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The Economic Impacts of Climate Change and Options for Adaptation: A Study of the Farming Sector in the European Union

Natalie Trapp

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Summary

Future changes in the weather, climate and climate variability could alter growing and production conditions in the agricultural sector and consequently affect food production negatively if technologies and farming practices are not adapted in anticipation of regional climate change impacts. The severity of climate and weather impacts on agriculture, however, highly depends on the vulnerability of farming activities and technologies as well as on the adaptation capacities of regions and farms. Although climate change impacts have been studied extensively, the net impact of climate change on northern latitudes is yet unclear.

The objective of this thesis is to evaluate the potential impacts of climate change on European agriculture. For this purpose, a novel and unique 20-year panel of 80,000 agricultural holdings represented in all the 27 EU member states is constructed, by pairing the farm data with a gridded weather and soil dataset. In a first step (Chapter 2-4), the impacts of climate and weather variability on production, as well as the financial and the operational performance of farms are assessed and efficient adaptation strategies are derived at a farm-level. These chapters are based on a set of econometric analyses and identify the most vulnerable regions in the European Union by investigating short-term to medium-term impacts of climate change - a time frame in which adaptation is limited. In a second step (Chapter 5), long-term climate change impacts on adapted production technologies are projected using a partial equilibrium model considering world market and policy adjustments. These simulations can assist in building more effective and efficient policy frameworks to support efficient adaptation of European farms in the long-run.

Following a brief literature review, the second chapter quantifies regional weather impacts on 45,000 irrigated and rainfed cereal farms using a production function approach and dynamic panel methods, which makes the consideration of agricultural input adjustments feasible. Subsequently, the sensitivity of yields is evaluated using temperature and precipitation averages for 2021-2050 and 2071-2100 obtained from the regional climate model REMO. The analyses reveal that southern and central European cereal farms are highly vulnerable to temperature and rainfall changes (e.g. a yield decrease by up to 55%), whereas Northern Europe is more likely to benefit from a long-term warming. Overall, net cereal yields could decrease by 19% without efficient adaptation in the A2 scenario by 2100. This could have serious long-term consequences for the

cereal production (e.g. shift of the production to Northern Europe).

The third chapter introduces a novel Ricardian approach to project potential climate change impacts on the welfare of European farmers. Using a 20-year panel of 1000 NUTS regions[1] in the EU-12, three Ricardian models are estimated applying spatial and aspatial cross-sectional methods and a novel long differences approach, which exploits long-run temperature and precipitation trends and reduces inter-annual fluctuations in land values. The long differences approach suggests that maximum gains occur at a temperature of 0.76°C higher than in the cross-sectional models. In the A2 scenario, this would result in a net reduction of land value of 17% for the long-differences approach but up to 64% for the cross-sectional models. Even though the novel approach suggests that climate damages could be significantly lower than expected, it also indicates a considerable influence of short-term variability on welfare. Both methods show that most losses are concentrated in southern Europe (−84% to −92%) despite the significant differences between the approaches.

The fourth chapter investigates the impact of climate change on the operational performance of farms and potential response strategies by empirically assessing (i) the impacts of climate variability on efficiency and (ii) options for adaptation. For this purpose, an output-oriented distance function for more than 100,000 farms in 12 EU member states is estimated. The inefficiency term is explicitly modelled as a function of farm characteristics and climate variability as a proxy for climate-related experience of farmers. The results suggest that a lack of climate-related experience reduces the efficiency significantly, confirming the hypothesis that temperature variability can also affect the production indirectly. A sensitivity analysis suggests that by 2100, the average efficiency level in the EU-12 could be reduced by 28% in the A2 scenario, whereas the efficiency level could drop by up to 50% in the Mediterranean regions. The results also indicate that adaptation through input adjustments (e.g. increased fertiliser) or crop choice (e.g. higher share of fruits) is possible to a certain degree, but a drop in the efficiency could additionally reduce productivity.

The last chapter integrates the statistical results into a partial equilibrium model to assess the value and effectiveness of farm-level (e.g. irrigation, crop portfolio, cropland expansion) and macro-economic adaptation strategies (e.g. trade liberalisation) on crop production in Europe. The results suggest that farm-level adaptation, especially cropland expansion and crop portfolio adjustments, can largely mitigate negative impacts

[1] NUTS (Nomenclature des unités territoriales statistiques) is a geocode standard for subdivisions of the European Union.

of climate change on regional crop production. The results further demonstrate that on the one hand crop production is significantly reduced by large-scale bioenergy policies because of resources shifting from crop production to bioenergy production, which can make large-scale adaptation necessary (i.e. cropland expansion), and on the other hand, that trade can play a moderating role by allowing for virtual land import which reduces domestic land use competition and pressure for extensive adaptation. Overall, the results stress the importance of linking trade, adaptation and bioenergy in climate impact assessments because of the interdependencies between farm and policy decisions and agricultural production and their influence on the value of adaptation.

Zusammenfassung

Eine global wachsende Bevölkerung, die steigende Nachfrage nach Nahrungsmitteln sowie die Veränderungen der Ernährungsgewohnheiten bei begrenzten Ressourcen stellt die Agrarproduktion vor wachsende Herausforderungen. Ungeachtet der steigenden Erträge durch technologische Fortschritte in der Europäischen Landwirtschaft (z.B. Gentechnologie) ist die Agrarproduktion und -produktivität direkt von den klimatischen Bedingungen und der Wettervariabilität abhängig. Klimatische Veränderungen beeinflussen die Anbau- und Produktionsbedingungen und somit die künftige Produktion von Nahrungsmitteln wobei der Einfluss von Klima- und Wetteränderungen auf die Agrarproduktion stark von der Vulnerabilität der Technologien abhängt. Um die Anfälligkeit von Agrartechnologien gegenüber Umweltveränderungen zu reduzieren, muss die Produktion an die Veränderungen angepasst werden. Hierfür werden Prognosen benötigt, die zeigen, wie sich die Bedingungen für die landwirtschaftliche Produktion bei unterschiedlichen klimatischen Bedingungen unter Berücksichtigung von technologischem Fortschritt und Anpassungsverhalten kurz- bis langfristig verändern.

Das Ziel dieser Arbeit ist es, eine erste Einschätzung der potentiellen Auswirkungen von Wetter- und Klimaveränderungen auf die europäische Landwirtschaft zu geben. Grundlage bildet die Zusammensetzung eines neuen Paneldatensatzes von etwa 80.000 landwirtschaftlichen Betrieben in 27 EU-Mitgliedsstaaten mit monatlichen Niederschlags- und Temperaturdaten sowie qualitativen und quantitativen Bodendaten auf NUTS-Ebene.[2] Im ersten Teil der Arbeit werden kurz- bis mittelfristige Auswirkungen künftiger Wetter- und Klimavariabilität durch retrospektive empirische Analysen der Produktion, finanziellen und operationellen Leistung landwirtschaftlicher Betriebe geschätzt, um so Betriebe in klimasensitiven Regionen zu identifizieren und effiziente Anpassungsstrategien aufzuzeigen. Um die Auswirkungen des Klimawandels unter Berücksichtigung langfristiger Anpassungsstrategien (z.B. Ausweitung der Agrarfläche) und Veränderungen am Weltmarkt zu simulieren, werden im zweiten Teil der Arbeit die Regressionsergebnisse in ein partielles Gleichgewichtsmodell integriert. Die Simulationen ermöglichen es, einen effektiveren politischen Rahmen zur Reduktion der Vulnerabilität zu bilden.

Im 2. Kapitel werden regionale Produktionsfunktionen empirisch geschätzt, um kurzfristige Auswirkungen von Wettervariabilität auf etwa 50,000 bewässerte und nicht

[2]NUTS (Nomenclature des unités territoriales statistiques) ist ein hierarchisches System zur Aufteilung des Wirtschaftsgebietes der EU.

bewässerte Getreidebetriebe zu quantifizieren. Mit Hilfe von dynamischen Panelmethoden kann erstmals auch die Anpassung landwirtschaftlicher Produktionsfaktoren an Produktivitätsschocks berücksichtigt werden. Anschließend werden die abgeschätzten Produktionsfunktionen mit Klimaszenarien des regionalen Klimamodells REMO verknüpft, um die Sensitivität der Getreideerträge für künftige Temperatur- und Niederschlagsänderungen zu bestimmen. Die Analysen zeigen, dass insbesondere süd- und osteuropäische Regionen anfällig für Temperatur- und Niederschlagsänderungen sind und ohne entsprechende Anpassung der Produktionstechnologien die Getreideerträge in den Mediterranen Regionen bis 2100 um bis zu 55% zurückgehen könnten, während die nordeuropäischen Regionen im gleichen Zeitraum von den klimatischen Änderungen profitieren könnten. Netto könnten im A2-Szenario die Erträge in der EU bis 2100 um 19% zurückgehen. Ohne klimatische Anpassung der Produktionstechnologien könnte dies erhebliche Konsequenzen für die Getreideproduktion in Europa haben und langfristig zu einer Verlagerung der Produktion in den Norden und zu entsprechenden Landnutzungsänderungen in Südeuropa führen.

Im 3. Kapitel wird ein neuer Ricardianischer Ansatz (long-differences) angewendet, der implizit Anpassungsstrategien berücksichtigt (z.B. Landnutzungsänderung) und so die mittelfristigen Auswirkungen des Klimawandels für 1000 NUTS-Regionen in 12 EU-Mitgliedsstaaten prognostizieren kann. Der long-differences Ansatz nutzt langfristige Temperatur- und Niederschlagstrends um Einflüsse wetterbedingter Schwankungen auf die Landpreise zu reduzieren und so Klimaeinflüsse besser von Wettereinflüssen unterscheiden zu können. Der Vergleich mit konventionellen räumlichen und nicht räumlichen Querschnittsanalysen zeigt, dass die Gewinne von Farmern, bei einem 0.76 °C höherem Temperaturanstieg maximiert werden. Im A2-Klimaszenario könnte dies einen Rückgang der Landwerte bis 2100 um 17% mit dem long differences-Ansatz bzw. bis zu 64% mit Querschnittsmethoden zur Folge haben. Obwohl der long-differences Ansatz hier andeutet, dass Schäden, die durch klimatische Veränderungen verursacht werden, geringer sein könnten als bisher angenommen, beleuchtet er auch das Schadenspotential von Wettervariabilität. Dessen ungeachtet zeigen beide Ansätze, dass die Schäden vor allem in den südeuropäischen Regionen konzentriert sind (84% bis 92%ige Reduktion der Landwerte).

Im 4. Kapitel werden mögliche indirekte Klimaeinflüsse auf die operationelle Leistung der landwirtschaftlichen Betriebe untersucht sowie mittelfristige Möglichkeiten zur Reduktion der Anfälligkeit aufgezeigt, indem empirisch die (i) Einflüsse von Klimavariabilität auf die Effizienz und (ii) Anpassungsstrategien abgeschätzt werden. Mit Hilfe einer output-orientierten Distanzfunktion wird die Ineffizienz von mehr als 100.000 Betrieben in 12 EU-Mitgliedsstaaten abgeschätzt, wobei die Ineffizienz von den Eigenschaften des Betriebes und der Klimaerfahrung des Farmers abhängt. Die Ergebnisse zeigen, dass fehlende oder geringe Klimaerfahrung die Effizienz signifikant reduzieren kann und deshalb Temperaturveränderungen auch indirekt die Produktion beeinflussen könnten. Verschiedene Adaptionsmaßnahmen, wie die Anpassung der landwirtschaftlichen Produktionsfaktoren (z.B. Erhöhung des Düngemitteleinsatzes) oder der Produktionsstrukturen (z.B. Mix der Feldfrüchte), könnten zwar die Anfälligkeit gegenüber Temperatur- und Niederschlagsänderungen zu einem gewissen Grad reduzieren, aber fehlende Erfahrung im Umgang mit klimatischen Änderungen könnten die Effizienz und somit die Produktivität signifikant mindern. Eine exemplarische Sensitivitätsanalyse zeigt auch hier, dass primär die südeuropäischen Regionen von einer Effizienzminderung betroffen wären. Bis 2100, könnte die Effizienz ohne Erfahrungszuwachs (z.B. klimabezogene Bildung, Training) netto um bis zu 50% sinken.

Im 5. Kapitel werden die empirischen Modelle in ein partielles Gleichgewichtsmodell integriert, um den Wert und die Wirksamkeit unterschiedlicher Anpassungsstrategien für die landwirtschaftliche Produktion auf Betriebsebene (z.B. Bewässerung, Anbauportfolio, Ausbau der landwirtschaftlichen Nutzflächen) und Politikebene (z.B. Handelsliberalisierung) beurteilen zu können. Die Ergebnisse zeigen, dass einerseits landwirtschaftliche Flächen für die Nahrungsmittelproduktion signifikant durch umfangreiche Bioenergieproduktion zurückgehen, da Ressourcen für die Nahrungsmittelproduktion zur Bioenergieproduktion verwendet werden sodass Anpassungsstrategien stark an Bedeutung gewinnen. Andererseits kann Handel den Anpassungsdruck und die Landnutzungskonkurrenz zwischen Nahrungsmittel und Energiepflanzen reduzieren, da durch eine Handelsliberalisierung mehr Land virtuell importiert werden kann. Die Ergebnisse weisen besonders auf die Bedeutung der Verkettung von Handel, Anpassung und Bioenergie in Modellen zur Klimafolgenabschätzung hin, da die Interdependenzen von Entscheidungen in der Landwirtschaft und der Politik die landwirtschaftliche Produktion und Wirksamkeit von Anpassungsmaßnahmen maßgeblich beeinflussen können.

“[...] We know that we need to feed 9 billion people by 2050 and the only way that we can do that is to make agriculture more resilient, more productive, in the changing landscapes that we will see due to climate change. Making sure that agriculture is good for people and the environment is one of the most important and pressing tasks.”

Jim Yong Kim
World Bank Group President
December 4, 2013

Introduction

Food is fundamental for social well-being and human prosperity. Projections suggest that current agricultural production has to increase by 60% to 70% between 2007 and 2050 in order to feed the growing population (Tilman et al., 2011; FAO, 2009; Bruinsma, 2009). Despite technological advances in agricultural production (e.g. improved seed varieties, genetically modified crops, or irrigation systems), its capacity to produce food is severely dependent on climatic conditions and weather patterns. Changes in the climate or weather variability can alter the growing conditions or production capacities and - without sufficient adaptation - affect food production considerably. The severity of climate or weather impacts, however, highly depends on the vulnerability of production technologies and the potential to adapt to changing environmental conditions. Both vulnerability and adaptation potential can vary considerably across regions, farms, crops and the degree of development. In the northern latitudes, especially, it is still unclear how changes in the climatic conditions will impact food production or alter resource demands (e.g. irrigation water, fertile land) and by which degree negative impacts can be mitigated. In order to ensure that food production is not negatively affected by climate change, policy makers and farmers require detailed projections of where and how climate change could alter production and growing conditions in the short-term, medium-term and long-term. Furthermore, detailed assessments of the influence of different farm characteristics and management practices on adaptation to climate change are required. This knowledge would enable farmers to use scarce resources more efficiently and assist policy makers in shaping policies to either reduce potential damages or increase potential benefits of climate change.

There are numerous climate impact assessments on the US, India or Africa because of the availability of data or an expected vulnerability (e.g. Mendelsohn et al., 1994; Schlenker et al., 2005, 2006; Deschênes & Greenstone, 2007; Massetti & Mendelsohn, 2011; Mendelsohn et al., 2001; Kumar, 2011), but the literature for Europe is still less extensive (Lang, 2007; Lippert et al., 2009; Van Passel et al., 2012), and the net impacts of climate change on northern latitudes are still uncertain (e.g. Mendelsohn & Seo, 2007). The European Union (EU) provides an exemplary region to study climate impacts on northern latitudes because of its good environmental and farm data quality[3] and the wide coverage of different climate zones. Being a major food supplier and amongst the world's largest food exporters (114 bn€)[4], the EU contributes to food security within and outside Europe.[5] Moreover, European agriculture adds to the primal energy production (e.g. 69 Mtoe agricultural biomass in 2003)[6] and accounts for 9.8 million full-time equivalent jobs (5% of total employment in the EU).[7]

Over the past century, the mean temperature in Europe has increased by 0.8 °C and is expected to rise by another 1°C to 5.5°C by 2080 (IPCC, 2007), with the greatest impact on the Mediterranean regions. This could put additional pressure on arid and semi-arid Mediterranean regions, which are chronically water-stressed due to high evaporation volumes and low soil moisture (Fereres & Soriano, 2007), and therefore requires increased adaptation of production technologies. On the other hand, northern European regions may benefit from an increase in temperature, for example, by prolongation of the growing season or an increase in heat accumulation. Irrespective of possible gains, a shift of the agricultural production from the South to the North would involve complex processes and structural changes.

Accordingly, the objectives of this thesis are

1. to investigate the short-term impacts of weather on production capacities of farms assuming that adaptation potential in the short-run is highly limited (i.e. constant production technologies),

2. to examine short-term to medium-term impacts of climate change on the financial and operational performance of farms assuming that only certain adaptation strategies are adopted in the medium-run (i.e. farm-level), and

3. to simulate medium-term to long-term climate change impacts, accounting for long-run adaptation strategies (i.e. farm-level and policy-level)

using interdisciplinary approaches (compare Fig. 1).

[3] Farm-level data for the European Union are highly confidential and the access is restricted, but detailed control procedures ensure a high quality of accounting data.

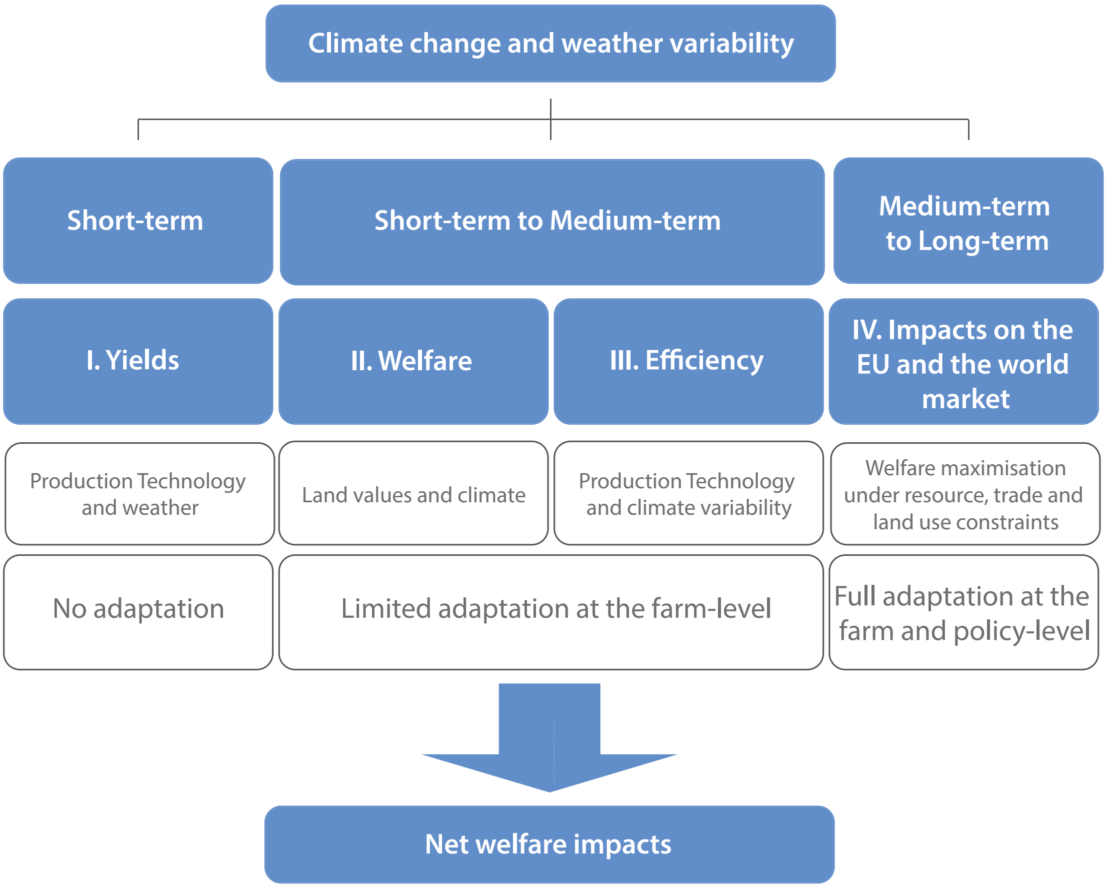
[4] `http://ec.europa.eu/agriculture/trade-analysis/statistics/index_en.htm`

[5] It should be noted that the EU is a major importer of some agricultural commodities and a major exporter for other agricultural commodities.

