565	***	0.141	0.082	*	0.044
T Spring²	-0.054	***	0.009	0.025	***	0.002	-0.054	***	0.009	0.025	***	0.002
T Summer	-2.173	***	0.349	0.447	***	0.075	-2.140	***	0.349	0.446	***	0.075
T Summer²	0.043	***	0.010	-0.018	***	0.002	0.042	***	0.01	-0.018	***	0.002
T Autumn	1.079	***	0.305	0.338	***	0.069	1.064	***	0.304	0.338	***	0.069
T Autumn²	-0.031	**	0.015	-0.026	***	0.003	-0.031	**	0.015	-0.026	***	0.003
P Winter	-0.025		0.116	0.109	***	0.016	-0.026		0.115	0.110	***	0.016
P Winter²	0.017		0.013	0.000		0.001	0.017		0.013	0.000		0.001
P Spring	-0.201		0.136	-0.200	***	0.029	-0.197		0.136	-0.202	***	0.029
P Spring²	-0.005		0.012	0.006	***	0.002	-0.006		0.012	0.006	***	0.002
P Summer	-0.435	***	0.076	0.113	***	0.020	-0.438	***	0.076	0.115	***	0.02
P Summer²	0.024	***	0.004	0.002	*	0.001	0.024	***	0.004	0.002	*	0.001
P Autumn	-0.020		0.095	0.127	***	0.015	-0.022		0.095	0.127	***	0.015
P Autumn²	0.002		0.007	-0.011	***	0.001	0.002		0.007	-0.011	***	0.001
Elev range	0.004		0.036	-0.011		0.012	0.002		0.036	-0.011		0.012
Elev mean	0.739	***	0.176	0.022		0.049	0.732	***	0.175	0.018		0.049
Subsidies	-0.005		0.050	0.464	***	0.017	-0.003		0.05	0.464	***	0.017
Distance ports	-1.101	***	0.106	-0.566	***	0.072	-1.104	***	0.106	-0.563	***	0.072
Distance cities	0.063		0.178	-0.951	***	0.085	0.056		0.178	-0.953	***	0.085
Pop density	-0.366	**	0.159	0.476	***	0.034	-0.366	**	0.159	0.476	***	0.034
GDP/inhabitant	0.046	***	0.005	0.001		0.001	0.046	***	0.005	0.001		0.001
Frei transport	0.011	**	0.004	0.003	***	0.001	0.011	**	0.004	0.003	***	0.001
Rented land	0.485	***	0.023	-0.084	***	0.018	0.485	***	0.023	-0.084	***	0.018
pH	5.301	***	0.302	0.159		0.121	5.293	***	0.301	0.163		0.121
pH squared	-0.411	***	0.023	0.010		0.010	-0.410	***	0.023	0.010		0.010
Gravel	0.022	**	0.009	-0.037	***	0.003	0.022	**	0.009	-0.037	***	0.003
Silt	0.018	***	0.004	-0.022	***	0.002	0.017	***	0.004	-0.022	***	0.002
Sand	0.004	**	0.002	-0.022	***	0.001	0.004	*	0.002	-0.022	***	0.001
Bulgaria	1.166	***	0.110									
Czech Republic	1.388	***	0.079									
Estonia	2.138	***	0.137									
Hungary	1.213	***	0.074									
Lithuania	1.592	***	0.090									
Latvia	1.696	***	0.106									
Poland	1.717	***	0.084									
Romania	0.060		0.087									
Slovenia	2.740	***	0.150									
Austria				-2.450	***	0.053						
Belgium				0.183	***	0.052						
Germany				0.134	***	0.037						
Denmark				1.436	***	0.047						
Spain				-0.205	***	0.054						
Finland				0.393	***	0.090						
France				-0.946	***	0.040						
Greece				0.496	***	0.073						
Ireland				0.948	***	0.032						
Italy				1.087	***	0.052						
Luxembourg				-0.396	***	0.069						
Netherlands				1.120	***	0.039						
Portugal				-2.275	***	0.066						
Sweden				0.667	***	0.060						
Adjusted R²				0.7532								
AIC									192,772			
BIC									193,349			

***p<0.01,**p<0.05,*p<0.1

Appendix D – Descriptive statistics data and resources (FADN 2012)