[6] `http://ec.europa.eu/agriculture/bioenergy/potential/index_en.htm`

[7] `http://ec.europa.eu/agriculture/rica/`

Figure 1: Thesis overview



Compilation of a Novel Dataset

A novel farm panel dataset, which covers approximately 80,000 farms observed between 1989 and 2008 and represented in all 27 EU member states (EU27), is composed for this purpose. The farm data is provided by the Farm Accountancy Data Network (FADN), which annually collects accountancy data from a sample of European agricultural holdings (FADN, 2010). The survey is conducted by each European Member State and is based on voluntary participation of the farmers.[8] It is the only harmonised microeconomic data which covers the entire European Union. The sample covers between 58,000 farms in 1989 and 88,000 agricultural holdings in 2008 and represents a total population of 5,000,000 agricultural holdings.[9] The population accounts for approximately

[8]Due to the voluntary participation, the farm panel is unbalanced.
[9]The survey only covers commercial agricultural holdings which are defined by their economic size.

90% of the total production and covers 90% of the utilised agricultural area (UAA). Each agricultural holding has an individual weight which allows for an extrapolation of the estimation results on the population of agricultural holdings in the entire EU. The field of observation is stratified in order to ensure that the sample of agricultural holdings appropriately reflects the heterogeneity of the population. Hence, the data is representative with respect to the region, the economic size and the type of farms. The data in the sample is highly confidential (i.e. farms are allocated to NUTS3[10] and FADN regions, respectively) and contains approximately 1,000 variables referring to structural (e.g. location, crop areas) and economic (e.g. profits, input costs) information of each farm.[11] The FADN data, however, does not contain any information on the environmental or geophysical characteristics of the farms.

Therefore, the farm information is paired with a gridded weather dataset drawn from the European Climate Assessment and Dataset (ECA&D)[12] and various soil type and quality data obtained from the European Soil Database. The ECA&D contains a high-resolution gridded dataset of daily precipitation and minimum and maximum temperature. The observations of meteorological stations across Europe are spatially interpolated to match grid cells of a 0.1° by 0.1° rotated pole grid. The ECA dataset additionally contains predefined series of extreme weather events and other weather variables (e.g. sunshine duration). The European Soil Database (ESDBv2)[13] contains soil data and information (e.g. organic content, water capacity, soil type) in a raster grid with cell sizes of 10×10 km.[14]

Lastly, the farm data is paired with precipitation and maximum/minimum temperature simulation data for three scenarios (A1B,A2,B1) of the Special Report on Emissions Scenarios (SRES) (IPCC, 2000) obtained from the regional climate model REMO (Jacob, 2005a,c,b).[15] The three SRES scenarios describe different paths for economic and population growth as well as for the usage of energy resources with the resulting emis-

[10]The NUTS (Nomenclature of Units for Territorial Statistics) is a system for dividing territories of the EU.

[11]For more detail view `http://ec.europa.eu/agriculture/rica/`

[12]For more detail view `http://eca.knmi.nl/`

[13]For more detail view `http://eusoils.jrc.ec.europa.eu/`

[14]50 evenly distributed centroid points within each grid cell are constructed in order to allocate the grid cell data of the ECA&D and the European Soil Database to the polygone shaped farm data (i.e. NUTS3 regions). Subsequently, the grid cell layer is laid on top of the polygone shape layer to calculate the average of all centroid points lying within one polygone shape. This ensures that more weight is given to those grid cells which have a larger proportion of area in the polygone shape than to grid cells with only a small proportion lying in a polygone shape. Percentages (e.g. percentage of high organic content) or averages (e.g. average temperature) are calculated depending on the variable.

[15]`http://www.remo-rcm.de/Regional-Climate-Modelling.1138.0.html`

sion paths. The A2/A1B/B1 scenarios thereby represent high/moderate/low emission scenarios, respectively. The climate change projection data of REMO is used to simulate future changes in the agricultural sector.

The unique dataset allows for a detailed investigation of the impacts of environmental conditions on European agriculture. The highly disaggregated farm data further allows for the consideration of farm management differences (e.g. rainfed vs. irrigated, organic vs. conventional, large-scale vs. small-scale, specialised vs. diversified), a distinction between various crop types and input adjustments so that more insight into the interdependencies of European agriculture, climate and weather as well as into the influence of production and policy adjustments can be gained.

Outline of this thesis

Following a brief literature review on climate change impacts on agriculture, new approaches are developed and applied in four studies which are self-contained analyses.

Chapter 2 **(The impacts of weather on European agriculture: Accounting for input choice)** empirically quantifies regional weather and extreme event impacts on more than 50,000 cereal farms in all the EU27. Using a production function approach in combination with dynamic panel methods, the sensitivity of irrigated and rainfed cereal yields to temperature and precipitation variability and extreme weather events is evaluated and the most vulnerable regions are identified. In contrast to previous research (e.g. Schlenker & Roberts, 2009), which commonly estimates reduced forms of the production function with weather variables, this study also considers farmers' input adjustments.

Subsequently, the sensitivity of cereals to climate change is investigated, using temperature and precipitation averages for 2021-2050 and 2071-2100 from the regional climate model REMO. This paper was presented at the Nachwuchsworkshop für Umwelt- und Ressourcenökonomen, AURÖ in Bern (February 2012) and at the 19th EAERE Annual Conference in Prague (June 2012).

Chapter 3 **(The economic impacts of climate change on European agriculture: A complementary Ricardian approach)** introduces a novel Ricardian approach, which additionally considers a wider range of adaptation options than the production function approach (e.g. change of the crop mix) in order to empirically assess the impacts of climate change on the entire agricultural sector. The typical Ricardian model is a purely cross-sectional approach which compares two farms that are the same in every respect, except for their climatic conditions. Some studies have used repeated cross-sections and estimated the Ricardian model separately for each year of data in order to assess the robustness of the climate coefficients, but could not replicate the results for the same sample of a different year (e.g. Mendelsohn et al., 1994; Schlenker et al., 2006; Deschênes & Greenstone, 2007; Massetti & Mendelsohn, 2011). This study suggests that farmers are influenced by weather variability, and therefore, land values are not stable over time. By using a long differences approach, which exploits long-run temperature and precipitation trends, the weather-related bias in the land values can be reduced and short-term impacts can be distinguished from medium-term impacts. The novel approach estimates climate impacts on the welfare of 1,000 NUTS regions in 12 EU member states, which are compared to the estimates from a typical aspatial and spatial cross-sectional model. Future welfare changes of European farms are simulated using temperature and rainfall data of the regional climate model REMO. This paper was presented at the Nachwuchsworkshop für Umwelt- und Ressourcenökonomen, AURÖ in Kiel (February 2014) and is accepted for presentation at the 5th World Congress of Environmental and Resource Economists in Istanbul (June 2014).

The production function approach and the Ricardian method consider the direct impacts of weather and climate on agriculture, but neglect impacts on the operational performance (e.g. efficiency, input substitution) and this way conceal efficient adaptation options. Chapter 4 **(Indirect impacts of climate variability on European farms and options for adaptation)**, therefore, empirically investigates possible indirect impacts of climate variability on farming activities as well as potential strategies to reduce the vulnerability by empirically assessing (i) the impacts of temperature variability on efficiency and (ii) options for adaptation. The efficiency level of more than 100,000 farms in 12 EU member states is estimated using a multi-output, multi-input production technology via an output-oriented stochastic distance function. The inefficiency term is modelled as a function of farm characteristics and long-run temperature variability in order to proxy the climate-related experience of farmers. The investigation of farm-specific determinants of levels of inefficiency can assist in directing policies aiming at increasing the efficiency, and hence, raise total agricultural production. If the influence of climate change on the operational performance is ignored, the effectiveness of policy measures could be reduced and impact estimations of future climate change can be biased. Regions with large or rapid temperature increases, for example, may require more assistance in reducing inefficiencies than regions with relatively stable temperatures. This chapter was presented at the European Climate Change Adaptation

Conference 2013, Hamburg, Germany and at the 20th EAERE Annual Conference in Toulouse (June 2013). It is in revision and will be re-submitted to the *Canadian Journal of Agricultural Economics*.

The three empirical studies in Chapter 2 to 4 address some of the shortcomings of existing impact studies including methodological limitations, influences of farm characteristics and management, and indirect climate impacts. Statistical approaches, however, are limited to retrospective observations and available data, and therefore, cannot simulate unobserved changes, such as policy change. Equilibrium models, on the other hand, allow for the consideration of long-run adaptation strategies (e.g. expansion of agricultural area), but often lack statistical specification. Accordingly, Chapter 5 **(Agricultural Adaptation to Climate Change in the European Union)** integrates the regression results into a partial equilibrium model in order to simulate medium-term to long-term climate change impacts on production changes and land allocation decisions more accurately and to assess the value of major adaptation strategies for different trade regimes and bioenergy policies.

On the one hand, the results demonstrate that crop production is significantly reduced by large-scale bioenergy policies because of resources shifting from crop production to bioenergy production, which make large-scale adaptation (i.e. cropland expansion) indispensable, especially in a high emission scenario. On the other hand, we find that trade can play a moderating role by allowing for virtual land import which reduces domestic land use competition and assists in balancing supply and demand; trade can consequently reduce pressure for large-scale adaptation. Farm-level adaptation, especially cropland expansion and crop portfolio adjustments, can largely mitigate negative impacts of climate change on regional crop production, whereas irrigation is a secondary adaptation strategy due to an increase in the production costs. Overall, the results stress the importance of linking trade, adaptation and bioenergy in climate impact assessments because of the interdependencies of agricultural production, climate change and political parameters and their influence on the value and effectiveness of adaptation.

Contributions at a Glance

This dissertation provides a deeper insight into the impacts of climate change on European agriculture. Chapter 2 implements a framework for integrating agricultural inputs into production function approaches aiming at assessing temperature and rainfall impacts in the short-term. Chapter 3 introduces a complementary Ricardian approach which aims at reducing the influence of weather in the Ricardian methodology. Chapter 4 demonstrates how climate change can affect also indirectly agriculture by reducing the efficiency of production technologies. The results indicate that the impacts of climate are indeed smaller than expected but also that weather will probably impose additional economic damage through short-term fluctuations in land values. Chapter 5 combines farm level scales (i.e. high resolution data of statistical models) with a representation of global markets (i.e. partial equilibrium model) in order to give an insight into the medium-term to long-term impacts of climate change on regional agriculture with consideration of various adaptation strategies, land use change and political parameters.

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A Brief Literature Review

Abstract
Climate conditions and weather patterns are the major determinants of agricultural productivity. Rising concerns about long-term changes of the climate and subsequent impacts on climate sensitive sectors, as in agricultural production, entailed an increasing number of studies and thorough research on climate change impacts. This paper briefly reviews the extensive literature on the economic impacts of climate change on the agricultural production, with particular emphasis given to studies covering European countries. However, in consequence of lack of European analyses and the significance of some international studies, other regions are also examined. Of particular interest are the methodologies applied to estimate and to assess climate impacts in agriculture. Limitations of each methodology are discussed and their benefits are highlighted. Findings, concerning the role of famers' adaptation as well as impacts of extreme weather events are considered. Finally, the importance of dealing with information on climate and agriculture as well as the necessity of circumspection when interpreting model results are substantiated.

Keywords: Crop simulation, Ricardian analysis, equilibrium model, integrated assessment **JEL-Classification:** Q12, Q51, L25, Q54

Chapter 1

Economic Impacts of Climate Change on Agriculture in Europe: A Brief Literature Review

There is a growing number of economic studies assessing the impacts of climate change on agriculture (e.g. Bach, 1979; Newman, 1982; Rosenzweig, 1985; Parry & Carter, 1988; Adams et al., 1990), but yet there is great uncertainty about the magnitude of potential impacts and the net effects in northern latitudes. Much of the uncertainty results from the various methodologies applied to quantify the economic impacts on agriculture (Fisher et al., 2012). Most previous research finds a significant negative relation between global warming and agriculture, especially for crop growth (e.g. Nordhaus, 1991; Rosenzweig & Parry, 1994; Tol, 2002; Mendelsohn & Williams, 2004; Parry et al., 2004; Fisher et al., 2012). Some of these studies, project damages to be concentrated in developing countries, due to the higher dependency on local agricultural production and higher vulnerability in consequence of their present climate conditions and lower adaptation capacities. Recent climate change impact assessments, however, are inconclusive about negative outcomes (e.g. Schlenker et al., 2005, 2006) or even suggest a positive relationship between climate change and agriculture (e.g. Deschênes & Greenstone, 2007).

In the following we briefly review the different approaches emphasizing the weaknesses and strengths. We distinguish five main approaches based on the review of Mendelsohn & Dinar (2009) and a recent study by Fisher et al. (2012): (i) studies that rely on crop simulation and agro-economic simulation models; (ii) econometric studies that rely on cross-sectional or panel analysis of yields or net revenues as well as hedonic approaches assessing land values, (iii) partial equilibrium models, (iv) general equilibrium models and (v) Integrated Assessment Models (IAMs) based on partial or general equilibrium frameworks.

1.1 Biophysical models

One of the most popular approach to assess climate change impacts on agriculture relies on biophysical models. Biophysical models use ecological functions to depict the relation between crop growth, climate conditions, soil characteristics and management practices. Different climate scenarios are applied to different regions and crops subject to specific farm tillage and management practices. Yield changes are then extrapolated to an aggregated effect (e.g. Rosenzweig et al., 1993; Rosenzweig & Parry, 1994).

Biophysical models are developed in three stages: model building, calibration and validation. Model building involves the formulation of an output equation (e.g. yield) and identifying factors that control plant growth. These factors need to be specified as mathematical functions with conditional rules. The mathematical functions are interlinked in order to specify interactions and crop reactions (e.g. phenological development, photosynthesis). In a second step, the model is calibrated by modifying the model parameters such that the model output fits the observed data. Often the model output does not comply with the real situation, for example, due to sampling errors or incomplete knowledge of the system. In a last step, the model is validated by showing that the model output closely represents the real situation by comparing simulated output with observed data which has not been used in the calibration stage. However, validation of all model components often is not possible due to lack of detailed data. Moreover, validation is difficult because a large set of hypothesis is tested simultaneously and some model components or behaviours of the system are not yet fully understood or not fully accounted for (e.g. farmers' decisions) so that model output often differs from the real system.

Within the biophysical model approach, we can distinguish (i) descriptive models and (ii) explanatory models. Descriptive models simulate the behaviour of a system, for example, a crop with its elements, plant organs (e.g. leaf, root) and processes (e.g. growth) (Miglietta & Bindi, 1993). In this approach experimental data is used to derive mathematical equations which describe the behaviour of a system. Explanatory models consist of quantitative descriptions of the processes responsible for the behaviour of a system (Miglietta & Bindi, 1993). An explanatory model calculates rate variables (e.g.

Table 1.1: Crop simulation growth models

Model	Description	References
EPIC	Erosion Productivity Impact Calculator (EPIC)	Williams et al. (1984); Williams (1990)
CERES-Maize/ CERES-Wheat	Dynamic crop simulation model for Wheat and Maize	(Ritchie & Otter, 1985; Ritchie & Godwin, 1987; Godwin & Singh, 1998)
CROPWAT	Empirical irrigation management model	Tao et al. (2008), FAO[1]
APES	Agricultural production and externalities simulator	Donatelli et al. (2010)
CROPSYST	Multi-crop simulation model to study cropping systems management	Stöckle et al. (2003)
DAISY	Soil-plant-atmosphere system model	Abrahamsen & Hansen (2000)
HERMES	Nitrogen and water dynamics in plant growth simulation model	Kersebaum & Beblik (2001)
DSSAT	Decision support system for agro-technology transfer	Jones et al. (2003)

photosynthesis rate) and state variables (e.g. yield) and processes are formulated as functions of environmental factors (e.g. radiation) (Miglietta & Bindi, 1993).

There are numerous crop simulation growth models built for different subsystems, often simulating a particular crop or component of the production system (Table 1.1). The models differ in various modelling aspects, such as the leaf area development, crop phenology, root distribution over depth, evapo-transpiration, or water dynamics.

The Erosion Productivity Impact Calculator (EPIC), for example, is a commonly used biophysical model which has been developed to assess soil erosion on soil productivity (Williams et al., 1984). EPIC allows for prediction of plant biomass through simulating carbon fixation as a result of photosynthesis, maintenance respiration, and growth respiration (Williams, 1990) taking into consideration management practices, environmental conditions and soil dynamics. Furthermore, EPIC can be used to evaluate a limited number of agronomic adaptation options, such as changes in the planting dates, tillage, crop rotations and irrigation. Daily weather (temperature, precipitation and wind speed) are explicit input variables in the EPIC model, and therefore, it may be applied to assess the impacts of extreme events on agricultural production. As EPIC only reflects biophysical feedbacks, it cannot assess the full range of economic impacts.

The CERES-Maize and CERES-Wheat simulation model for maize and wheat is a dynamic, deterministic crop simulation model that was formerly developed by the United States Department of Agriculture – Agricultural Research Service (Ritchie & Otter, 1985; Ritchie & Godwin, 1987). The model has been tested successfully using real data from around the world and gives results for biomass accumulation and partitioning, crop growth and yields based on daily intervals (Godwin & Singh, 1998; Ritchie et al., 1998). It can be for example used for management decision making.

CROPWAT is an empirical irrigation management model developed by the Food and Agricultural Organization (FAO) estimating crop water and irrigation requirements based on soil, climate and crop data.[2] It is used as a decision support system for planning and irrigation management. The CROPWAT model does not only estimate yield reductions due to crop stress, but also crop water requirements. Apart from irrigation changes no other input intensity change is considered. In general, the results of biophysical models consistently predict decreasing crop yields with increasing temperature and declining precipitation rates (e.g. Tao et al., 2008).

The Agricultural Production and Externalities Simulator (APES) has several simulation tools to investigate the impact of specific production activities (e.g. grassland, arable crops) in different environments.

The Cropping Systems Simulation Model (CROPSYST) is a multi-crop simulation model with a daily interval developed to investigate the impacts of crop management on yields and the environment. It simulates various production conditions (e.g. soil water and nitrogen budget, crop growth, erosion) while accounting for various management options (e.g. crop rotation, irrigation).[3] DAISY is a mechanistic model simulating the physical and biological processes which studies the production, environmental impact and change in the soil qualities.[4] DSSAT simulates growth, development and yield for more than 28 crops subject to soil-plant-atmosphere dynamics.[5] The model has been used for various applications ranging from farm management to climate change impact assessments.

1.1.1 Discussion

Biophysical models are suitable to determine the impact of atmospheric CO_2 concentrations, temperature and precipitation on growth and development due to the detailed

[2] http://www.fao.org/nr/water/infores_databases_cropwat.html
[3] http://www.bsyse.wsu.edu/CS_Suite/CropSyst/index.html
[4] http://code.google.com/p/daisy-model/wiki/About
[5] http://dssat.net/

agronomic foundation, which integrates hydrological conditions, atmospheric impacts and detailed plant growth processes and because the models can be calibrated to local conditions. However, biophysical models also face several limitations. The models simulate only agronomic interactions and disregard adaptation efforts of farmers to market changes (e.g. output and input prices), ignore possible input substitutions and fail to depict yield variability as a result of profit maximisation or cost minimisation behaviour. Due to the data-intensity (daily data) and the limited application to different locations under controlled experiments, these models can only simulate impacts on selective crops and locations. Although, these models can be accurate short-term prediction tools, they tend to overestimate the impacts of climate change when crops are less suitable for warmer climates (Mendelsohn & Dinar, 2009).

1.2 Econometric Models

Econometric models are based on economic theory and use statistical methods to study economic relations. We can distinguish three broad categories of econometric models which are used to investigate climate change impacts on agriculture: (i) Empirical Yield Models which are based on production function theory using crop yield data, (ii) Ricardian models which are based on the Ricardian theory (Ricardo, 1817) using farm revenue or land value data, and (iii) qualitative and limited dependent variable models using crop insurance data. In the following, we briefly review previous research applying econometric methods.

1.2.1 Empirical Yield Models

Empirical Yield Models built on production function theory, which allows for an isolation of weather impacts from other production factors. This approach links climate, farm inputs and economic factors to crop yields (e.g. Onyeji & Fischer, 1994; Gbetibouo & Hassan, 2005; Sands & Edmonds, 2005). The production function approach relies on “real” experiments, and therefore, can provide estimates of weather impacts as well as input intensities for different production technologies and crops. Econometric analysis of production functions probably began in the 70’s (e.g. Lau & Yotopoulos, 1972; Yotopoulos et al., 1976; Diewert, 1973); joint production functions date back perhaps to Klein (1947). Most agricultural production research examines technological progress, input substitution elasticities, the treatment of outliers or the adequate formulation of production technologies. Built on major achievements of agricultural production functions by Lau & Yotopoulos (1972), weather or climate are considered as specific input factors. More recently, production functions are used to study impacts of climate change. Schlenker & Roberts (2008), for example, paired crop yield panel data for the US with high resolution weather data (maximum and minimum temperatures). They show that corn yields increase up to 29 °C, soybean yields increase up to 30 °C, and cotton yields up to to 32 °C, but temperatures above these thresholds are harmful for crops. They conclude that potential for adaptation is very limited, because yield response shows a nonlinear asymmetric trend, where the yield decrease beyond the optimal or maximum temperature is significantly steeper than the yield increase up to the optimum.

Even though production functions are straightforward to assess the impacts of weather variability on agriculture, they are hardly used for long-term impact assessments (e.g. climate change). Two main difficulties have been noted in the application of production functions: (i) the allocation of inputs to different outputs is unknown, and (ii) a method of estimation (e.g. Least Squares) cannot have more than one dependent variable. The inability of most estimation methods to deal with multiple dependent variables and different forms of production function for different outputs lead to the construction of composite output functions, which assume that farmers continue cultivating the same crops with the same production technology. Moreover, the potential of adaptation is likely to be underestimated when focusing only on a limited set of crops. For example, an unexpected decline of rainfall could lead to a dry spell or drought. In the short run, the farmer can increase irrigation or fertiliser application to reduce negative impacts on crops. As a result, the production costs may increase and cause a profit loss. If the change is persistent, the farmer can decide to plant different crops that are less water intensive to reduce the production costs. In the long run, the farmer may decide that it is unprofitable to plant crops, and convert the land into residential land or provide it for other purposes. The production function approach ignores the various adaptation options and strategies (e.g. change of crop mix, planting dates, adoption of irrigation technologies) and thus tends to overestimate the climate change impacts. Mendelsohn et al. (1994) call this bias the “dumb farmer scenario”, because the production function approach does not account for farmers’ adaptation to societal, economic or environmental changes. Chang (2002) attempts to overcome this limitation by combining the production function approach with optimisation modelling and estimates long-term impacts of temperature and precipitation changes on Taiwan’s agricultural sector. Chang (2002) employs a regression model using yield data for 60 crops and a price-endogenous mathematical programming model that subsequently simulates yield changes for several climate change scenarios. The author demonstrates that climate change has a significant non-monotonic effect on crop yields but precipitation increases can be even devastating for farmers.

1.2.2 Ricardian Analyses and Land Values

To overcome the shortcomings of the production function approach, Mendelsohn et al. (1994) developed the Ricardian analysis, based on the achievements of Ricardo (1817). This method is also referred to the hedonic approach, because the Ricardian analysis is comparable to the hedonic pricing technique of environmental valuation. In contrast to other climate impact assessment methods which have failed to fully include farmers' adaptation choices (Rosenzweig & Parry, 1994; Schlenker et al., 2005; Deschênes & Greenstone, 2007), the Ricardian analysis implicitly accounts for adaptation behaviour (e.g. crop choice, input adjustments) by linking net productivity of farmland (e.g. land value, farm revenue) to climate (e.g. annual or 30-year average temperature and precipitation), soil characteristics (moisture, nutrient content), environmental factors (altitude, slope) and other control variables (Mendelsohn et al., 1994). This allows crop mix, input application or labour choices to be endogenous.

The Ricardian method is a cross-sectional approach. By using cross-sectional variation of different agro-climatic zones, the sensitivity of land value to climate can be assessed. Kolstad (2000) based the Ricardian approach on the assumption that, "by examining two agricultural areas that are similar in all respects except that one has a climate on average 3°C warmer than the other, one would be able to infer the willingness to pay in agriculture to avoid a 3 °C temperature rise". Economic theory suggests that land value equals the discounted sum of future profits, it should reflect the expectation of farmers on how well they can cope with a change in the climatic conditions. Accordingly, if farmers allocate land among different agricultural activities (e.g. crop choice, livestock) in order to maximise revenues, the farmland value will equal the discounted sum of future expected cash flows when land is at its most productive use. Farm net revenues, in contrast, represent the short or medium-term value of farmland.

The Ricardian approach has been applied to a large number of regions, ranging from the US and Canada (Mendelsohn et al., 1994; Schlenker et al., 2007; Mendelsohn & Reinsborough, 2007), Latin America (Seo & Mendelsohn, 2008), Africa (Seo, 2010; Schlenker & Lobell, 2010), and India (Kumar, 2011) to few novel studies on Europe (Lang, 2007; Lippert et al., 2009; De Salvo et al., 2011; Van Passel et al., 2012). Built on the first achievements, Ricardian models have been applied more specifically to measure the sensitivity of cropland to climate (Mendelsohn et al., 1996), the role of water shortages (Mendelsohn & Dinar, 2003) as well as the sensitivity of rain-fed farms to climate by testing whether surface water run-off can explain variations in farm values in the US (Mendelsohn & Dinar, 2003) and Israel (Fleischer et al., 2008). The results suggest that the value of irrigated farmland is independent of precipitation changes, but increases with temperature. Finally, Mendelsohn & Dinar (2003) conclude that investing in irrigation infrastructure can be a potential adaptation for farmers to climatic changes. Likewise, Kurukulasuriya et al. (2006) used cross-sectional data of more than 9000 farms across 11 African countries, estimating how farm net revenues are influenced by climate change in comparison to current average temperatures. The results indicate that revenues for rainfed crops decline with warming and increase for irrigated crops. Moreover, the authors demonstrate that the net impact highly depends on precipitation changes. Schlenker et al. (2006, 2007) integrated an agronomic concept into the Ricardian model and find that degree days for the growing season can explain a large proportion of the variance. However, growing seasons are endogenous and are likely to be altered when the climate changes (Mendelsohn & Dinar, 2009). Deschênes & Greenstone (2007) estimated the impact of weather change on farm net revenue over time using a fixed effects panel data model to control for individual farm heterogeneity, such as differences in climate, soil characteristics as well as other constant differences that are difficult to quantify. They argue that fixed effects also control for adaptation behaviour of farmers to changing climatic conditions and suggest that climate change will raise annual net revenues of US agriculture by \$1.3 billion in 2002 dollars or by 4%. Farm net revenue, though, does not represent expectations about future streams of profits, and therefore, can only predict short to medium-term impacts.

Most Ricardian analyses focus on regions with good data availability and fair climate variations (e.g. US or India Sanghi et al., 1997; Dinar et al., 1998; Kumar & Parikh, 2001; Sanghi et al., 1998; Mendelsohn & Dinar, 1999; Mendelsohn et al., 2001). However, there are yet only few studies on selected European countries. Maddison (2000), for example, investigates climate impacts on England and Wales, using data of 400 farms within a hedonic framework. Although, the results demonstrate that climate is an important factor, the paper focuses on reasons for productivity differences (e.g. regulated tenancies). By using panel data for western German farms, Lang (2001) estimated a restricted profit function based on the concept of shadow prices. The study results indicate that German agricultural production could significantly gain from global warming, when ignoring the economic impacts of increasing weather variability with more climate extremes. Van Passel et al. (2012) are the first to conduct a comprehensive Ricardian study on 38,000 farms across the European Union. The results suggest aggregate losses by 2100 of 8% in a low emission based climate scenario to a loss of 44% in a high emission based climate scenario. Van Passel et al. (2012), however, do not correct for spatial correlation.

The main advantage of the Ricardian approach is the implicit consideration of efficient adaptation of farming activities to environmental, economic or climatic changes (Mendelsohn & Dinar, 2009). However, the ability of farmers to adapt to new climates may change over time (e.g. technological options, human capital, infrastructure, output and input prices). Fertilisers and pesticides, for example, are likely to respond to energy price changes or climate policies intending to reduce GHG emissions. Moreover, Schlenker et al. (2005) and Darwin (1999) criticise that the Ricardian analysis does not consider the impact of other important variables explaining variations in farm income (e.g. irrigation). To obtain consistent estimates of the relationship between climate and land values, however, all unobserved influences on land values have to be orthogonal to climate (Rosen, 1994; Deschênes & Greenstone, 2007). For example, Deschênes & Greenstone (2007) show that temperature and precipitation norms co-vary with population density, per capita income, soil characteristics and latitude whereas Schlenker et al. (2005) demonstrate that the availability of irrigation water co-varies with climate. Kurkulasuriya & Mendelsohn (2008) and Schlenker et al. (2005) addressed some of the limitations by including irrigation in the model or by distinguishing between irrigated and rainfed farmland. Despite these inaccuracies, the implicit modelling of farmers' adaptation does not provide any insights into adaptation options and strategies, so that policy makers cannot respond to specific needs in the agricultural sector. Information about farmers' adaptation behaviour is essential for efficient and effective climate and agricultural policy modelling.

Furthermore, the Ricardian model tends to underestimate climate change impacts. Firstly, the hedonic approach assumes that land will be turned into other uses (e.g. residential land) if climate warming inhibits crop production and reduces food production. The Ricardian analysis ignores the potential welfare loss as a consequence of price inelasticities of demand for food (Cline, 1996). Secondly, the Ricardian model is a comparative steady state analysis of long-term climate impacts (Mendelsohn & Dinar, 2009) and ignores adjustment costs from one equilibrium to a future one (Kaiser et al., 1993; Quiggin & Horowitz, 1999; Kelly et al., 2005). And thirdly, by exploiting cross-sectional variation this approach is not suitable to account for short-term weather variability, and therefore, ignores extreme weather event damages. Production functions are better at measuring the short-term responses of weather extremes (Mendelsohn & Dinar, 2009).

1.2.3 Qualitative and Limited Dependent Models

Logit and Tobit models are qualitative and limited dependent variable models and can be used to analyse agricultural insurance data or farmers' crop decisions under climate change.

Logit models represent discrete choice, where dichotomous data is analysed in a binary logistic regression and categorical data in a multinomial logistic regression. Seo (2010), for example, examines whether integrated farms (e.g. livestock and crop farms) are more resilient to climate change than specialised farms (e.g. cereal specialist), by testing how farm types and revenues vary across the range of climates in Africa. The model is estimated via a multinomial logit choice regression and indicates that integrated farms will increase in number whereas specialised farms will decrease across Africa up until 2060. The results also suggest that integrated farms become more profitable (9% loss to 27% gain dependeing on the scenario).

Tobit models are used if the dependent variable is censored (e.g. lower or upper limit), hence, least squares estimators would biased and inconsistent (Hill et al., 2008). Tobit models are solved via a maximum likelihood procedure that recognises the censored data. Botzen et al. (2010) employed a Tobit model using insurance data to register hailstorms that are not recorded by weather stations. This way Botzen et al. (2010) investigates economic impacts of an increased frequency of extreme weather events on agriculture. By estimating a range of Tobit models that link insured hailstorm damage and climate indicators for greenhouse and outdoor cultivation in the Netherlands, they find an increase of hailstorm damage of around 25% to 50% for outdoor farming and of up to 200% for greenhouse cultivation.

Probit and Logit models are very useful for censored or choice data and can give insights into farmer's behaviour, choice of crops or insurance damage under climatic changes. However, these models are very limited and cannot estimate the full range of costs and benefits of climate change in the agricultural sector.

1.2.4 Discussion

Overall, econometric approaches are based on historical data and build on economic theory which makes them very precise. Despite their numerous advantages, there are several limitations associated with econometric models. The production function approach is superior in analysing weather impacts on specific crops, and therefore, a favourable tool for short-term predictions, but it ignores farmers' adaptation to long-term changes and profit maximizing behaviour, and thus, tends to overestimate climate change impacts. The Ricardian approach can overcome some of the limitations of the production function approach by accounting for adaptation behaviour and hence can give long-term predictions, but it does not give any insights on adaptation strategies or options to derive policy implications and disregards potential welfare loss through land-use changes, and therefore, tends to underestimate the climate change impacts. The qualitative and limited dependent variable models are able to give insight on adaptation strategies, but cannot, due to the data structure, account for the range of benefits and damages of climate change. The econometric approaches, therefore, have limited forecasting potential and are constrained by the available data.

1.3 Partial Equilibrium Models

Partial equilibrium models depict parts of a whole economy, assume that industries are independent of each other and treat the remaining part of the economy as exogenous. They can depict the agricultural sector in high detail and are able to consider various agricultural policies (e.g. CAP) and different components of agricultural markets and can evaluate local economic and environmental consequences.

Partial equilibrium models are usually used for the evaluation of various policies, for example, European Simulation Model (ESIM), Food and Agricultural Policy Research Institute-Centre for Agricultural and Rural Development (FAPRI-CARD)[6], Modle International Simplifi de Simulation (MISS) or Common Agricultural Policy Regionalized Impact Modelling System (CAPRI). Most policy models, however, are not suitable for climate impact assessments due to missing climate equations.

Recent work by Schneider et al. (2008), who developed the European Forestry and Agricultural Sector Optimization Model (EU-FASOM), which is a dynamic partial equilibrium model for the forestry and agricultural sectors in the European Union, is

[6] `http://www.fapri.iastate.edu/models/cropinsurance.aspx`

very suitable for estimating climate impacts on agriculture. EUFASOM includes climate equations and can be linked to the crop simulation model EPIC. This model is discussed in more detail in chapter 1.5 because it incorporates biophysical feedbacks and thus belongs to the Integrated Assessment Models (IAMs).

Tobey et al. (1992) developed a partial equilibrium model for climate impact assessments in agriculture, by building a world agricultural model in a partial equilibrium framework, assuming no response of farmers to changing climatic conditions, no technological progress, constant population and other growth conditions. Using empirical results they provide a coarse picture on the economic impacts of atmospheric CO_2 doubling on world agricultural production. Tobey et al. (1992) uses a partial equilibrium model, assuming that agricultural production in industrialised countries plays a minor role, and therefore, has only a moderate impact on resource allocation in other economic sectors. Their results indicate moderate productivity losses in major agricultural production areas, partly due to interregional adjustments in production and consumption. Consequently, climate change has relatively small effects for the domestic economy. A major limitation of their model is that they cannot identify winners and losers on the basis of domestic yields or changes in world food prices and world trade patterns. Furthermore, the model assumes no adaptation, and therefore, is likely to overestimate the impacts of climate change.

Kan & Kimhi (2012) developed a partial equilibrium approach that introduces land allocation decisions as a result of climate change and endogenous pricing to simulate climate change effects on crop portfolios. The simulations show that agricultural revenues increase under fixed prices, but decline considerably when prices are flexible. However, prices for rainfed and irrigated crops and crop categories (e.g. fruits, vegetables) are aggregated. Hence, important adaptation strategies cannot be simulated so that climate change impacts are likely to be overestimated.

1.3.1 Discussion

Partial equilibrium models allow for a detailed representation of the agricultural sector. They are able to incorporate biophysical land use characteristics in detail as well as to simulate policy decisions such as carbon taxes. Partial equilibrium models even allow for the explicit modelling of the factor market for land, which can give necessary insights to policy makers. However, these models do not account for the linkage between economic sectors. The agricultural sector is likely to be dependent on non-agricultural sectors, such as the chemical industries (fertilizer, pesticides) or the energy sector. Furthermore, partial equilibrium models do not constrain the aggregated land use and are weak in modelling competition between alternative land uses, although some models can implicitly depict land use competition in the cross-price elasticity of the area response equations. Therefore, important adaptation strategies are ignored. The interaction of the agricultural and non-agricultural sectors as well as land use competition is typically covered in general equilibrium models, which are presented in the following chapter.

1.4 General Equilibrium Models

All heretofore discussed methods depict changes within the agricultural sector and ignore changes in the economy, e.g. labour costs or interest rates, assuming that industries are independent of each other and do not affect the rest of the economy. If climate change, however, has a large impact on the economy, input and output prices in the agricultural as well as in non-agricultural sectors are susceptible to changes. General equilibrium models are able to account for these changes, by modelling economies as a complete interdependent system, linking the agricultural and non-agricultural sectors and thereby providing an economy-wide analysis. The main advantage is that general equilibrium models can predict the extent of shifts in supply and demand as well as in prices, and thus, portray changes that partial equilibrium models cannot simulate.

General equilibrium models are usually simulated with Computable General Equilibrium (CGE) models and consist of mathematical equations (e.g. nested CES functions to model the production in each economic sector) and a model database which usually consists of an input-output table or a social accounting matrix, a comprehensive economy-wide square matrix representing the economy, as well as data for parameters which represent behavioural response (e.g. import demand elasticities) (Lofgren et al., 2002). The climate change CGE models, additionally use aggregated information based on a Geographic Information System (GIS) and General Circulation Models (GCMs) (Mendelsohn & Dinar, 2009). The simultaneous equations define the behaviour of different actors (e.g. production or consumption decisions) which are driven by profit or utility maximisation (Lofgren et al., 2002). CGE models can be comparative-static or dynamic. Comparative-static models show the difference in the economy between two alternative future states (e.g. with and without a policy shock), ignoring dynamic transitions toward an economic steady-state (e.g. Böhringer, 2000), whereas dynamic models explicitly model the transition between the economic steady states (e.g. Bosello et al.,

2006) and recursive-dynamic CGE models are solved sequentially.

Although there are numerous CGE models to simulate climate mitigation (e.g. Golub et al., 2009; Pizer, 2002; Burniaux et al., 2009)[7], there are only few CGE models to simulate climate change impacts. Winters et al. (1998) compares climate impacts on the macroeconomic performance, sectoral resource allocation and household welfare of Africa, Asia and Latin America under different policy interventions, using static equilibrium models. The model suggests that all countries potentially suffer from production and income losses, with Africa being mostly affected, due to low substitution possibilities between domestic and imported food products. The model, however, examines the impacts of climate change via anticipated average yield and price shocks, which might not be a significant cost of climate change, and ignores other important changes, such changes in the energy-sector or water shortages. In addition, the comparative-static nature of the models are likely to underestimate the damages of climate change because transition costs and processes are ignored. Jorgensen et al. (2004) applies a dynamic CGE model to estimate the aggregated climate impacts on the US economy, human health and water supply. The estimates of the net impact of climate change on the economic performance show that the effects on agriculture dominate the effects on other market sectors, at such a rate that the field crop and forestry sector alone account for over 70% to 80% of the total predicted climate change effects on real GDP. Furthermore, Jorgensen et al. (2004) find that moving from wetter to drier climatic conditions will further increase damage costs. The model, however, is limited to US market impacts only, many climate-sensitive sectors are excluded and possible externalities and spill-over effects are not simulated. Especially, environmental feedbacks cannot be simulated due to the missing links to detailed environmental information. Accordingly, this model is very likely to underestimate the climate change impacts or overestimate the share of overall damages in the agricultural sector. Onyeji & Fischer (1994) investigates the impacts of climate change on the Egyptian agriculture in a recursively dynamic general equilibrium framework. The model projects climate change impacts on crop yields ignoring adaptation and taking into consideration adaptation. The model indicated that climate change potentially causes increases in the level of food and crop prices by up to 30% and 90% respectively, as well as loss in national GDP by up to 60%. This model, however, does not simulate the interdependencies to other sectors and the impacts of climate change on irrigation water availability, which in Egypt will play a major role for future agriculture. Darwin et al. (1995, 1996) developed a global CGE model (Fu-

[7]Climate mitigation aims at reducing anthropogenic greenhouse gas emissions in order to limit the degree of long-term changes in the climate conditions.

ture Agricultural Resources Model) and combined it with a GIS model to examine the effects of climate change on US agricultural systems, which significantly improves the representation of environmental effects on the economy. The GIS component controls for geophysical characteristics and production possibilities in eight world regions (US, Canada, Australia, New Zealand, Japan, several Asian regions and the European Community) as well as for climate induced changes of land classes and water supply, whereas the CGE model estimates how changes in the production possibilities affect production, consumption and trade for 13 commodities. In contrast to previous research, Darwin et al. (1995) finds a reduction in non-grain crop production but an increase in grain production. Furthermore, climate change benefits in the agricultural are unequally distributed. While Canada will increase food production, Southeast Asia will suffer from lower output. However, Darwin et al. (1996) assume that world food demand remains relatively stable while farmers increase the amount of land under cultivation. Furthermore, the location of climate-induced changes in the economy are not simulated and environmental feedbacks are still ignored.