	Variable	Description	Units	Mean	Min	Max	Sd	Source
Farm-specific	Agricultural land value	Valuation based on prices (net of acquisition costs) that apply in the region for non-rented land of similar situation and quality sold for agricultural purposes. Replacement value is divided by 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 socio-economic	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/km²	139.3	2.00	8,058.00	230.67	Eurostat
Adap-tive capa-city	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
Clim-ate	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 CL 2.0
	Temperature		° C	1.47	8.31	18.02	10.63	

WSD = Word Soil Database (FAO/IIASA/ISRIC/ISSCAS/JRC, 2009); NED = Natural Earth Data (Natural Earth, 2014); WPI = World Port Index (National Geospatial-Intelligence Agency, 2014); Climatic Research Unit (CRU) CL 2.0 (New et al., 2002); Eurostat (Eurostat, 2016); ESRI = Environmental Systems Research Institute (ESRI, 2014); ESPON = European Spatial Planning Observation Network (ESPON, 2011)

Appendix E – Summary data and variable description 2007 and 2012

				2007			2012			
	Variable	Description	Units	Mean	Min	Max	Mean	Min	Max	Source
Farm specific	Agricultural land value	is valued on the basis of prices (net of acquisition costs) applying in the region for non-rented land of similar situation and quality sold for agricultrual purposes. The replacement value is divided by the amount of land owned.	€/ha	19047	54.70	621899	20921	78.30	654000	FADN
	Land owned	consists of land in owner occupation and land in share-cropping	ha	31.60	1.00	2076	32.82	1.00	2488	FADN
	UAA	utilized agricultural aread consists of land in owner occupation, rented land, land in share-cropping.	ha	71.96	1.00	8744.64	63.81	1.00	5656	FADN
	Farms represented	Sum of weighting coefficients of individual holdings in the sample	#	74.78	1.00	10550	68.39	1.33	2792	FADN
	Subsidies	Subsidies on current operations linked to production (not investments) per UAA	€/ha	352.71	0.00	4981.49	437.90	0.00	4917	FADN
	Irrigation	% of land irrigated	ha/ha	26.24	0.00	100	19.84	0.00	1.00	FADN
	Economic farm size	is expressed in European size units (ESU) on the basis of the Community typology. It is the total standard gross margin in euro divided by 1200.	ESU	71.96	2.00	8745	123.70	4.00	9192	FADN
	Share rented land	total leased land per total utilized agricultural land	ha/ha	0.26	0.00	0.99	0.30	0.00	1.00	FADN
Soil	Gravel	Volume % gravel (materials in a soil larger than 2mm) in the topsoil	%vol	9.92	2.44	16.49	9.92	2.44	18.35	World Soil database
	Sand	Weight % sand content in the topsoil	%wt	44.67	28.97	83.02	44.34	28.25	83.02	World Soil database
	Silt	Weight % silt content in the topsoil	%wt	31.97	10.83	45.93	32.09	10.83	45.93	World Soil database
	pH	pH measured in a soil-water solution		6.56	4.18	7.88	6.55	4.18	7.88	World Soil database

Appendix E – Continued

				2007			2012			
	Variable	Description	Units	Mean	Min	Max	Mean	Min	Max	Source
Climate	Temperature Spring	30-year normal period for temperature and precipitation from 1961–1990 from the Climatic Research Unit (CRU) CL 2.0	°C	10.50	-2.77	15.96	10.50	-2.77	15.96	New et al. (2002)
	Temperature Summer		°C	19.81	6.83	26.15	19.78	6.83	26.15	
	Temperature Autumn		°C	12.92	-1.80	19.67	12.83	-1.80	19.67	
	Temperature Winter		°C	4.40	-14.95	12.01	4.27	-14.95	12.01	
	Precipitation Spring		mm	5.80	2.69	17.06	5.72	2.08	17.06	
	Precipitation Summer		mm	4.77	0.15	20.98	4.74	0.15	20.98	
	Precipitation Autumn		mm	6.94	3.59	19.66	6.71	3.59	17.26	
	Precipitation Winter		mm	6.63	2.45	19.46	6.56	1.89	20.79	
Geographic and socio-economic	Cities	Distance from cities with population > 500000	km	106.58	0.97	792.72	106.08	0.97	842.84	Natural Earth data
	Ports	Distance from medium and large ports	km	164.00	0.91	536.51	164.77	0.91	536.51	World port index
	Elevation mean	Elevation mean	m	402.00	0.00	2091.87	393.54	0.01	2076.45	ESRI
	Elevation range	Elevation range	m	1299.00	1.00	4255.00	1263.00	1.00	4255.00	ESRI
	Population density	Population density in 2010	cap/km²	163.00	2.00	2883.00	164.00	2.00	3093.00	Eurostat

Appendix F – OLS regressions for irrigation threshold 50%.