A second strand of CGE models assessing climate change impacts on the agriculture arose from the Global Trade Analysis Project (GTAP). The GTAP-AEZ model integrates different agro-ecological zones into the GTAP model. The Agro-ecological Zones (AEZ) methodology follows an environmental approach and defines zones on the basis of combinations of soil, land and climatic characteristics for improved land-use planning based on an evaluation of the biophysical conditions. The AEZ methodology also examines synergies and trade-offs of alternative uses of agro-economic resources (e.g. land, water, technologies, food production, energy production).[8] Accordingly, the GTAP-AEZ model (e.g. Lee, 2005) includes different land types that are imperfectly substitutable in the production technology within but not across climatic zones, assuming that each sector using land in a certain AEZ has its individual production function. The maize sector in AEZ 1, for example, has a different function from the maize sector in AEZ 2. Consequently, land productivity differences for various climatic characteristics can be more accurately identified.

1.4.1 Discussion

CGE models are able to depict macroeconomic feedbacks through changes in relative input and output prices. In CGE models, the agricultural sector is only one part of the model linked with non-agricultural sectors through output supply and input demand

[8] `http://webarchive.iiasa.ac.at/Research/LUC`

in the production process and via trade there is a link to the rest of the world. The main advantage of CGE models is the possibility to estimate impacts of climate change on subsequent industries as well as the ability to assess impacts on the whole economy and to compare climate policies. However, CGE models are often criticised for an over simplification and lack of econometric specification. Moreover, there is an enormous loss in details for the agricultural sector due to the high level of aggregation within sectors and regions. Another major disadvantages of global models is the inaccurate measurement of the sensitivity of each sector to climate change (Mendelsohn & Dinar, 2009). For example, climate change impacts are examined for the EU, US, Canada, Japan, China, Australia, New Zealand and the "rest of the world", thus, treating all developing countries as a single region. By using such high level of aggregation, CGE models conceal interactions of climate and agriculture and thereby obscure insights on adaptation potential or behaviour.

1.5 Integrated Assessment Models

Integrated Assessment Models (IAMs) combine two or more models within a discipline or couple different models from several disciplines and are often used for environmental policy analysis as a result of the interdisciplinary nature of environmental problems with the objective of providing information to policy makers. In the following we discuss two approaches of integrated assessment models: (i) crop simulation models coupled with bottom-up partial equilibrium models and (ii) crop simulation or climate models coupled with top-down general equilibrium models.

1.5.1 Integrated Assessment Models in a Partial Equilibrium Framework

Biophysical models (e.g. EPIC) and GCMs can be integrated into a partial equilibrium framework, which gives more detail on the biophysical and economic feedbacks of climate change on the agricultural sector. This way, estimates of changes in acreage, supply by crop and by region and subsequent market effects (e.g. price change) can be obtained. By coupling climate, biophysical and economic components into one model, a more integrated assessment can be provided and policy makers can evaluate policies and their feedback not only on the agricultural sector, but also on the biophysical processes and climate conditions.

There is a numerous number of IAMs dealing with the impacts of climate change policies (e.g. DICE, FUND, RICE Nordhaus, 1994; Tol, 1995; Nordhaus & Yang, 1996), but only few specific IAMs for the agricultural sector. Schneider et al. (2008) developed a dynamic nonlinear partial equilibrium programming model of the agricultural and forestry sectors (EUFASOM) in the European Union. The system of joint, price-endogenous, spatial equilibrium market structure with explicit land-use competition between the forestry and agricultural sectors, allows for an evaluation of welfare and market impacts of various policies aiming at reducing carbon dioxide emissions. The EUFASOM is coupled with the crop simulation model EPIC and this way accounts for the biological and economic feedbacks of land-use. Land scarcity and competition between agriculture, forests, nature reserves, pastures, and bio-energy plantations are explicitly represented, whereas environmental change, technological progress, and policies can be examined in the model. EUFASOM is able to estimate competitive economic potentials of land based mitigation, leakage, as well as synergies and trade-offs between multiple environmental objectives. Even though, it has been developed as a multi-period model to investigate changes in policies, technologies, resources, and markets, it can also simulate the effects of climate change and climate policies on the agricultural sector. Similarly, Mestre-Sanchs & Feijo-Bello (2009) developed a multi-criteria mathematical programming model which incorporates model results obtained from the Erosion-Productivity Impact Calculator (EPIC) and a General Circulation Model (GCM).

Integrating biophysical models and global climate models into a partial equilibrium framework significantly improves simulations and allow for a more detailed assessment of biophysical, climatic and agricultural economic feedbacks. However, integrated assessment models often suffer from inconsistencies due to different spatial or temporal resolutions or quality of data and model uncertainty is growing with the number of models and disciplines (e.g. uncertainty about future emissions, impacts, adaptation and mitigation policies). In addition, IAMs based on partial equilibrium approaches face do not account for the interaction between economic sectors, and therefore, show weaknesses in modelling competition between alternative land uses.

1.5.2 Integrated Assessment Models in a General Equilibrium Framework

Crop simulation and global climate models can also be coupled with a general equilibrium model. Beside biophysical, climatic and agricultural feedbacks these models can also evaluate the effects on other economic sectors, which gives policy makers a more comprehensive evaluation of political interventions. The IIASA LUC model for China, for example, investigates the effects of agricultural policies by using a spatially explicit, inter-temporal, welfare-maximization model which takes into account the biophysical and socio-economic characteristics that drive land-use change (Fischer et al., 1996; Fischer & Sun, 2001; Hubacek & Sun, 2001; Albersen et al., 2002). Bosello & Zhang (2005) evaluate climate change impacts on agriculture, by coupling a global CGE model based on GTAP-E with a climate model and a biophysical model, which estimates changes in cereal productivity. The model suggests that climate change has limited impacts on the agriculture (e.g. food supply, welfare) due to adaptation in the economy, but the real costs of adaptation and the adaptation potential are highly uncertain. Therefore, the authors acknowledge that the model faces several limitations such as the simplification and generalisation of climate conditions and crop responses along with a limited number of observations and the negligence of interrelations of climate change with water availability. Furthermore, adaptation at a farm-level is ignored and the model only considers a few kinds of cereal crops. Ronneberger et al. (2009) coupled a global agricultural land-use model, Kleines Land Use Model (KLUM) with a GTAP-based CGE model to globally assess integrated impacts of climate change on cropland allocation. A major difficulty in linking KLUM with the CGE model was the different data format. While the GTAP uses land data measured in value terms with prices normalised to unity, KLUM uses a quantity format, which lead to incomparability between the models. Therefore, Ronneberger et al. (2009) conclude that monetary impacts on the crop producing sector can be underestimated by more than 200% or overestimated if changes in land-use are ignored. Extrapolation of price trends, thus, leads to implausible results.

These models can give a very comprehensive assessment of the whole economy in addition to climate and crop growth responses, but suffer from simplification and lack of econometric foundations as well as loss in details of the agricultural sector.

1.5.3 Discussion

The main advantage of integrated assessment models (IAMs) is the ability to link the climate and biophysical plant processes with detailed agricultural and land-use aspects and to give more detailed economic and environmental feedbacks. Therefore, integrated land-use or assessment models can overcome some of the deficits of pure partial or general equilibrium models, such as an improved representation of land supply or the integration of biophysical impacts of climate change on crop growth and economic response.

Despite these achievements, the complete potential of integrating crop simulation into general or partial equilibrium frameworks is yet unexplored. IAMs increase the risk of inconsistencies and face problems in data formatting (e.g. data formats cause incomparability), sophisticated programming and computational limitations. Often, models require a more detailed feedback of agricultural management with soil and water as well as an improved representation of adaptation at a farm-level. Moreover, most IAMs focus on average temperature changes, and thus, are restricted in their ability to simulate extreme weather events or any other large scale discontinuities and shocks. Also, the probability of obtaining errors strongly increases and the extent of uncertainty may be unmanageable due to the large number of simulated data in IAMs. There is, for example, much uncertainty about future emissions and their driving forces (e.g. mankind, melting of permafrost) or the implementation of adaptation and mitigation policies (Gupta et al., 2003). However, these models are the first attempts to overcome the limitations of prevailing approaches and give more insight into environmental and economic feedbacks and interdependencies.

1.6 Conclusion

The assessment of climate change impacts on agriculture is exceedingly complex and challenging and results vary greatly over time and space. This brief review could only give a general overview on the vast number of studies on climate change impacts on agriculture. Previous research indicates that there will be potential 'climate winners' (e.g. Canada) and potential 'climate losers' (e.g. Egypt) in farming. In some regions, the impacts are more likely to be positive for moderate and gradual climatic changes, but with more severe climate change, impacts are expected to be negative in most regions. The net impacts of climate change and the consequences for producers and consumers are yet unclear and highly controversial.

Accurate assessments of potential net impacts of climate change are essential in order to find the right balance between climate change mitigation and adaptation. Differences between climate change impact assessments often result from methodological limitations or poor data quality (e.g. resolution, sampling). Empirical methods, for example, are based on observed data and examine actual response, hence, allowing for an evaluation of observable impacts and historical adaptation strategies (e.g. irrigation, crop mix). Accordingly, adaptation options under current conditions can be deduced. Statistical estimates can be used to give precise short-term to medium-term predictions.

In the long-term, however, technological progress may improve the adaptation potential or an expansion of agricultural land could increase the production capacities so that empirical models may overestimate the costs of climate change. Equilibrium models, on the other hand, can model technological progress explicitly, and this way consider future adaptation options. Despite the improved long-term predictions of equilibrium models, they often use ad-hoc parameters and ignore the economic viability of response strategies or potential adjustment costs. Therefore, equilibrium models may underestimate the costs of adaptation and climate change.

Both approaches have different shortcomings and only allow for a limited investigation of the range of impacts and behavioural responses. These methodological limitations are likely to introduce bias into simulations of future impacts, and hence, in the assessment of climate impacts. Integrated assessment models combine different models or approaches to overcome some of the limitations of individual approaches. This way, they can give more comprehensive assessments of climate change impacts. Most integrated assessment models, however, require better empirical specification to increase the precision of the model parameters and to reduce the model uncertainty. Further development of integrated land assessment models can significantly improve the accuracy of climate impact assessments for the agriculture.

In addition to methodological uncertainties, there are also regional uncertainties. Most previous research focuses on the US, Africa and India. There are only few studies on regions in the northern latitudes (e.g. Canada, Europe). Europe's agriculture, for example, is highly industrialised, uses modern technologies and is well developed, and thus, European farms are expected to be less vulnerable to changes in the climatic conditions. In addition, the climate in the northern latitudes is more moderate, and thus, more likely to benefit from a long-term warming. These effects are still poorly studied. Moreover, most previous research focuses on assessing the direct impacts of climate change. Future warming may as well alter production technologies (e.g. input substitution, resource efficiency, technical efficiency), and thus, will affect agriculture indirectly.

Climate change impacts on agriculture are still highly uncertain (Alig et al., 2002). Policy makers require spatially and economically disaggregated information on potential climate benefits and costs in order to direct policies aiming at reducing climate change damages (i.e. adaptation) as well as to justify policies aiming at limiting long-term warming (i.e. mitigation). The more accurate climate impact assessments are, the better mitigation and adaptation policies can be balanced and directed to where they are most economic, efficient and effective.

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The Impact of Weather on European Agriculture: Accounting for Input Choice

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Abstract
This study quantifies regional weather impacts on the European agriculture. We use a highly disaggregated 20-year panel covering more than 50,000 agricultural holdings and merge it with high resolution weather data. Using a production function approach, we estimate the impact of temperature and precipitation on irrigated and rainfed cereal yields. Subsequently, we analyse the sensitivity of yields using temperature and precipitation averages for 2021-2050 and 2071-2100 from the regional climate model REMO. The spatial variability reveals that Southern and Central Europe, where losses can rise to more than 55%, are vulnerable to changes in the climatic conditions while Northern Europe benefits from a long-term warming. Overall, yields could be reduced by 19% by 2100.

Keywords: Weather, cereals, yields, agriculture, production function, European Union
JEL-Classification: Q12, Q51, L25, Q54

Chapter 2

The Impacts of Weather on European Agriculture: Accounting for Input Choice

2.1 Motivation

The agricultural sector is expected to be significantly affected by climate change, because it directly depends on the climate and weather, but yet it is unclear whether changes in the climatic conditions and linked weather patterns result in a net gain or loss for agricultural production in northern latitudes and to what extent farm management adaptation could mitigate potential losses. The main objective of this paper is to quantify the impacts of weather on European cereal yields and the sensitivity of cereals to climatic changes, taking into consideration regional and farm-specific differences.

Many existing studies assessing the impacts of climate change on agriculture focus on the US (a major agricultural producer), India or Africa, due to data availability or because they are expected to be more vulnerable to climatic changes (e.g. Kurukulasuriya et al., 2006; Kumar, 2011; Schlenker & Roberts, 2009). These studies show large negative impacts on agriculture due to climate change and emphasize the importance of adaptation in order to limit negative effects (Schlenker et al., 2006, 2007; Schlenker & Roberts, 2009; Deschênes & Greenstone, 2007). The northern latitudes, such as Europe or Canada, are more likely to benefit from climate change, due to a prolongation of the growing season or increased heat accumulation. Despite a number of climate change impact assessment studies on selected countries in Europe across different disciplines, the net impacts of climate change on northern latitudes are still uncertain (e.g. Parry et al., 2004; Ewert et al., 2005; Lang, 2007; Lippert et al., 2009; De Salvo et al., 2011).

Most prior studies employ biophysical models or econometric methodologies. Process based biophysical models use mechanistic equations based on long-term experiments in order to simulate agricultural activities and their interactions within the environment on a daily basis. These models are used to study crop growth by calculating crop growth response to the environment and are based on plant growth functions which are directly linked to climate and nutrient parameters and this way can analyse specific crop types and their management under different weather, soil, or water conditions, and various management practices (e.g. Adams et al., 1995, 1998; Rosenzweig et al., 1993; Rosenzweig & Parry, 1994; Rosenberg & Scott, 1994).

They can be distinguished as descriptive and explanatory (Marcelis et al., 1998). Descriptive models describe crops with their elements, plant organs and processes by using mathematical equations, whereas explanatory models consist of quantitative descriptions of the mechanisms and processes, which simulates the response of a system. Accordingly, biophysical models rely on a broad scientific base and benefit from a rich theoretical structure. This allows for an extrapolation to different conditions, alternative management practices or cropping schemes (e.g. Adams et al., 1995, 1998; Rosenzweig et al., 1993; Rosenzweig & Parry, 1994; Rosenberg & Scott, 1994; Aggarwal & Mall, 2002).

Despite the complexity of such models, the parameters are only validated under relatively small deviations from normal conditions and may perform poorly under extreme events. Furthermore, biophysical process models explicitly prescribe production factors and optimal management decisions. As a result, these models may not adequately reflect input adjustments motivated by profit maximising or cost minimising behaviour (Schlenker et al., 2006). In contrast, statistical models assess historical decisions and incorporate observed input adjustments of farmers. These models have the ability to portray the combined effects of weather fluctuations, climatic conditions, and soil characteristics while controlling for farm management decisions. Due to their structure, statistical models also enable the examination of a limited number of adaptation options of farmers (e.g. Onyeji & Fischer, 1994; Gbetibouo & Hassan, 2005; Schlenker & Roberts, 2009). Therefore, statistical models have been applied to various regions such as India or the US (e.g. Kumar, 2011; Schlenker & Roberts, 2009). There are, however, only a few studies on European regions. These mainly use biophysical approaches in combination with statistical analyses (e.g. Reidsma et al., 2010; Iglesias et al., 2012;

Harrison & Butterfield, 1996) but there are no European-wide statistical crop yield models. Moreover, previous statistical crop yield response studies have avoided dealing with agricultural inputs and typically estimate reduced forms of production functions with weather parameters. These models ignore inputs because of the difficulty in capturing input-related adaptation decisions of farmers (e.g. Schlenker et al., 2006). The input decisions, however, are very likely to be correlated with the weather parameters so that the omission could lead to biased weather coefficients and long-term climate simulations.

This paper presents a detailed statistical analysis of regional production functions in which temperature and precipitation are linked with cereal yields in the EU-25 and explicitly control for input choices.[1] The European Commission for Agriculture and Rural Development provided a highly disaggregated dataset for cereal production at a farm-level. Pairing the farm data with a high resolution weather dataset, we construct a novel and unique panel that covers 25 EU member states from 1989 to 2008. The weather data includes temperature averages and precipitation totals for different growth stages and indicators for extreme events. This study adds to previous research by allowing weather coefficients to vary between different climatic regions within the EU. Our model benefits from the richness in data and enables us to distinguish between different management practices while controlling for various agricultural inputs, farm characteristics, and environmental conditions.

The results contribute to existing literature by using a consistent empirical framework that addresses the important issue of endogeneity in a productivity shock and agricultural input adjustments. Viz. we apply the system Generalized Method of Moments (GMM) estimator in order to consistently estimate temperature and precipitation impacts on cereal yields. The estimated parameters could confirm Computable General Equilibrium (CGE) models and Integrated Assessment Models (IAMs) that are increasingly used for policy analyses but often implement "expert parameters" without empirical verification. An improvement of these models may provide more reliable policy guidance.

The following section (2.2.1) presents the methodology including the theoretical framework, econometric specification and estimation. In section 2.3, we describe the data and introduce the variables. Section 2.4 presents the regression results and section 2.5 applies a regional climate model to assess the sensitivity of yields. We conclude in section 2.6.

[1] Cereals include oats, rye, barley, durum wheat, soft wheat, summer cereal mix and one other cereal category.

2.2 Methodology

2.2.1 Theoretical Framework

Econometricians depict production technologies either through primal (production) or dual (profit) approaches. The latter approach links the profit or net revenue of a farm to weather or climate and implicitly incorporates the management adaptations of the farmer. Thus, dual approaches do not explicitly estimate the technical coefficients of production, which are essential parameters for IAMs. The primal approach, on the contrary, builds on an output-input relationship and thus estimates production parameters at different input intensities.