Note that this implies that countries that have no values, have no farms that irrigate more than 50% of the UAA. Greece for instance does have a lot of farms that 'irrigate' but they all irrigate less than 50% of their farm land in our sample.

	2007 Irrigation			**2007 Rainfed**			**2012 Irrigation**			**2012 Rainfed**		
	Coef	**St Er**	**Sig**	**Coef**	**St Er**	**Sig**	**Coef**	**St Er**	**Sig**	**Coef**	**St Er**	**Sig**
Intercept	-4.579	2.077	**	2.979	0.779	***	7.601	2.629	***	11.876	0.800	***
T Winter	-0.123	0.076		-0.017	0.031		-0.288	0.116	**	0.088	0.031	***
T Winter^2	-0.010	0.007		0.008	0.002	***	-0.014	0.009		0.003	0.002	
T Spring	-1.182	0.190	***	-0.535	0.075	***	0.301	0.252		-0.446	0.073	***
T Spring^2	0.066	0.007	***	0.056	0.004	***	-0.005	0.010		0.046	0.004	***
T Summer	1.429	0.302	***	-0.049	0.119		-0.269	0.406		-0.278	0.114	**
T Summer^2	-0.040	0.007	***	-0.004	0.003		-0.002	0.009		0.001	0.003	
T Autumn	0.305	0.316		0.927	0.118	***	-0.228	0.438		0.714	0.119	***
T Autumn^2	-0.003	0.011		-0.051	0.005	***	0.032	0.015	**	-0.040	0.005	***
P Winter	-0.480	0.044	***	0.066	0.027	**	-0.620	0.060	***	0.057	0.025	**
P Winter^2	0.028	0.002	***	0.000	0.001		0.031	0.003	***	-0.001	0.001	
P Spring	1.256	0.092	***	0.078	0.048		0.802	0.135	***	0.432	0.051	***
P Spring^2	-0.080	0.005	***	-0.015	0.003	***	-0.054	0.007	***	-0.027	0.003	***
P Summer	-0.361	0.051	***	-0.065	0.033	*	-0.219	0.079	***	-0.052	0.033	
P Summer^2	0.029	0.003	***	0.015	0.002	***	0.022	0.005	***	0.013	0.002	***
P Autumn	-0.233	0.055	***	0.168	0.034	***	0.255	0.085	***	0.004	0.031	
P Autumn^2	0.011	0.003	***	-0.009	0.002	***	-0.009	0.004		-0.005	0.002	***
Pop density	0.716	0.074	***	0.377	0.035	***	0.366	0.082	***	0.199	0.028	***
Distance ports	-1.381	0.175	***	-0.324	0.097	***	-1.136	0.222	***	0.047	0.093	
Distance cities	-0.395	0.198	**	-1.270	0.118	***	-1.390	0.280	***	-1.437	0.117	***
Rented land	-0.022	0.041		-0.219	0.024	***	0.073	0.048		-0.009	0.024	
Subsidies	-0.067	0.019	***	0.201	0.027	***	0.096	0.023	***	0.267	0.025	***
Elev mean	-0.282	0.104	***	0.537	0.075	***	-0.144	0.147		-0.149	0.076	**
Elev range	0.135	0.020	***	-0.044	0.016	***	-0.023	0.029		-0.008	0.016	
Gravel soil	0.029	0.008	***	-0.055	0.005	***	0.085	0.013	***	-0.011	0.005	**
pH	0.960	0.445	**	0.751	0.178	***	0.818	0.440	*	-1.161	0.176	***
pH squared	-0.092	0.034	***	-0.042	0.014	***	-0.078	0.034	**	0.108	0.014	***
Silt soil	-0.008	0.006		-0.016	0.003	***	-0.012	0.009		-0.024	0.003	***
Sand soil	-0.018	0.004	***	-0.022	0.002	***	-0.022	0.005	***	-0.023	0.002	***
Austria	(base)			(base)			(base)			(base)		
Belgium	2.691	0.373	***	2.328	0.099	***	3.396	0.675	***	2.206	0.091	***
Denmark	2.800	0.206	***	3.211	0.071	***	3.429	0.277	***	3.597	0.069	***
Spain	1.357	0.157	***	1.322	0.080	***	2.074	0.212	***	1.327	0.082	***
France	0.800	0.146	***	1.073	0.069	***	1.380	0.194	***	0.825	0.071	***
Greece	1.530	0.155	***	2.087	0.088	***				2.435	0.080	***
Ireland				3.139	0.132	***				1.956	0.129	***
Finland				2.262	0.131	***				3.264	0.121	***
Luxembourg				2.311	0.196	***				2.028	0.180	***
Netherlands				3.171	0.073	***				3.189	0.071	***
Italy	2.529	0.150	***	2.688	0.072	***	2.831	0.201		2.910	0.072	***
Portugal	-1.187	0.181	***	0.040	0.099		0.452	0.236		-0.064	0.100	
Sweden	1.595	0.268	***	2.841	0.086	***	2.254	0.705		3.291	0.084	***
Germany	3.016	0.276	***	2.242	0.051	***				2.116	0.051	***
U. Kingdom	2.678	0.208	***	1.970	0.083	***				1.941	0.084	***