We face two major challenges when analysing agricultural data in the framework of a production function: (i) simultaneity and (ii) the adequate representation of the production technology. Firstly, Griliches & Mairesse (1995) argue that input variables are chosen in some behavioural manner by the farmer (e.g. profit-maximization, cost-minimization). Productivity shocks (e.g. droughts, nutrient deficiencies, or pest outbreaks) affect the farmer's choice of variable inputs and with, some delay, fixed inputs (Griliches & Mairesse, 1995). This suggests that the input variables are not strictly exogenous but partly predetermined or endogenous, i.e. observed inputs are correlated with unobserved shocks. In this case, simple Ordinary Least Squares (OLS) would be biased. Marschak & William (1944) argue that in particular inputs that are likely to be adjusted to shocks, are subject to simultaneity. Secondly, the production technology needs to be represented by an appropriate functional form, which should ensure theoretical consistency and flexibility (Tchale et al., 2005). Most previous research applies the Cobb-Douglas (CD), Von-Liebig (VL), Mitscherlich-Baule (MB) or the transcendental logarithm function. While the CD is the easiest to estimate, it is based on simplifying neoclassical properties assuming unitary elasticity of substitution (Tchale et al., 2005). Unitary elasticity of substitution places high restrictions on the elasticity values, which can lead to an overestimation of the optimal input quantities (Ackello-Ogutu et al., 1985). The VL and MB functions are based on agronomic theory and are widely used in crop simulation models. However, Tchale et al. (2005) argue that their estimation is difficult and liable to parametric restrictions, when a large number of inputs is involved. These functions become computationally very demanding, especially in statistical models. Furthermore, the MB function does not allow for negative marginal productivities (Finger & Hediger, 2008). The transcendental logarithm (translog) production function imposes no a priori restrictions on the substitution elasticity and the returns to scale. It is a more general production function having numerous applications in agricultural economics (Tchale et al., 2005). Previous studies have shown that the translog function performs statistically better than alternative functional forms and it does not tend to overestimate the impacts of inputs (e.g. Lyu et al., 1984). Additional parameters, contained in this function, allow for a more flexible approximation of the response surface. Despite these advantages, there are two important drawbacks to the translog function. Due to the considerable number of input variables and parameters the function becomes computationally very demanding and tends to result in multicollinearity. However, with a large dataset, e.g. a large panel data set, multicollinearity can be mitigated (Lyu et al., 1984). Accounting for the advantages and disadvantages of the discussed production functions and the fit of the available data for this study, we apply a semi-log production function which is formulated as follows

$$\exp^{(}Y_{it}) = \alpha \prod_{j=1}^{J} X_{jit}^{(\beta_j + \sum_{\tilde{j}=1}^{\tilde{J}} \beta_{\tilde{j}} ln X_{\tilde{j}it})} \times \exp(\sum_{k=1}^{K} \beta_k C_{kit}(1 + C_{kit}) + \sum_{l=1}^{L} \beta_l F_{lit} + \sum_{m=1}^{M} \beta_m P_{mit})$$
$$\times \exp(\delta_1 t + \delta_2 t^2 + \delta_3 t^3 + \epsilon_{it}) \text{ with } \epsilon_{it} = \eta_i + \upsilon_{it} + \psi_{it} \text{ where } \psi_{it} = \rho\psi_{i,t-1}$$
$$\upsilon_{it} MA(0), \psi_{it} AR(1), \quad (2.1)$$

where $j = 1, ..., J$, $\widetilde{j} = 1, ..., \widetilde{J}$, $k = 1, ..., K$ and $l = 1, ..., L$. The yield Y_{it} for farm i with $i = 1, ..., N$ in year t with $t = 1, ..., T$ is dependent on variable (e.g. fertilisers) and quasi-fixed inputs (e.g. machinery) X_{jit}, climatic conditions C_{kit}, farm characteristics F_{lit} and policy changes P_{mit}. Technological progress is represented by a polynomial of degree three t, t^2 and t^3.[2] The error term ϵ_{it} is divided into three components: η_i, υ_{it} and ψ_{it}. The first component, η_i, represents a time-invariant and farm-specific effect, υ_{it} indicates serially uncorrelated errors (e.g. misspecification of the production function) and ψ_{it} denotes a productivity shock with $|\rho < 1|$. Note that Y_{it} is a $NT \times 1$ vector of cereal yields written in an exponential function because the yields are normally distributed and a transformation would lead to a skewed distribution. X_{jit}, $X_{\tilde{j}it}$, C_{kit}, F_{lit} are $NT \times J$, $NT \times K$ and $NT \times L$ matrices of agricultural inputs, weather variables, and farm specific characteristics, respectively. β and δ are vectors of parameters to be estimated with dimension $J \times 1$, $K \times 1$, and $L \times 1$. α is a scalar times a vector of dimension $1 \times NT$.

[2]The cubic time trend showed the best fit and allows for a more flexible technological progress (Doll, 1967).

2.2.2 Empirical Specification

Taking the natural logarithm on both sides of the production function formulated in equation (2.1) gives the following regression model

$$\begin{aligned} Y_{it} = \alpha + \sum_{j=1}^{J} \beta_j x_{jit} + \sum_{j=1}^{J} \sum_{\tilde{j}=1}^{\tilde{J}} \beta_{\tilde{j}j} x_{jit} x_{\tilde{j}it} + \sum_{k=1}^{K} \beta_k C_{kit}(1 + C_{kit}) + \sum_{l=1}^{L} \beta_l F_{lit} \\ + \sum_{m=1}^{M} \beta_m P_{mit} + \delta_1 t + \delta_2 t^2 + \delta_3 t^3 + \epsilon_{it} \end{aligned} \tag{2.2}$$

with $x_{jit} = log(X_{jit})$ and $x_{\tilde{j}it} = log(X_{\tilde{j}it})$.[3] Schlenker et al. (2005) argue that agricultural production on irrigated and rainfed farmland may be differently affected by weather or climate. Irrigation is an adaptation strategy that allows farmers to respond to a reduction in precipitation or increase in temperature. Previous studies estimate separate response functions suggesting that irrigated farms are less vulnerable to climatic changes (e.g. Schlenker et al., 2005; Seo & Mendelsohn, 2008). To account for different responses, we estimate the crop yield functions for irrigated and rainfed farmland separately.

2.2.3 Estimation

Using a large panel data set enables us to exploit the cross-sectional variation to estimate climate effects and the time-series variation to examine weather effects. A major concern about estimating equation (2.2) is the simultaneity of the productivity shock ψ_{it} and the input decisions of the farmer. Ackerberg et al. (2007) propose using the Generalized Method of Moments (GMM) estimator by Blundell & Bond (2000). This is a suitable approach to control for seemingly persistent simultaneity bias, especially when the number of individuals N is large and the number of years T is fixed.[4] GMM consistently estimates the parameters of interest, by modelling equation (2.3) as a dynamic process and using lagged input variables as internal instruments

[3] Taking the natural logarithm has two major advantages: (i) it reduces estimation problems with large annual variations in inputs and the influence of outliers and (ii) the regression coefficients become elasticities and have a meaningful economic interpretation.

[4] Moreover, modelling yield response as a dynamic process allows for the consideration of farming practices or extreme weather influences in the previous year. Soil moisture, for example, is known to show distinctive persistence characteristics by governing major land-atmosphere feedbacks (Orth & Seneviratne, 2012). Moreover, crop rotation or excess fertiliser in the soil due to lower yields caused by a drought will affect the soil conditions and thus farm management in the following year. Hence, yields in the previous year can be used as a proxy for soil moisture memory or farm management.

$$Y_{it} = \alpha + \gamma Y_{i,t-1} + \sum_{j=1}^{J} \beta_j x_{jit} + \sum_{j=1}^{J} \sum_{\tilde{j}=1}^{\tilde{J}} \beta_{jj} x_{jit} x_{\tilde{j}it} + \sum_{k=1}^{K} \beta_k C_{kit}(1 + C_{kit})$$
$$+ \sum_{l=1}^{L} \beta_l F_{lit} + \sum_{m=1}^{M} \beta_m P_{mit} + \delta_1 t + \delta_2 t^2 + \delta_3 t^3 + \epsilon_{it}. \quad (2.3)$$

We adopt the two-step System GMM estimator which is based on two sets of moment conditions following Blundell & Bond (2000). In a first-step, lagged levels are used as instruments in the first-differenced equation. In a second-step, lagged differences are used as instruments in the level equation. Because Windmeijer (2005) shows that the standard errors of the two-step System GMM are severely downward biased, we use a finite-sample correction for the two-step covariance matrix, which enables us to obtain more robust and efficient estimates (Roodman, 2009a). Finally, we include a lagged dependent variable as an explanatory variable assuming that farmer's expectation on y_{it} depends on past realizations of $y_{i,t-s}$ with $s \geq 1$ to consistently estimate other parameters in presence of an autoregressive productivity shock.

2.3 Data

We construct a detailed and novel 20-year farm panel (1989-2008) of more than 50,000 individual farms represented in 25 EU member states. The number of surveyed farms varies within countries and years and some countries are not observed over the entire period due to the enlargements in 1995 and 2004. Accordingly, the panel is unbalanced and contains structural changes. In order to avoid bias and to allow for different production technologies and responses to temperature and precipitation, we estimate separate equations for different regions (compare Table 2.1).

2.3.1 Agricultural Data and Variables

We use a panel of Europe's cereal farms drawn from the Farm Accountancy Data Network provided by the European Commission on Agriculture and Rural Development. The data contains information on the annual production and expenditure on agricultural inputs, the type and size of a farm as well as the irrigated area. The farms in the dataset were surveyed annually and are representative for all cereal farms in the EU-25.[5] For

[5] We include all crop farms that solely or partially produce cereal crops.

confidentiality reasons, NUTS-3 level is the highest resolution available for this data.[6]

The dependent variable Y_{it} denotes the cereal production in tons divided by the area devoted to cereal production (tha^{-1}). The explanatory farm variables consist of agricultural inputs x_{it} and farm characteristics F_{it}. The first set of covariates x_{it}, controls for impacts of major agricultural inputs. $FERT$ denotes fertilisers and controls for nutrients added by the farmer including inorganic and organic fertilisers (e.g. lime, compost, peat, manure). $CROPPROT$ controls for all materials used to protect the crop (e.g. fences, pesticides, frost protection, bird scarer). $MACH$ denotes machinery and controls for agricultural machines used in the operation of a farm, including tractors, cars, lorries and irrigation equipment. These agricultural inputs are measured by the annual expenditure of a farm averaged per hectare farmland. LAB represents the working hours of labour per year to allow for unpaid labour input. By taking the natural logarithm, the input variables become log-normally distributed. Hence, the coefficients represent semi-elasticities. The second set of covariates F_{it}, controls for farm-specific characteristics including altitude, economic size and management practices. Altitude affects the growth of crops and is considered a good proxy for solar radiation (Deressa et al, 2005). The FADN data assigns the farms to three altitude categories. Therefore, we construct binary variables for farms between 300m and 600m above sea level (a.s.l.) and farms above 600m a.s.l. and compare them to the reference group of farms lying below 300m a.s.l.

The economic size of a farm is measured in European Size Units (ESU) and controls for economies of scale.[7] The FADN data assign farms to different ESU categories. Accordingly, we add binary variables for the farm size, where Medium takes on a value of 1 for farms ranging from 8 to 40 ESU and 0 otherwise, Large takes on a value of 1 for farms larger than 40 ESU and 0 otherwise, whereas smaller farms (less than 8 ESU) represent the reference group. Moreover, Organic production controls for management differences and takes on the value of 1 if the farm produces organically and 0 for conventional production. In addition to the farm-specific variables, a time trend is added to reflect technological progress during the sample period (e.g. new crop varieties, improved fertilisers, and cropping practices). The mean values are presented in Table 2.2.

[6] The Nomenclature of Territorial Units for Statistics (NUTS) is a geo-code standard for the subdivisions of the EU countries for statistical purposes.

[7] The ESU is a fixed number of €/ECU of Farm Gross Margin e.g. 1200€. Note that the number of €/ECU per ESU has changed over time to reflect inflation `http://ec.europa.eu/agriculture/rica/methodology1_en.cfm`.

2.3.2 Climate Data and Variables

Pairing the yield data with high resolution weather data, obtained from the European Climate Assessment and Dataset (ECA&D), we construct a new panel for the EU-25.[8]

In this study, we use short-term temperature and precipitation variables to cover yield variations driven by weather changes. We add a linear and quadratic term thereby permitting temperature and precipitation variables to depict possible non-constant effects on yields. A positive linear and a negative quadratic term indicate a hill-shaped relation between yields and the corresponding weather variable. A negative linear and positive quadratic term may indicate part of an S-shaped curve or reflect gaps in varietal adaptation across weather regimes.

Furthermore, we distinguish three main growth stages: (i) the seeding season for the initial development, (ii) the vegetative growth stage for the stem extension and (iii) the generative growth stage for the ripening and harvesting of the plant. We assume that each growth stage has a different length for different regions as indicated in Table 2.1.

To examine the impact of extreme events, we construct two variables controlling for abnormally wet or dry growing seasons. Wet Growing Season indicates if a farm has more rain than the 90th percentile of seasonal rain while Dry Growing Season denotes farms that had less than the 10th percentile of seasonal precipitation. The mean values can be obtained from Table 2.2.

2.3.3 Soil Data and Variables

Consistent estimation requires that the temperature and precipitation variables are uncorrelated with other explanatory variables. Therefore, soil variables indicating the type and quality were drawn from the European Soil Database.[9] $AGRICUL$ denotes the soil type, which takes on a value of 1 if the soil has no limitations to agricultural use and 0 otherwise. High water holding capacity HWC, takes on a value of 1 for high water holding capacity and 0 for low water holding capacity. The organic content of the top-

[8]We use weather data obtained from the E-OBS gridded dataset. Mean temperature and precipitation data are given in a grid-cell format. Averaging the grid-cells for each NUTS-3 region, the temperature and precipitation averages can be allocated to the corresponding farms within the NUTS-3 region.

[9]The soil grid cell data is obtained from : `http://eusoils.jrc.ec.europa.eu`. We calculate the share for each soil type and quality of all grid cells lying within a polygon NUTS-3 region and assign the highest percentage of each type and quality to the corresponding NUTS-3 regions.

Table 2.1: Regions[a]

Region	Countries	Seeding	Vegetative	Generative
Boreal	Sweden and Finland	June	July-August	September
North Atlantic	United Kingdom and Ireland	May	June-July	August
Centre	Belgium, Denmark, Germany, Luxembourg and The Netherlands	April	May-June	July-August
Alpine	Austria	June	July-August	September
Continental	Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia and Slovenia	April	May-June	July-August
North Mediterranean	France	March	April-May	June
South Mediterranean	Cyprus, Greece, Italy, Malta, Portugal and Spain	March	April-May	June

[a]Growth stages are construed from Rötzer & Chmielewski (2001); Trnka et al. (2011); Iglesias et al. (2012).

and subsoil is captured by LOC, where 1 indicates low organic content and 0 indicates high to medium organic content. The mean values are shown in Table 2.2.

2.4 Results and Discussion

The cereal yield functions[10] are estimated via the two-step System GMM estimator with Windmeijer corrected robust standard errors. The validity of the instruments for the System GMM estimator can be evaluated by a set of specification tests (Arellano & Bond, 1991). We apply Hansen's J-test of over-identifying restrictions, with the joint null hypothesis of valid instruments. Validity requires that the instruments are exogenous and uncorrelated with the error term. Because an excessive number of instruments weakens the power of the Hansen test, we limit the number of instruments by reducing the number of lags (Roodman, 2009b). The reported J-statistic is consistent in the presence of heteroscedasticity. The P-values are reported for each model (compare Table 2.3) and indicate no rejection of the validity of the instruments. Also reported in the Tables, a second specification test that examines serial correlation of the residuals of the regression in differences. The Arellano-Bond test for $AR(1)$ and $AR(2)$ indicate first-order serial correlation in the first-differenced equation and no second-order serial correlation.[11]

2.4.1 Temperature and Precipitation Impacts

The temperature and precipitation coefficients of the cereal production functions are reported for each of the six regions in Table 2.3 and Figure 2.1 and represent the mean impact on cereal yields. The last column of the Table presents the results for the irrigated production in the Southern Mediterranean region.[12]

The coefficients reveal that yields are sensitive to both temperature and precipitation. As expected, the coefficients vary between different growth stages. Most quadratic terms are significant, indicating a non-linear response function. Depending on the growth stage of the crop, we find diverse impacts of increasing temperature and precipitation on cereal yields. A warmer spring-time allows the farmer to plant earlier, and a warm generative growth stage allows the crop to mature better, thus increasing yields. The

[10] We controlled for several policy changes (e.g. reforms of the Common Agricultural Policy aiming at reducing environmental pressure in agriculture) in the initial model, but all policy variables were tested insignificant. Therefore, we do not include policy variables in the final model specification.

[11] All estimates approximately lie within the range of OLS and Within Groups estimates, demonstrating the robustness of our findings.

[12] Irrigated cereal production in Europe is concentrated in the southern Mediterranean region.

Table 2.2: Summary statistics[a]

Variable	Unit	Boreal	No Atlantic	Central	Continental	Alpine	No Medi.	So Medi.	So Medi. irr
Y_{it}	tha^{-1}	3.89	6.34	5.99	3.86	4.59	5.91	3.43	4.34
CROPPROT	€ha^{-1}	2651.10	13516.51	9376.95	6593.86	1567.50	8511.72	1567.41	2350.65
FERT	€ha^{-1}	7218.22	15778.81	10435.48	9578.59	2332.60	10062.55	2668.77	4260.11
MACH	€ha^{-1}	68539.06	108573.20	118745.40	74449.87	59778.41	64630.64	28384.54	26442.23
LAB	h ha^{-1}	3688.05	6297.67	5708.67	9170.04	4079.97	3721.66	3795.11	3275.56
Organic production	% of farms	0.07	0	0.02	0.01	0.07	0	0.01	0
Medium	% of farms	0.41	0.38	0.40	0.29	0.25	0.48	0.30	0.29
Large	% of farms	0.07	0.11	0.11	0.18	0	0	0.19	0.16
>600 m.s.l.	% of farms	0	0	0.01	0.01	0.18	0	0.19	0.32
300-600 m.s.l.	% of farms	0	0.01	0.19	0.17	0.48	.17	0.36	0.26
T seeding	°C	14.25	9.99	7.43	12.67	17.15	8.10	9.19	8.89
T vegetative	°C	16.44	14.77	14.37	17.74	18.39	12.18	14.74	12.98
T generative	°C	11.51	15.72	17.84	18.76	13.52	17.22	20.43	19.61
P seeding	mm	63.63	122.42	89.23	53.38	96.96	107.49	44.59	39.87
P vegetative	mm	142.39	129.55	117.66	85.43	217.55	131.77	110.53	119.92
P generative	mm	48.39	72.51	143.09	80.15	88.15	55.25	35.91	32.82
Dry Growing Season	% of farms	0.27	0.18	0.26	0.12	0.27	0.25	0.20	0.25
Wet Growing Season	% of farms	0.27	0.59	0.30	0.67	0.20	0.25	0.23	0.28
LOC	% of farms	0.54	0.24	0.60	0.29	0.70	0.94	0.88	0.81
AGRICUL	% of farms	0.16	0.50	0.54	0.37	0.77	0.82	0.41	0.30
HWC	% of farms	0	0.18	0.64	0.13	0.72	0.74	0.68	0.72

[a] Mean and percentage values by region

Boreal and Continental regions, especially, benefit from higher spring temperatures. In the North Atlantic region an increase of temperature in the spring reduces yields. These temperature effects, however, are highly dependent on the assumed planting dates. Temperature increases during the vegetative growth stage, result in significant negative effects on yields in the southern Mediterranean regions, which have relatively warm conditions already.

Surprisingly, yield reductions are also large in irrigated production, although the vulnerability can be reduced compared to rainfed production. Excess temperature may put the crop under additional heat stress and hence reduce plant growth. During the generative growth stage temperature increases are beneficial, because it increases the grain filling and allows a later harvest (also compare Figure 2.1). This has important implications for adaptation in southern Europe. Even though the yield level of irrigated cereals is higher than for rainfed cereals in the Mediterranean regions, the results indicate limitations to irrigation. Temperature increases, further reduce yields and thus put additional pressure on southern cereal production, because it can, for example, reduce the competitiveness of cereal production in comparison to other land-use options (e.g. crop choice, tourism, housing).

Increasing precipitation is associated with a rise of yields in relatively dry regions at all growth stages. Additional precipitation can assist the plant with nutrient uptake, and supports the plant with reducing heat stress and evaporation. In relatively wet regions, however, we do find a significant negative effect of increasing precipitation on cereal production. If total precipitation exceeds the optimal amount, yields can decrease.

Although, the quadratic specification for the cereal response functions only represent a simplification of the complex agronomic yield theory, the results clearly show that the sensitivity of cereals to temperature and precipitation changes, indicated by the size of the quadratic terms, is highly dependent on the region. For example, while in the Mediterranean North the yield level is amongst the highest, the vulnerability of cereals to temperature increase is more than three times larger than in the Mediterranean South. This calls for more differentiated econometric yield functions that account for the varying sensitivity of yields.

The extreme event variables are only significant for a few regions. In a dry growing season yields decrease by up to 0.23 tha^{-1}. This confirms the effects of reduced carbon assimilation, grain filling and nutrient uptake (Johnson & Moss, 1976). A wet growing season decreases yields in most regions, suggesting that excessive precipitation can lead to flooding or drowning of the plant. In the Alpine region, however, a wet growing season has a significantly positive effect on yields which may be due to the high water capacity in the soil of most farms or an accelerated water run-off in mountainous regions. Overall, the results of extreme precipitation events have to be viewed with caution because the variables do not control for daily maxima or minima.

2.4.2 Farm-Specific Impacts

To the best of our knowledge, this is the first econometric model accounting for input adjustments and productivity shocks in crop yield response functions. We argue that not controlling for farm inputs may confound temperature or precipitation impacts with agricultural input adjustments, and therefore, is more likely to overestimate or underestimate temperature or precipitation impacts. The non-climatic farm-related characteristics are generally in line with agro-economic expectations, but we only find few significant farm-specific variables. This may indicate that input variations between farms do not always yield substantial productivity impacts.