***p<0.01,**p<0.05,*p<0.1

Appendix G – Irrigation and crop choice per country and farm type

		Olives		Rice		Cereals		Fieldcrops		Fruits		Rootcrops		Wine		All crops		
		Rain	**Irri**	**Rain**	**Irri**	**Rain**	**Irri**	**Rain**	**Irri**	**Rain**	**Irri**	**Rain**	**Irri**	**Rain**	**Irri**	**Rain**	**Irri**	**Full**
Austria	**Small**					163	6	87	9	24	2	15	2	100	3	389	22	411
	Large					8		22	8	29	1	4	2	59	4	122	15	137
	Full					171	6	109	17	53	3	19	4	159	7	511	37	548
Belgium	**Small**					16		18		1		9				44		44
	Large					11		49		57		37	5			154	5	159
	Full					27		67		58		46	5			198	5	203
Germany	**Small**					534		312		36		20		287		1,189		1,189
	Large					521		275		111		163		239		1,309		1,309
	Full					1,055		587		147		183		526		2,498		2,498
Spain	**Small**	333	137		88	601	492	292	342	33	465	8	346	592	88	1,859	1,958	3,817
	Large	12	11		6	19	30	13	32	4	62	8	172	24	4	80	317	397
	Full	345	148		94	620	522	305	374	37	527	16	518	616	92	1,939	2,275	4,214
France	**Small**		5			245	84	51	30	8	16	11	14	150	36	465	185	650
	Large					131	39	36	17	10	42	13	34	230	48	420	180	600
	Full		5			376	123	87	47	18	58	24	48	380	84	885	365	1,250
Greece	**Small**	250	237		40	124	271	199	892	39	230	59	383	139	124	810	2,177	2,987
	Large		2			1	3	5	21		2	1	25			7	53	60
	Full	250	239		40	125	274	204	913	39	232	60	408	139	124	817	2,230	3,047
Ireland	**Small**					36										36		36
	Large					7										7		7
	Full					43										43		43
Italy	**Small**	354	82	1	18	569	275	577	476	42	424	26	271	478	294	2,047	1,840	3,887
	Large	19	9	2	38	38	29	65	121	4	90	7	166	222	138	357	591	948
	Full	373	91	3	56	607	304	642	597	46	514	33	437	700	432	2,404	2,431	4,835
Luxembourg	**Small**					5		5						14		24		24
	Large													11		11		11
	Full					5		5						25		35		35
Netherlands	**Small**					14		13	4	5	1	11	7			43	12	55
	Large					4		35	31	26	13	88	51			153	95	248
	Full					18		48	35	31	14	99	58			196	107	303
Portugal	**Small**	21	11		10	14	8	38	87	27	71	6	27	114	57	220	271	491
	Large					3		6	3		3	6	6			15	12	27
	Full	21	11		10	17	8	44	90	27	74	12	33	114	57	235	283	518
U. Kingdom	**Small**					145	1	13		13		3		1		175	1	176
	Large					218	15	64	8	32		23	6			337	29	366
	Full					363	16	77	8	45		26	6	1		512	30	542
Total	**Small**	958	472	1	156	2,466	1,137	1,605	1,840	228	1,209	168	1,050	1,875	602	7,301	6,466	13,767
	Large	31	22	2	44	961	116	570	241	273	213	350	467	785	194	2,972	1,297	4,269
	Full	989	494	3	200	3,427	1,253	2,175	2,081	501	1,422	518	1,517	2,660	796	10,273	5,763	18,036

Appendix H – Summary variables GSEM model (FADN 2012)