The results confirm that increasing farm inputs, such as fertilisers or crop protection, generally enhance the yields. Organic farms do not use mineral fertilisers and pesticides. These farms show significantly lower yields, especially in the Mediterranean regions where yields are up to 12% lower compared to conventional farms. In addition to the lack of mineral fertilisers and pesticides, Wolfe et al. (2008) observed that organic farmers lack seed varieties that can adapt to organic conditions.

Our results further indicate that medium sized farms are likely to have higher yields than small farms. Medium sized farms are often more industrialised, more professionally managed and have better technical equipment. Large-scale farms, may cultivate extensively and show lower yields than small-scale farms. An enlargement or merge of small farms could increase the yields and may partially compensate for losses resulting from temperature increases.

2.4.3 Geophysical Impacts and Technological Progress

The estimated coefficients for the soil variables suggest that a low organic content (LOC) in the topsoil does not reduce yield in most regions, except for the Mediterranean regions (compare Table 2.3). Agricultural soil ($AGRICUL$) indicates a positive impact on yields in most regions, but in the southern Mediterranean region agricultural soil shows a negative impact on yields. Mediterranean soils are soils which are formed under Mediterranean climate and often show large differences in, for example, the phosphorus

Table 2.3: System GMM results for rainfed and irrigated cereal yields

Variable	Boreal	N Atlantic	Central	Continental	Alpine	N Medi.	S Medi.	S Medi. irr
$Y_{i,t-1}$	-0.0163	0.0840***	0.0450	-0.0772	-0.00544	0.0338	0.242***	0.213***
	(0.125)	(0.0293)	(0.0972)	(0.176)	(0.0449)	(0.0659)	(0.0709)	(0.0260)
Seed temp	1.075***	-0.644***	0.119***	0.780**	0.288***	0.159***	0.0568***	0.1000
	(0.179)	(0.167)	(0.0330)	(0.387)	(0.104)	(0.0429)	(0.0165)	(0.0680)
Seed temp sq.	-0.0380***	0.0340***	-0.00611***	-0.0287**	-0.0111***	-0.0170***	-0.00542***	-0.00887**
	(0.00607)	(0.00827)	(0.00190)	(0.0128)	(0.00305)	(0.00309)	(0.000804)	(0.00374)
Vegetative temp	0.800***	0.529***	0.625***	0.665	0.188	0.461***	-0.155***	-0.267**
	(0.251)	(0.203)	(0.0703)	(0.466)	(0.173)	(0.0905)	(0.0418)	(0.120)
Vegetative temp sq.	-0.0230***	-0.0177***	-0.0279***	-0.0163	-0.00602	-0.0275***	0.00435**	0.00898**
	(0.00757)	(0.00639)	(0.00263)	(0.0123)	(0.00476)	(0.00385)	(0.00174)	(0.00449)
Generative temp	0.0553	-0.169	0.0263	-0.388	0.134**	0.352***	0.458***	-0.146
	(0.0995)	(0.127)	(0.136)	(0.248)	(0.0558)	(0.115)	(0.0457)	(0.0917)
Generative temp sq.	-0.00298	0.00377	-0.00264	0.0120*	-0.00499**	-0.0143***	-0.0102***	0.00433*
	(0.00402)	(0.00394)	(0.00386)	(0.00655)	(0.00202)	(0.00297)	(0.00111)	(0.00242)
No. of obs.	7,634	6,931	69,695	16,806	7,751	41,288	67,981	8,406
No. of farms	1,134	1,151	14,033	4,220	1,427	6,907	13,786	2,738
AR(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.434	0.497	0.771	0.516	0.106	0.175	0.171	0.779
Hansen Test	0.251	0.195	0.490	0.979	0.132	0.151	0.593	0.128

Note: For all regressions robust and Windmeijer corrected robust standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10%level.

Table 2.3 (continued): System GMM results for rainfed and irrigated cereal yields

Variable	**Boreal**	**N Atlantic**	**Central**	**Continental**	**Alpine**	**N Medi.**	**S Medi.**	**S Medi. irr**
Seed precip	0.00937***	0.00174	0.00203***	0.0239***	0.0102***	-0.00314***	0.00322***	0.00439**
	(0.00161)	(0.00200)	(0.000680)	(0.00336)	(0.00135)	(0.000289)	(0.000446)	(0.00176)
Seed precip sq.	-4.05e-05***	-2.15e-05***	-8.83e-06***	-0.000130***	-4.40e-05***	2.63e-06***	-1.61e-05***	-3.89e-05***
	(9.22e-06)	(7.05e-06)	(2.07e-06)	(2.43e-05)	(5.98e-06)	(6.08e-07)	(2.91e-06)	(1.10e-05)
Vegetative precip	-0.00506***	-0.00443***	0.00730***	0.00402	0.00231***	-0.00315***	0.00886***	0.0112***
	(0.00152)	(0.00138)	(0.00102)	(0.00286)	(0.000856)	(0.00103)	(0.000484)	(0.00176)
Vegetative precip sq.	8.57e-06*	5.90e-07	-2.91e-05***	-1.14e-05	-4.98e-06***	-1.39e-06	-1.93e-05***	-3.51e-05***
	(4.80e-06)	(4.14e-06)	(2.96e-06)	(7.88e-06)	(1.73e-06)	(3.18e-06)	(1.23e-06)	(6.38e-06)
Generative precip	-0.00621***	0.00403***	-0.00214***	0.00285*	0.00523***	-0.000710	0.00521***	-0.000363
	(0.00199)	(0.00113)	(0.000508)	(0.00172)	(0.00122)	(0.00117)	(0.00108)	(0.00234)
Generative precip sq.	4.62e-05***	-2.16e-05***	6.65e-06***	-1.35e-05**	-2.47e-05***	-1.21e-05**	-7.22e-06*	1.47e-05
	(1.54e-05)	(5.76e-06)	(1.78e-06)	(6.67e-06)	(5.25e-06)	(5.75e-06)	(4.39e-06)	(1.92e-05)
Dry Growing Season	-0.194***	0.0624	-0.117***	-0.00521	-0.0812***	-0.230***	-0.0220	0.00209
	(0.0362)	(0.0390)	(0.0157)	(0.0369)	(0.0273)	(0.0184)	(0.0159)	(0.0457)
Wet Growing Season	-0.0346	0.0893	-0.0242	-0.0805**	0.123**	-0.0868***	-0.129***	0.0724
	(0.0486)	(0.0608)	(0.0182)	(0.0374)	(0.0514)	(0.0260)	(0.0167)	(0.0616)
No. of obs.	7,634	6,931	69,695	16,806	7,751	41,288	67,981	8,406
No. of farms	1,134	1,151	14,033	4,220	1,427	6,907	13,786	2,738
AR(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.434	0.497	0.771	0.516	0.106	0.175	0.171	0.779
Hansen Test	0.251	0.195	0.490	0.979	0.132	0.151	0.593	0.128

Note: For all regressions robust and Windmeijer corrected robust standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10%level.

Table 2.3 (continued): System GMM results for rainfed and irrigated cereal yields

Variable	Boreal	N Atlantic	Central	Continental	Alpine	N Medi.	S Medi.	S Medi. irr
FERT	2.027	-0.384	1.413	2.659**	0.445	-0.962	0.403	1.522*
	(2.691)	(0.912)	(1.550)	(1.345)	(0.466)	(2.572)	(0.370)	(0.826)
FERT2	0.167	-0.0322	0.0737	0.248	0.0416	0.217	0.0262	-0.240***
	(0.157)	(0.0883)	(0.0594)	(0.180)	(0.0284)	(0.236)	(0.0513)	(0.0926)
CROPPROT	-0.741	-0.219	-2.502*	-1.562	-0.986**	0.199	0.322	-0.363
	(2.506)	(0.373)	(1.510)	(1.333)	(0.459)	(1.347)	(0.277)	(0.536)
CROPPROT2	0.146**	0.0915***	0.175**	0.0401	0.0275	-0.0805	0.00164	-0.116**
	(0.0635)	(0.0208)	(0.0763)	(0.195)	(0.0294)	(0.0734)	(0.0322)	(0.0477)
LAB	5.277*	-0.424	-1.988	4.420**	0.569	1.512	1.006	0.502
	(2.876)	(0.761)	(1.926)	(1.968)	(0.645)	(2.046)	(0.701)	(1.067)
LAB2	-0.249	-0.0125	0.247	-0.247	-0.0793	-0.0574	-0.0130	-0.249*
	(0.181)	(0.0961)	(0.274)	(0.182)	(0.0693)	(0.244)	(0.0581)	(0.145)
MACH	-0.144	1.346*	-2.456	0.510	-0.755	1.275	-0.0835	-1.500**
	(2.002)	(0.762)	(1.993)	(1.143)	(0.785)	(1.731)	(0.319)	(0.666)
MACH2	0.0950	-0.142**	0.0970	0.0150	0.0282	-0.0210	0.0543**	0.178***
	(0.0913)	(0.0656)	(0.100)	(0.0951)	(0.0613)	(0.0571)	(0.0223)	(0.0441)
No. of obs.	7,634	6,931	69,695	16,806	7,751	41,288	67,981	8,406
No. of farms	1,134	1,151	14,033	4,220	1,427	6,907	13,786	2,738
AR(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.434	0.497	0.771	0.516	0.106	0.175	0.171	0.779
Hansen Test	0.251	0.195	0.490	0.979	0.132	0.151	0.593	0.128

Note: For all regressions robust and Windmeijer corrected robust standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10%level.

Table 2.3 (continued): System GMM results for rainfed and irrigated cereal yields

Variable	Boreal	N Atlantic	Central	Continental	Alpine	N Medi.	S Medi.	S Medi. irr
FERTCROPPROT	-0.214	0.0415	-0.0125	-0.0962	0.0621**	0.243	-0.00945	0.317***
	(0.230)	(0.0704)	(0.122)	(0.276)	(0.0249)	(0.187)	(0.0651)	(0.118)
FERTLAB	-0.115	0.201	-0.400*	-0.537**	0.00224	-0.249	-0.00417	0.0185
	(0.318)	(0.154)	(0.230)	(0.218)	(0.0735)	(0.292)	(0.0657)	(0.165)
FERTMACH	-0.249	-0.0110	-0.0107	-0.189	-0.0696	-0.103	-0.0269	-0.102
	(0.254)	(0.133)	(0.197)	(0.176)	(0.0606)	(0.313)	(0.0487)	(0.107)
CROPPROTLAB	-0.0859	-0.217***	0.125	0.0896	-0.0774	0.0525	-0.0655	0.196*
	(0.212)	(0.0632)	(0.260)	(0.232)	(0.0628)	(0.219)	(0.0492)	(0.117)
CROPPROTMACH	0.136	0.152**	0.212	0.224	0.159**	-0.0593	0.00347	-0.197***
	(0.208)	(0.0615)	(0.166)	(0.209)	(0.0663)	(0.136)	(0.0351)	(0.0738)
LABMACH	-0.0281	0.00833	0.137	-0.111	0.0231	-0.0574	-0.102*	0.184
	(0.254)	(0.111)	(0.245)	(0.226)	(0.0959)	(0.178)	(0.0602)	(0.120)
ORGANICPROD	-0.362***	0.0631	-1.327	-0.246	-0.465***	-0.416*	-0.142	.
	(0.130)	(0.504)	(1.188)	(0.482)	(0.162)	(0.235)	(0.100)	.
Large	0.153	0.0422	-0.279***	0.134*	.	.	-0.0583**	-0.0175
	(0.297)	(0.0841)	(0.0729)	(0.0808)	.	.	(0.0252)	(0.0744)
Medium	-0.00522	0.0659	0.100*	0.0126	0.246***	-0.0194	-0.00279	0.149**
	(0.0900)	(0.0476)	(0.0546)	(0.0729)	(0.0599)	(0.0711)	(0.0183)	(0.0611)
No. of obs.	7,634	6,931	69,695	16,806	7,751	41,288	67,981	8,406
No. of farms	1,134	1,151	14,033	4,220	1,427	6,907	13,786	2,738
AR(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.434	0.497	0.771	0.516	0.106	0.175	0.171	0.779
Hansen Test	0.251	0.195	0.490	0.979	0.132	0.151	0.593	0.128

Note: For all regressions robust and Windmeijer corrected robust standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10%level.

deficit (e.g. Torrent et al., 2007) and hence a lack in certain nutrients. If the soil shows limitations to agricultural usage, crop-specific nutrients need to be added, which may explain why in the Mediterranean regions soils with no limitations to agricultural usage do not add to the yield level. Our results further show a significant positive impact of high water capacity in the topsoil on yields. This can improve storage of moisture and thus reduce water stress, but it is also possible that in some regions higher water capacities endanger plant growth by reducing nutrient mineralisation or oxygen supply to roots. However, our results indicate that the marginal benefits still outweigh the marginal cost.

The results show lower yield levels for higher altitudes. In particular, we find that yields of farms above 600m a.s.l. are considerably lower than of farms at 300m to 600m as compared to farms below 300m. Only the Continental region shows higher yields for farms between 300m and 600m a.s.l. The polynomial time trend t controls for technological progress in the agricultural sector. Due to significant technological progress yields on average have increased between 1989 and 2008 by up to 0.54 tha^{-1}.[13] In highly industrialised agricultural regions (e.g. Boreal), technological progress has been considerably lower.

2.4.4 Marginal Temperature and Precipitation Effects

We calculate and graphically present the marginal effects for each region in Fig. 2.1. Previous research claims that southern farms are warmer and much closer to the top of the yield plateau, while northern farms are much colder and to the left of the optimal temperature (e.g. Mendelsohn & Reinsborough, 2007). Warming, therefore, is expected to be more beneficial for northern regions. As expected, we find that the yield levels in southern Europe are amongst the lowest, whereas in central Europe and the North Atlantic region yield levels are amongst the highest. We find, however, that Southern European yields respond less sensitively to temperature increases during than northern European yields (compare column a of Figure 2.1). This indicates that southern European farmers adapted seed varieties that are less sensitive to temperature changes compared to the seed varieties in northern Europe, suggesting that northern European farmers with current seed varieties are more susceptible to temperature changes than southern European farmers. On the other hand, this finding suggests that southern European farmers have fewer adaptation options with regard to seed varieties. Irrigation,

[13] $\frac{\partial y}{\partial t} = \delta_1 + 2 * \delta_2 t + 3 * \delta_3 t^2$

Table 2.3 (continued): System GMM results for rainfed and irrigated cereal yields

Variable	Boreal	N Atlantic	Central	Continental	Alpine	N Medi.	S Medi.	S Medi. irr
LOC	1.368***	0.153**	0.233***	-0.115	-0.0400	-0.227*	0.000272	-0.502***
	(0.181)	(0.0697)	(0.0809)	(0.0754)	(0.178)	(0.121)	(0.0654)	(0.171)
AGRICUL	-0.126	0.0929	0.565***	0.145	0.359***	0.187**	-0.450***	0.257***
	(0.120)	(0.197)	(0.108)	(0.172)	(0.0845)	(0.0777)	(0.0597)	(0.0871)
HWC	.	0.0719	0.587***	-0.0176	-0.0505	0.0912	0.672***	0.491***
	.	(0.0842)	(0.101)	(0.107)	(0.179)	(0.0607)	(0.0817)	(0.117)
300-600 m.s.l.	.	.	0.00751	0.273***	0.0247	-0.675***	-0.160***	-0.104
	.	.	(0.119)	(0.101)	(0.0872)	(0.176)	(0.0456)	(0.0962)
> 600 m.s.l.	.	.	0.00181	0.227	-0.291*	.	-0.239*	0.150
	.	.	(0.157)	(0.314)	(0.168)	.	(0.122)	(0.106)
t	-1.822***	-0.0402	0.211***	-3.287	0.614***	-0.0195	-0.101***	0.262***
	(0.433)	(0.0467)	(0.0320)	(58.74)	(0.204)	(0.0408)	(0.0260)	(0.0916)
t2	0.123***	0.00508	-0.0147***	-0.146	-0.0363**	0.0119***	0.00799***	-0.0269***
	(0.0297)	(0.00492)	(0.00314)	(3.203)	(0.0149)	(0.00383)	(0.00284)	(0.00861)
t3	-0.00265***	-0.000129	0.000350***	0.00838	0.000691**	-0.000492***	-0.000172**	0.000817***
	(0.000681)	(0.000153)	(0.000117)	(0.0581)	(0.000351)	(0.000116)	(8.76e-05)	(0.000247)
Constant	-29.35	3.088	11.79	35.51	-2.243	-3.918	-6.331***	4.308
	(19.49)	(3.693)	(9.424)	(357.9)	(3.439)	(8.203)	(2.125)	(3.349)
No. of obs.	7,634	6,931	69,695	16,806	7,751	41,288	67,981	8,406
No. of farms	1,134	1,151	14,033	4,220	1,427	6,907	13,786	2,738
AR(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.434	0.497	0.771	0.516	0.106	0.175	0.171	0.779
Hansen Test	0.251	0.195	0.490	0.979	0.132	0.151	0.593	0.128

Note: For all regressions robust and Windmeijer corrected robust standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10%level.

however, reduces the vulnerability to temperature changes as indicated by the slopes of the irrigated and rainfed response function.[14]

Compared to temperature changes, the yields respond less sensitively to precipitation changes. Increasing precipitation shows a significantly positive marginal impact on cereal yields in most regions (compare column b of Figure 2.1). In the North Atlantic, the Boreal and the northern Mediterranean regions the precipitation rates are amongst the highest in Europe. In these regions, increasing precipitation has more heterogeneous effects, with negative marginal impacts on yields during seasons with high average precipitation rates as well as in the subsequent season. On the other hand, our results imply that a reduction in precipitation can have significant negative impacts, especially in the southern Mediterranean region. During the main growth stage of cereals, a precipitation decrease is particularly damaging. Interestingly, the irrigated yields also decrease with lower precipitation, indicating that there are limitations of irrigation.

2.5 Sensitivity Analysis using Climate Change Scenario Data from a Regional Climate Model

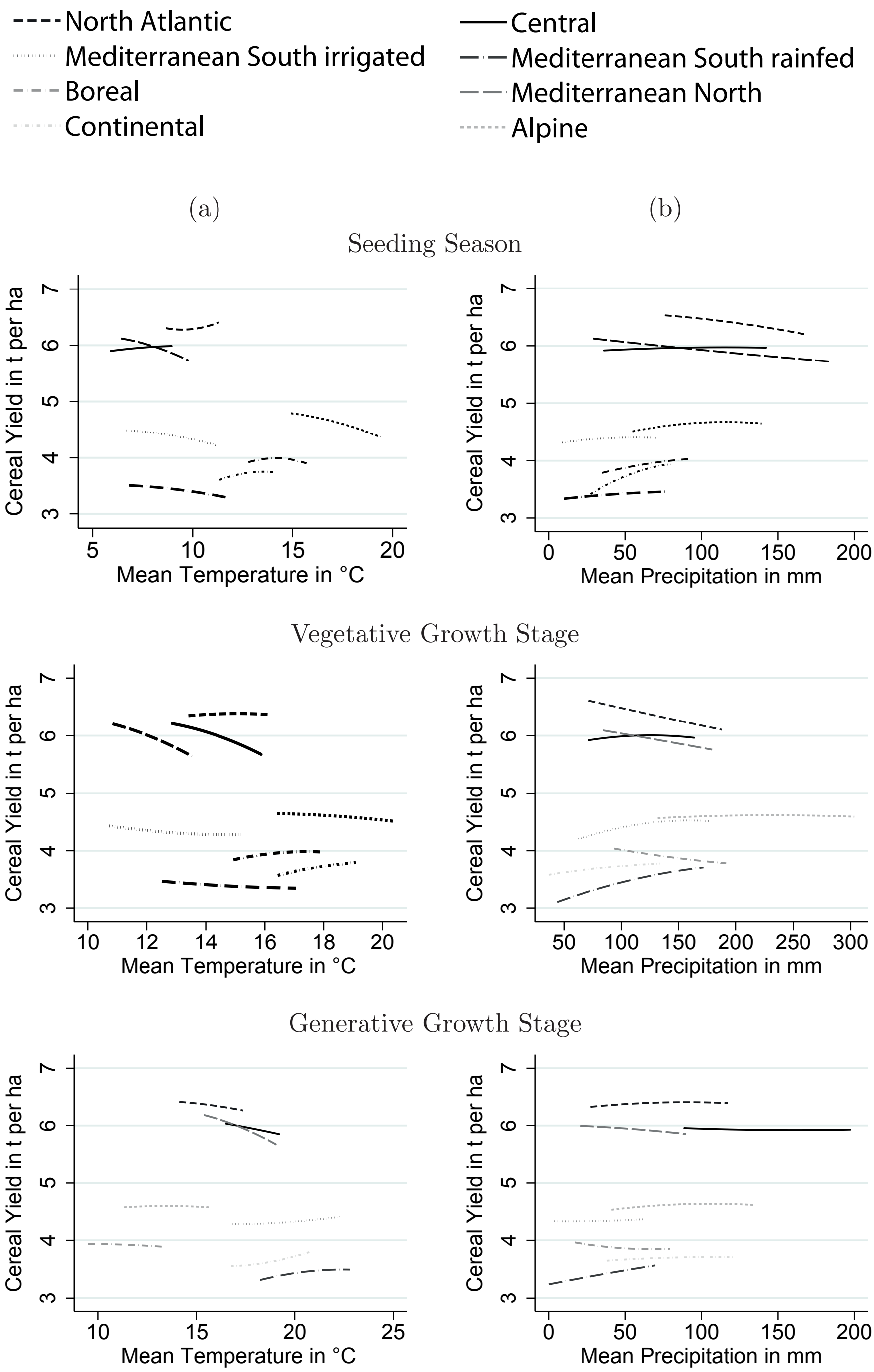
The standard representation of climate uses weather patterns averaged over 30 years. Here, we use REMO weather simulations for the three IPCC scenarios, taken from the regional climate model REMO, a former numerical weather prediction model (Jacob, 2001, 2005a,c,b).

The REMO model simulates the three IPCC scenarios A1B, A2, and B1. The A1B storyline describes a scenario of fast economic growth and an increasing global population until the mid-century and a decline thereafter (IPCC, 2007). This scenario is associated with a rapid introduction of new and more efficient technologies and a balanced use of fossil fuels and renewable energies. The A2 scenario describes a heterogeneous world with a constantly increasing population, a locally oriented economic development and fragmented technological progress which is slower than for other scenarios (IPCC, 2007). The B1 scenario depicts a convergent world with population growth similar to the A1B scenario, but with rapid economic change towards a service oriented economy, reduced material intensity and usage of clean and resource-efficient technologies (IPCC, 2007).

To assess the sensitivity of cereal yields to long-term changes of temperature and

[14]Note that we do not control for increases in the maximum or minimum temperature which require better data and could reveal different impacts as examined by Schlenker & Roberts (2009).

Figure 2.1: Marginal temperature (a) and precipitation impacts (b) on cereal yields



precipitation, we use the REMO Ensemble data for the three IPPC scenarios. The climate variables in REMO cover air temperature (TEMP2), stratiform precipitation (APRL) and convective precipitation (APRC). The average seasonal precipitation was calculated as a sum of stratiform and convective precipitation. The initial data is measured in mm/h. The average temperature is measured in absolute values and is converted to Centigrade. Because the REMO data is given on a 0.5 degree grid, we use ArcGIS to approximate the average temperature and precipitation of each NUTS-2 region by calculating a mean over all central points of each grid cell lying within the NUTS shape.

We compare average growing season precipitation totals and temperatures in the three IPCC scenarios for the periods 2021-2050 and 2071-2100 to 1989-2008 and predict the average yields for each scenario in Table 2.4. The largest change in temperature is found in scenario A2 with an average increase of 4.3 °C, whereas the greatest precipitation change is observed in scenario A1B with an average increase of 8.4 mm. The smallest change in temperature is given in scenario B1. By 2100 the average yield levels of the EU-25 decrease in all three scenarios, with the largest reduction (19%) in scenario A2 and the smallest reduction (5%) in B1.[15] Compared to previous research, the net loss is relatively small (e.g. Schlenker & Roberts, 2009) due to yield gains in the northern regions. In the southern Mediterranean, however, the yield losses are substantial (55%). Even with irrigation, the losses in the southern Mediterranean regions cannot be mitigated by more than 10% and are still significant (46%). This has serious implications for land-use decisions in southern and northern Europe (e.g. crop mix). Therefore, in the short-term, decision makers need to assist in the adaptation process, especially in southern Europe (e.g. education programs, financial assistance, promotion of adaptation). In the long-term, farmers in southern regions need to adopt crop mixes that are less temperature sensitive whereas farmers in northern regions are able to increase cereal yields which can reduce the net loss within Europe.

The spatial distribution of yield changes are shown in Fig. 2.2-2.3. It should be noted that the change of yields is the difference between the yields for the reference period 1989-2008 and the projected yields under the climatic conditions in 2021-2050 and 2071-2100. In the Boreal region, yields increase in all three scenarios, with the largest increases by 2100. In Central Europe and the Mediterranean North, yields decline in most regions and in particular under the A2 scenario. In the Mediterranean South, yields decline in Greece and Italy in most regions. In Spain and Portugal, however, the yield response to temperature and precipitation changes is more heterogeneous. This may be due to

[15] We only consider rainfed cereal yields for the REMO simulations.

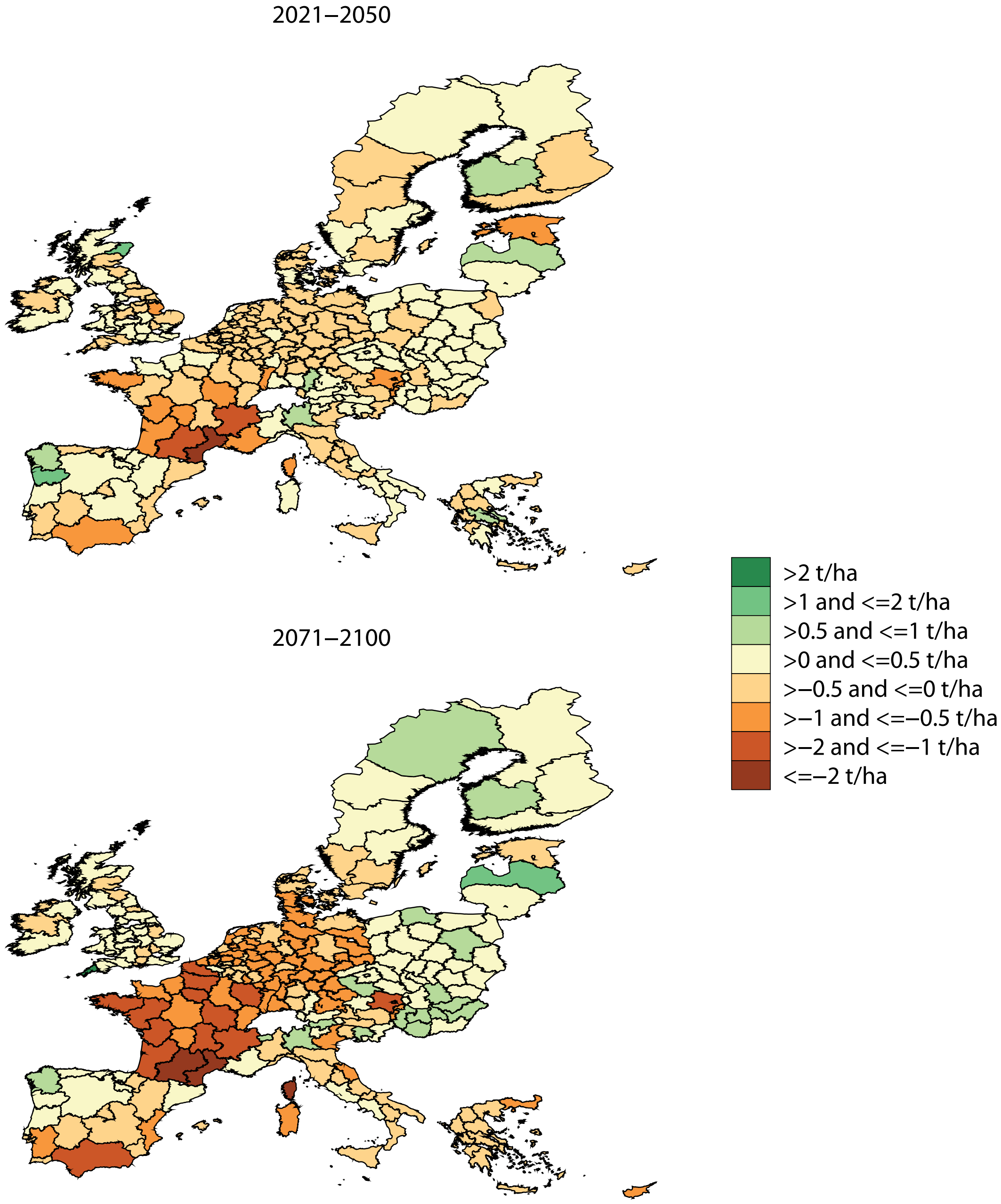
Table 2.4: Sensitivity of Yields to climate change

Scenario		**A1B**	**A2**	**B1**
Mean seasonal temperature	1989-2008	13.8	13.5	13.8
	2021-2050	15.3	14.9	14.5
	2071-2100	16.3	17.8	15.1
Seasonal precipitation sums	1989-2008	292.1	234.7	340.8
	2021-2050	300.0	225.0	341.8
	2071-2100	300.5	240.2	348.1
ΔYield in tha^{-1}	2021-2050	-0.22	-0.25	-0.20
	2071-2100	-0.42	-0.91	-0.25
ΔRainfed yields in tha^{-1}[a]	2021-2050	-1.48	-1.87	-1.19
	2071-2100	-1.42	-2.63	-1.24
ΔIrrigated yields in tha^{-1}[a]	2021-2050	-1.45	-1.69	-1.44
	2071-2100	-1.68	-2.21	-1.56

Source: Calculations based on REMO Scenario Data. [a]Calculations based on the southern Mediterranean region.

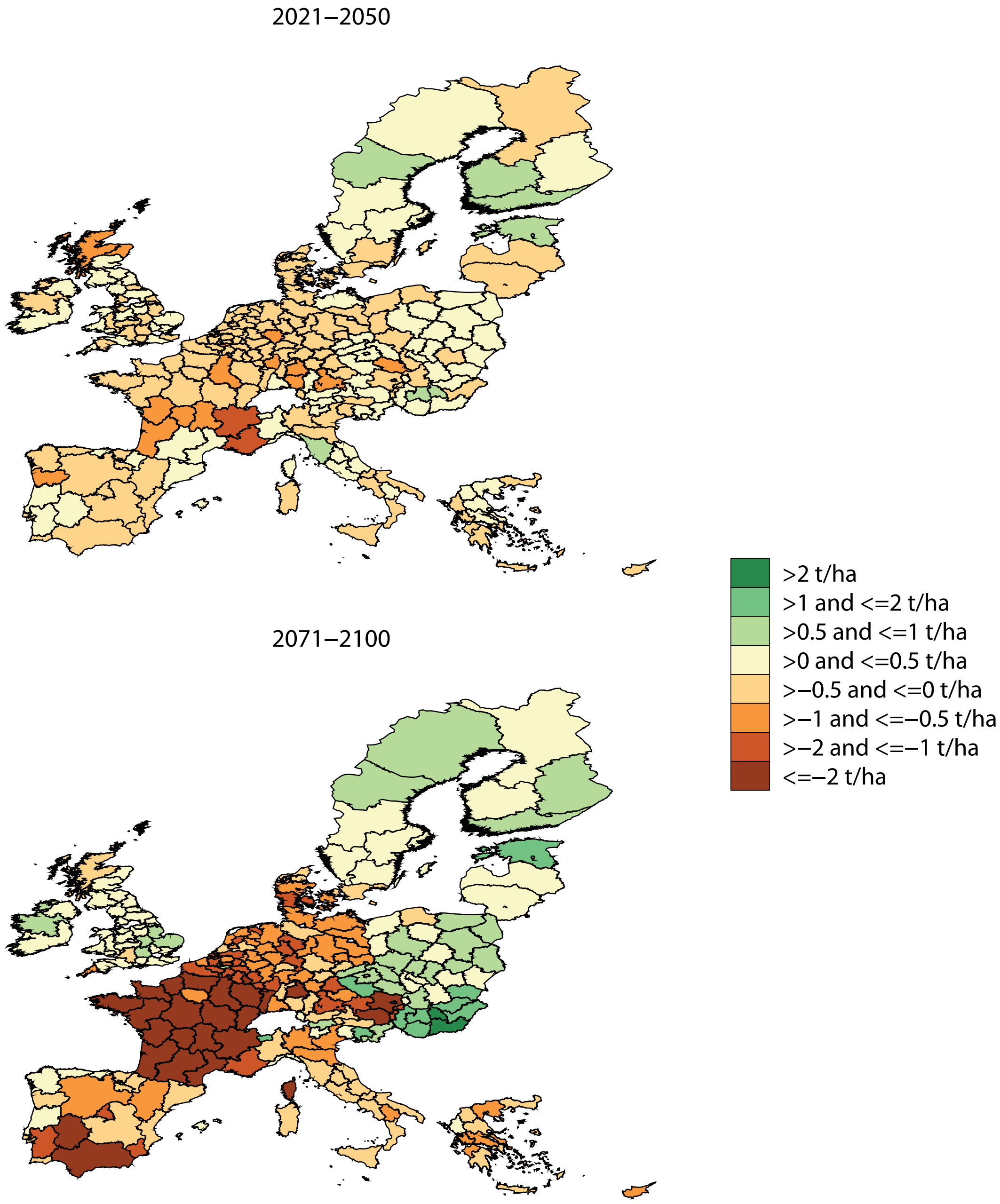
the REMO predictions, which show great temperature variability between the NUTS-2 regions. Additionally, the precipitation in the REMO model is overestimated for the regions bordering the Atlantic Ocean. Accordingly, we cannot draw clear conclusions about the sensitivity of yields in these regions. It should be noted that these scenarios do not project changes in the cereal production by 2050 and 2100, but indicate the yield variability in three exemplary SRES scenarios only.

Figure 2.2: Change of cereal yields under the A1B scenario



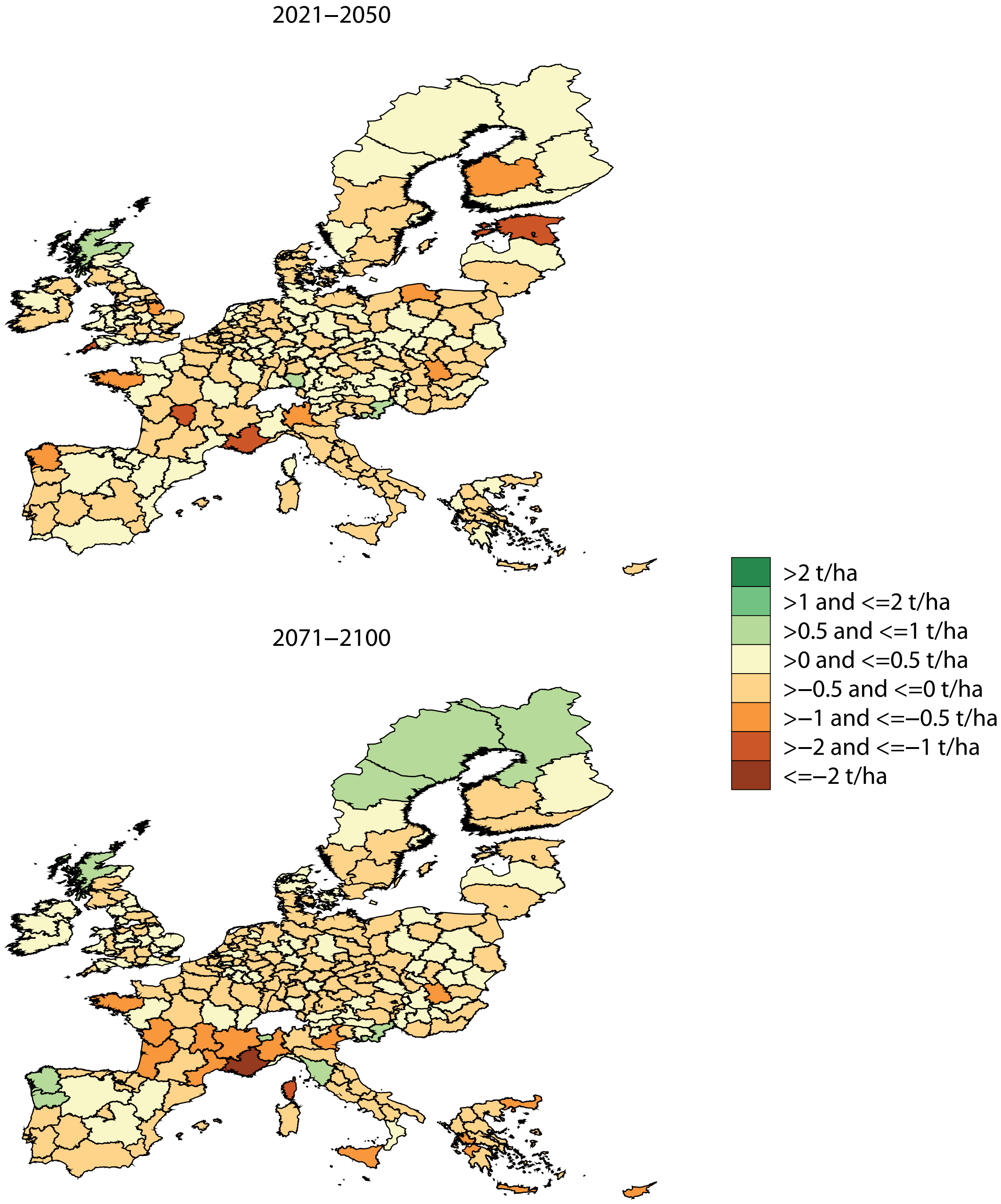
Source: Simulations based on REMO scenario data. Average yield level for 1989-2008 compared to the predicted average yield level for the periods 2021-2050 and 2081-2100.

Figure 2.3: Change of cereal yields under the A2 scenario



Source: Simulations based on REMO scenario data. Average yield level for 1989-2008 compared to the predicted average yield level for the periods 2021-2050 and 2081-2100.

Figure 2.4: Change of cereal yields under the B1 scenario



Source: Simulations based on REMO scenario data. Average yield level for 1989-2008 compared to the predicted average yield level for the periods 2021-2050 and 2081-2100.

2.6 Conclusion

This study evaluates the impact of climatic and non-climatic factors on the mean cereal yields in the EU-25. For this purpose, we construct a novel 20-year panel which combines disaggregated agricultural data covering approximately 50,000 individual cereal farms and high resolution weather and soil data. By using a production function approach with dynamic regression methods, we account for the simultaneity of productivity shocks and agricultural input decisions so that the weather parameters can be consistently estimated.

We find that annual weather variation is highly significant in explaining annual variation and indicates a significant non-linear relationship between temperature and cereal yields, leading either to a boost or a reduction of yields depending on the region and farm management practices. However, we do not find a consistent climate response function for European cereal farming. The regional response functions and the associated vulnerability of yields to temperature and precipitation changes differ significantly. We suggest that southern European farmers adopted seed varieties that are less vulnerable, and therefore, respond less sensitively to temperature changes and have lower yield levels than northern Europe. Irrigation can increase the total level of yields by about 1 tha^{-1} compared to rainfed cereal production, but the yield level remains below average European yield levels. Moreover, we find that irrigation reduces the vulnerability to temperature increases, which is in line with previous studies on US agriculture(e.g. Schlenker et al., 2005) and Latin America (e.g. Mendelsohn & Seo, 2007), which find that irrigated farms are less sensitive to climatic changes. On the other hand, we find that northern Europe, irrespective of its higher total yield levels, is more vulnerable with prevailing seed varieties and production technologies, but has higher adaptation capacities than southern Europe (e.g. adoption of heat resistant seed varieties or irrigation technologies). These results have serious implications for cereal production in southern Europe. Firstly, yield levels in southern Europe are closer to the maximum so that a future temperature rise is more likely to further reduce yields. And secondly, irrigation can reduce the vulnerability of cereal yields, but can increase the production cost, and hence, reduce the competitiveness of cereal farmers in southern Europe.

Precipitation changes have considerably smaller, but more adverse effects on the yields. On the one hand, we find that cereal yields in relatively wet regions (e.g. United Kingdom) are reduced by up to 0.5 tha^{-1} by 100 mm more precipitation. On the other hand, more precipitation is highly beneficial for relatively dry regions (e.g. southern

Mediterranean regions), where yields can be increased by up to 0.5 tha^{-1} by the same increase in precipitation, confirming that farmers can increase yields with irrigation.