	Variable	Description	Units	Mean	Min	Max	Sd	Source
Farm specific	Agricultural land value	Valued on the basis of prices (net of acquisition costs) applying 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	21287.40	50.40	990189.70	37769.66	FADN
	Land owned	Consists of land in owner occupation and land in share-cropping	ha	31.48	1.00	2451.91	6.53	FADN
	UAA	Utilized agricultural area consists of land in owner occupation, rented land, land in share-cropping	ha	60.67	1.00	5601.92	150.76	FADN
	Farms represented	Sum of weighting coefficients of individual holdings in the sample	#	70.02	2.00	6030.00	131.85	FADN
	Subsidies	Subsidies on current operations linked to production (not investments) per UAA	€/ha	438.00	0.00	4912.40	469.29	FADN
	Crop type	Subdivision of farm type		See appendix G				FADN
	Irrigation	% of land irrigated	%/ha	19.24	0.00	100.00	34.24	FADN
	Economic farm size	Expressed in European size units (ESU) on the basis of the Community typology. It is the total standard gross margin in euro divided by 1200.	ESU	117.00	4.01	9139.00	0.27	FADN
	Share rented land	Total leased land per total utilized agricultural land	ha/ha	0.31	0.00	1.00	0.33	FADN

Appendix H – Continued

Soil	Gravel	Volume % gravel (materials in a soil larger than 2mm) in the topsoil	%vol	10.16	2.44	18.35	2.66	World Soil Database
	Sand	Weight % sand content in the topsoil	%wt	43.22	28.25	83.02	7.59	World Soil Database
	Silt	Weight % silt content in the topsoil	%wt	32.60	10.83	45.93	4.90	World Soil Database
	Clay	Weight % clay content in the topsoil	%wt	22.75	5.80	40.22	4.23	World Soil Database
	Organic Carbon	Topsoil organic carbon		1.47	0.76	29.88	1.26	World Soil Database
	pH	pH measured in a soil-water solution		6.60	4.18	7.88	0.60	World Soil Database
Water	Return flow ratio	Percentage of available water previously used and discharged upstream as wastewater, presented on a scale	Scale	0.39	0.01	7.98	0.61	World Resources Institute (Gassert et al., 2013)
	Baseline water stress	Total annual water withdrawals of all sectors expressed as a percentage of the total annual available flow, presented on a scale	Scale	0.75	0.01	12.09	1.12	World Resources Institute (Gassert et al., 2013)

Appendix H – Continued

	Variable	Description	Units	Mean	Min	Max	Sd	Source
Climate	Drought severity	Drought severity from 1901 to 2008	Scale	24.02	0.00	35.18	6.25	Sheffield and Wood (2008)
	Drought frequency	Drought hazard frequency typology	Scale	3.68	1.00	5.00	1.25	ESPON (2011)
	Flood Occurence	Number of floods recorded in each catchment between 1985 and 2011	#	7.27	0.00	25.00	4.82	World Resources Institute (Gassert et al., 2013)
	Temperature Spring	30-year normal period for temperature and precipitation from 1961–1990 from the Climatic Research Unit (CRU) CL 2.0	°C	10.79	-1.72	15.96	2.48	New et al. (2002)
	Temperature Summer		°C	20.03	6.83	26.15	2.98	
	Temperature Autumn		°C	13.13	1.68	19.67	3.09	
	Temperature Winter		°C	4.63	-6.39	12.01	3.41	
	Precipitation Spring		cm	5.80	2.83	17.06	1.88	
	Precipitation Summer		cm	4.64	0.15	20.98	3.13	
	Precipitation Autumn		cm	6.70	3.59	19.66	2.14	
	Precipitation Winter		cm	6.68	3.05	20.79	2.33	
Geographic and socio-economic	Cities	Distance from cities with population > 500,000	km	103.64	0.97	367.82	65.50	Natural Earth data
	Ports	Distance from medium and large ports	km	167.91	3.08	536.51	110.12	World port index
	Elevation mean	Elevation mean	m	411.70	0.01	2076.4	297.5	ESRI
	Elevation range	Elevation range	m	1322.0	1.00	4255.0	876.8	ESRI
	Population density	Population density in 2010	cap /km²	160.00	10.00	3090.0	2.37	Eurostat
	Motorways	Length of motorways per 1000 km²	km	24.71	0.00	219.39	20.55	ESPON (2011)
	GDP per capita	Gross domestic product per capita	€ / cap	21.65	8.87	67.40	6.59	Eurostat

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