Our approach can be used to reveal the climate sensitivity of yields at various input levels. Accounting for decisions on the input level is a crucial part for farm level adaptation which often is neglected in statistical crop yields models. Comparing the marginal impacts of climate change by applying the regional climate model REMO, we find that yields respond very sensitively to changes in climatic conditions. The projections using three exemplary climate change scenarios indicate that the Mediterranean regions and central Europe are more vulnerable to warming and have a more heterogeneous yield response (e.g. yield increase in some regions and yield loss in other regions). The largest net yield reductions ($\approx$1 tha^{-1}) are shown in the A2 scenario by 2100. While southern Europe has profound yield losses ($>$2.5 tha^{-1}), northern European regions, are likely to benefit ($>$0.5 tha^{-1}). Overall, yields are reduced by 19% by 2100 in the A2 scenario.

It should be noted that this study focuses on the unmitigated yield response of cereals to temperature and precipitation. Technological progress (e.g. increased drought resistance or water use efficiency) and input use adjustments, for example, can reduce the impact of climate change on cereal yields. Moreover, welfare effects depend on how agricultural producers and markets adjust to changing climate (Rosenzweig & Hillel, 1998; Schlenker et al., 2006). For example, if production shifts to northern Europe, consumers may not be affected but farmers in central and southern Europe have to bear the production losses. If farmers in dry regions shift to different crops and crop varieties or install irrigation technologies, consumers may encounter welfare losses as a result of higher prices.

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The Economic Impacts of Climate Change on European Agriculture: A Complementary Ricardian Approach

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Abstract
This study introduces a novel Ricardian approach, which exploits long-run temperature and precipitation trends to project potential impacts of climate change on European agriculture. Using a 20-year panel of 1000 NUTS regions in the EU-12, we estimate three Ricardian models applying cross-sectional methods and a novel long differences approach, which reduces short-term variation of the land values. The long differences approach suggests that maximum gains occur at a temperature of 0.76°C higher than the cross-sectional models. In the A2 scenario, this would result in a net land value reduction in the EU-12 of 17% to 64%, depending on the method. Both approaches, however, indicate that most losses are concentrated in southern Europe (−84% to −92%). Given the large difference between the cross-sectional and long differences estimates, a clearer distinction weather and climate variability is needed and although net losses from modest gradual climate change may be limited with continuing adaptation, the damages may be significantly increased by short-term variability.

Keywords: Agriculture, climate change, Europe, Ricardian analysis, welfare
JEL-Classification: Q11, Q51, Q54, O52

Chapter 3

The Economic Impacts of Climate Change on European Agriculture: A Complementary Ricardian Approach

3.1 Motivation

The mean temperature in Europe has increased by 0.8 °C over the past century and is expected to increase by 1 to 5.5°C by 2080 (IPCC, 2007), with the largest warming in the Mediterranean regions. These changes are expected to affect agriculture more than other sectors, because it depends on climatic conditions and weather patterns. Policy makers require comprehensive impact assessments on agriculture in order to derive adequate response strategies.

Agricultural impact assessments using empirical data mainly apply two methods: (1) the estimation of crop yield response functions or (2) a hedonic approach. Crop yield response functions allow analysing the direct impact of weather and climate on different crop types, but they do not account for adjustments that help farmers maintain economic viability in the face of changing temperatures and precipitation patterns (e.g. crop choice, production technology). The hedonic approach (Ricardian model) is based on cross-sectional methods and thus implicitly accounts for adaptation by estimating the impacts of temperature on the land value. Land values represent the present expected value of the future stream of profits, and therefore, in theory, embody any possible or expected adaptation to average changes in the climate. Using cross-sectional variation with land value as the dependent variable would then determine the desired long-run relationship between climate and the value of productivity, when land is put at its most profitable use (e.g. reached its long-term equilibrium). Comparing two different regions that are the same in every respect except that one is warmer than the other, then allows for an estimation of climate change impacts on adapted agriculture.

Ricardian models are well established and widely applied because of their advantages. While there are numerous studies on the US, India or Africa (e.g. Mendelsohn et al., 1994; Schlenker et al., 2005, 2006; Deschênes & Greenstone, 2007; Massetti & Mendelsohn, 2011; Mendelsohn et al., 2001; Kumar, 2011), the literature for Europe is limited (Lang, 2007; Lippert et al., 2009; Van Passel et al., 2012).

Most previous research relies on single cross-sectional analysis, but some studies have used repeated cross-sections and estimated the Ricardian model separately for each year of data in order to assess the robustness of the climate coefficients (e.g. Mendelsohn et al., 1994; Deschênes & Greenstone, 2007; Massetti & Mendelsohn, 2011; Mendelsohn et al., 2001). Most of these studies, however, could not replicate the results for the same sample of a different year and thus the climate coefficients varied over time and were unstable (Massetti & Mendelsohn, 2012). This could lead to ambiguous welfare projections in the long-run.

Massetti & Mendelsohn (2012) argue that repeated cross-sectional estimations are effectively misspecified because the estimates of time-varying variables should not vary over time. This study argues that also purely cross-sectional methods are biased intertemporal approaches, because they may not reflect undistorted expectations about long-term profits. Instead, we suggest that farmers' expectations about future streams of profits are also driven by the current variability in inter-annual temperatures which often lead to fluctuations in farm outcomes (e.g. yields, profits). Positive changes in farm outcomes may increase expectations about future streams of profits, whereas negative outcomes may reduce expectations about future streams of profits. The changes in farmers' expectations are embedded in the land values. For this reason, we suggest that the climate coefficients which are estimated for a single cross-section, are biased when land values contain an additional arbitrary value of changing expectations. In addition, to the influence of inter-annual temperature fluctuations, farmers are also uncertain about the actual impacts of future climate. This uncertainty may be larger in single-cross-sections than for repeated cross-sections or panel data, and therefore, the entire dataset should be exploited. Accordingly, the objectives of this study are as follows:

i How does climate (change) impact agricultural land values in the EU?

ii Are there notable differences between short-term (weather variability) and long-term (climate change) impacts on welfare?

iii How do the quantitative welfare impacts differ between regions?

In order to overcome the limitations of the cross-sectional approach we adopt an approach developed by Burke & Emerick (2012) and implement the long differences method. We use a 20-year panel and construct averages for two decades. By first-differencing the two decades, the influence of short-term temperature variability is reduced and fluctuations of farmers' expectations about future profits are reduced. This approach explains the difference in long-term land value by using long-term temperature difference. In addition, it enables us to compare regions with a long-run temperature increase to regions with constant or decreasing long-run temperatures. By comparing the impact of the variation in trends (e.g. climate) we can draw better conclusions on the impact of changes in climate on agriculture.

The remainder of the paper is structured as follows: In section 3.2, we describe the methodology including the theoretical framework, econometric specification and estimation. In section 3.3 we describe the data and introduce the variables. Section 3.4 presents the regression results. This is followed by a scenario analysis using a regional climate model in section 3.5 and a conclusion in section 3.6.

3.2 Model

3.2.1 Theoretical Framework

The Ricardian method is a cross-sectional approach which allows for an examination the impacts of climate change on agricultural production and implicitly takes into account farmers' adaptation strategies. This method builds on the "law of rent" by Ricardo (1817), which implies that land rents reflect the net productivity of farmland (Mendelsohn & Reinsborough, 2007). Economic theory suggests that land value equals the discounted sum of future profits, it should reflect the expectation of farmers on how well they can cope with a change in the climatic conditions. Accordingly, if farmers allocate land among different agricultural activities (e.g. crop choice, livestock) in order to maximise revenues, the farmland value V will equal the discounted sum of future expected cash flows when land is at its most productive use. When markets expect productivity to be persistently reduced by higher temperatures in the future, in spite of any adaptation efforts, then land values should decline in regions that have warmed. Therefore, farmland value per hectare (V) can be formulated as

$$V_{ik} = \int R_{ik,t} e^{\phi t} dt = \int \left[\sum_{k=1}^{K} p^o_{k,it} q^o_{k,it} (q^a_{k,it}, c_{it}, s_{it}) - \sum_{k=1}^{K} p^a_{k,it} q^a_{k,it} \right] e^{\phi t} dt \tag{3.1}$$

where $R_{ik,t}$ is the net revenue of farm i for output k in year t. p^o and q^o denote the output price and output quantity, p^a and q^a indicate agricultural input prices and quantities, c_{it} are climatic conditions and s_{it} are other exogenous influences, such as soil characteristics or socio-economic determinants, and ϕ is the discount rate. The farmer chooses the outputs q^o and inputs q^a to maximise net revenue. The Ricardian method does not explicitly model land allocation or input and output choices, but estimates the total value of land so that equation 3.1 can be reduced to

$$V_i = f(c_i, s_i) \text{ where } c_i = f(t, p) \tag{3.2}$$

where V_i is the value of land for farm i, c_i is a function of temperature t and precipitation p. The functional form of $f(\cdot)$ is unknown a priori. We estimate: (i) two conventional cross-sectional Ricardian models and (ii) a novel Ricardian model using a long differences approach following Burke & Emerick (2012) to examine a possible bias in single cross-sectional models. The "conventional Ricardian models" can be specified as

$$V_i = \alpha + \beta_1 t_i + \beta_2 t_i^2 + \beta_3 p_i + \beta_4 p_i^2 + \beta_5 t_i p_i + \sum_{j=1}^{J} \gamma_j s_i + \epsilon_i \tag{3.3}$$

where V_i is the value of land for farm i with $i = 1, ..., N$. t_i and p_i are temperature and precipitation means, respectively. s_i is a NJ times 1 matrix of soil and environmental characteristics. The alternative approach makes use of the panel structure by constructing two long-run averages. Following Burke & Emerick (2012) we use equation 3.3 to construct long-term land value, temperature and precipitation averages for two multi-year samples and calculate changes in average land value, average temperature and average precipitation. We use two decades a and b and average the years in period a by $V_{i,a} = \frac{1}{10} \sum_{t \in a} V_{it}$ and do the same for period b. Equation 3.3 for period a becomes

$$\bar{V}_{i,a} = (\beta_1 \bar{t}_{i,a} + \beta_2 \bar{t}^2_{i,a} + \beta_3 \bar{p}_{i,a} + \beta_4 \bar{p}^2_{i,a} + \beta_5 \bar{t_{i,a} p_{i,a}} + \gamma s_i + \epsilon_{i,a}) \tag{3.4}$$

where s_i are time-invariant variables. Defining period b similarly, we "long difference" and get

$$\begin{aligned} \bar{V}_{i,b} - \bar{V}_{i,a} = \beta_1(\bar{t}_{i,b} - \bar{t}_{i,a}) + \beta_2(\bar{t}^2_{i,b} - \bar{t}^2_{i,a}) + \beta_3(\bar{p}_{i,b} - \bar{p}_{i,a}) \\ +\beta_4(\bar{p}^2_{i,b} - \bar{p}^2_{i,a}) + \beta_5(\bar{t_{i,b}p_{i,b}} - \bar{t_{i,a}p_{i,a}}) + \gamma(s_i - s_i) + (\epsilon_{i,b} - \epsilon_{i,a}) \end{aligned} \tag{3.5}$$

The time-invariant variables drop out and equation 3.5 simplifies to the (ii) "long differences Ricardian model" as follows

$$\Delta\bar{V}_i = \beta_1\Delta\bar{t}_i + \beta_2\Delta\bar{t}^2_i + \beta_3\Delta\bar{p}_i + \beta_4\Delta\bar{p}^2_i + \beta_5\Delta\bar{t}_i\bar{p}_i + \Delta\epsilon_i \tag{3.6}$$

The expected marginal impacts of an increase in the temperature t and $\bar{t}$, respectively, on land value can be derived by

$$E\left(\frac{\delta V_i}{\delta t_i}\right) = E\left[V_i\right]\left(\beta_1 + 2 * \beta_2 t_i + \beta_5 p_i\right) \tag{3.7}$$

$$E\left(\frac{\delta \bar{V}_i}{\delta \bar{t}_i}\right) = E\left[\bar{V}_i\right]\left(\beta_1 + 2 * \beta_2 \bar{t}_i + \beta_5 \bar{p}_i\right) \tag{3.8}$$

The impact of precipitation can be derived similarly, but previous research found only small impacts from precipitation changes, partly because farmers can easily adapt by implementing irrigation if necessary. In order to calculate the total impact of climate change or the welfare loss ΔW_n in region n, we compare the estimated value of land under different temperature and precipitation scenarios (T_{A1B}, W_{A1B}) to the value of land under present climatic conditions (T_0, W_0). In addition, we use weighting factors to weight each location by ω_i which represents the total area for each NUTS 3 region. This way, we do not restrict an expansion of agricultural area. Accordingly, welfare changes are calculated as follows

$$\Delta W_n = E_{V_{in}}\left(T_{A2}, W_{A2}\right) - E_{V_{in}}\left(T_0, W_0\right) * \omega_n. \tag{3.9}$$

The total impact is equal to the sum of the regional impacts

$$\Delta W_{n,A2} = \sum_{n=1}^{N} E_{V_{in}}\left(T_{A2}, W_{A1B}\right) - E_{V_{in}}\left(T_0, W_0\right) * \omega_n \tag{3.10}$$

where N is the total number of regions and ω_i is the weighting factor. We repeat these calculations for the B1 $(\Delta W_{n,B1})$ scenario.

3.2.2 Empirical Specification

The long differences model (LD) is specified as follows

$$\Delta V_i = \sum_{c=1}^{C} \beta_c \Delta c_{n,\Delta c>0} + \sum_{c=1}^{C} \beta_c \Delta c_{n,\Delta c<0} + \Delta\epsilon \tag{3.11}$$

where ΔV_i denotes the "long differenced" land values, Δc_n denote the "long differenced" temperature and precipitation. ϵ denotes the standard error and is assumed to be spatially correlated (compare diagnostic tests for spatial dependence in Appendix 4A). Therefore, we adjust for spatial correlation by clustering the NUTS 2 regions.

In order to compare the LD approach to typical Ricardian approaches, we estimate two cross-sectional Ricardian models. Previous research has used spatial and aspatial models. Modellers, however, disagree which specification should be preferred. Seo (2008) shows that spatial models capture complex spatial dependence better and result in lower impacts of climate change than aspatial models. In order to account for uncertainty in the correct specification, we estimate both a spatial autoregressive (SP) and a least squares model (LS), where the simple least squares model is specified as follows

$$V_i = \alpha + \sum_{c=1}^{C} \beta_c c_n + \sum_{s=1}^{S} \beta_s s_n + \sum_{f=1}^{F} \beta_f f_n + \epsilon \tag{3.12}$$

where V_i denotes the land value, c_n indicates the climatic conditions, s_n are the socio-economic conditions. Additionally, we control for some soil and farm characteristics denoted by f_n. The standard errors are clustered at the NUTS 2 level due to spatial correlation. The spatial autoregressive model is formulated as

$$V_i = \alpha + \rho W V_i + \sum_{c=1}^{C} \beta_c c_n + \sum_{s=1}^{S} \beta_s s_n + \sum_{f=1}^{F} \beta_f f_n + \epsilon \text{ where } \epsilon \; N(0, \sigma^2 I) \tag{3.13}$$

where ϵ is a spatially uncorrelated error term. The parameter ρ denotes the degree to which nearby locations, given by the weighting matrix W, are correlated with each other. The spatial model is estimated via maximum likelihood.

3.3 Data and Variables

This study uses a farm-level panel dataset constructed by Trapp & Schneider (2013), which is based on the *Farm Accountancy Data Network (FADN)* of the European Commission on Agriculture and Rural Development. The farm dataset is a highly unbalanced panel covering approx. 65,000 farms represented in the NUTS 3 regions[1] of the EU-12 and ranges from 1989-2008. The farm data is paired with detailed soil and climate information from the *European Soil Database* and the *European Climate Assessment & Dataset (ECA&D)*.

The FADN data contains detailed information about individual farms including, the value of land and the utilised agricultural area (UAA) owned by the farmer. In order to compare the results of the cross-sectional and long differences approach, we aggregated the data to the NUTS 3 level and obtain a balanced panel dataset.

Overall, the dataset covers approx. 4,000,000 hectares of the utilised agricultural area (UAA), which corresponds to 8% of the total UAA in the EU-12. We use farm-specific land value in € per hectare as the dependent variable (V_i).[2] Using land value rather than land rent has several advantages. The land rent concept builds on the assumption of perfect competition, so that excess profits are driven to zero and rents equal net income (Ricardo, 1817; Mendelsohn et al., 1994). This is a highly restrictive assumption, particularly for Europe, where agriculture is largely subsidiesed. Furthermore, European land rent contracts expire and get renewed after several years. Therefore, rental prices do not reflect the future expected cash flows of farmers, but the current agricultural productivity of the land. The purchase price of farmland (in theory) reflects future expected cash flows.

In order to account for heterogeneous adaptation strategies, we use the complete sample with diverse farm types, including field crop, cereals, oilseeds, protein crops, horticulture, wine, orchards, fruits, olives, permanent crops, mixed crops, mixed crops/livestock, and granivores specialists.[3]

In addition, we control for different altitudes assuming that farmers are willing to pay differently for different altitudes. We distinguish between the share of farms

[1] Nomenclature of Territorial Units for Statistics

[2] Land value in the FADN dataset is defined as the net of acquisition costs that a farmer has to pay for non-rented land of similar situation and quality. The FADN dataset contains an opening and closing valuation for the land, therefore, we calculated the average of the opening and closing valuation.

[3] For a more detailed definition of the various farm types: `http://ec.europa.eu/agriculture/rica/detailtf_en.cfm?TF=TF14&tf_Version=8900`.

above 600m above sea level (> 600) and the share of farms below 600m above sea level. Furthermore, we distinguish between coastal and land-locked regions due to the differing agro-climatic conditions (e.g. saline air or water) by creating a binary variable for each NUTS 3 region with a coastal border. Livestock density, organic farming and other controls are not included in the model, because they are assumed to be possible adaptation measures of farmers, and therefore, are not expected to stay constant over time.

Temperature and precipitation information is drawn from the ECA&D. The data is stored in a 0.25 degree regular latitude-longitude grid. The grid cell information is allocated to the NUTS 3 regions, which have polygon shapes, by creating 50 centroid points for each grid cell and calculating the average of all centroid points of all grid cells lying within a NUTS region.[4] This way we give more weight to the value of grid cells with larger shares in the polygon NUTS region and vice versa.

Average seasonal temperatures and seasonal precipitation totals are calculated from observations between 1960 and 2008. Annual values are assumed to represent weather fluctuations and are likely to introduce bias due to their high variability. Therefore, we approximate the impacts of climate, by constructing 30-year average temperatures (t_{30}) and 30-year mean precipitations sums (p_{30}) for the main growing season[5]. The climate variables comprise linear and quadratic terms to allow for a non-monotonic response (Lippert et al., 2009; Mendelsohn & Seo, 2007).

Soil information is drawn from the European Soil Database. The 10km x 10km grid data files are similarly allocated to each NUTS-3 region, by creating 50 centroid points for each grid cell and overlaying all centroid points on the NUTS shape file. Shares for three soil related parameters and characteristics are constructed for each NUTS region. This way we can assess the impact of different soil types on land values.

Soil texture influences the capacity for water storage in the topsoil and is available to growing crops. We distinguish high (>140mm/m), moderate (100-140mm/m) and low (<100mm/m) water capacity indicated by hwc (high) and mwc (moderate). The organic carbon content of the topsoil, which holds a great proportion of nutrient cations and trace elements that are important to crop growth, indicates the degree of natural fertiliser available for crops. We distinguish high (>6%), moderate (2-6%), and low (<2%) organic carbon content indicated by hoc (high) and moc (moderate).

[4] 50 centroid points are considered sufficient to accurately allocate the environmental data to the NUTS 3 regions.

[5] For simplification, we follow the literature and assume that April-September have the largest impact on agricultural production.

The summary statistics for all variables can be obtained from Table 3.1.

Table 3.1: Summary statistics

Variable	**Unit**	**1989-1998**		**1999-2008**		**2008**	
		Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
V	€ ha^{-1}	9,747.76	15,705.38	11,279.14	18,289.72	12,846.60	4,765.52
t30	°C	13.31	2.09	13.80	2.17	13.29	2.47
p30	mm	184.63	58.43	169.39	72.07	177.33	78.27
hoc	%	0.67	8.18	0.99	9.78	1.05	10.19
moc	%	21.90	41.35	24.84	42.88	27.12	44.49
hwc	%	60.99	48.81	59.91	48.86	63.21	48.25
mwc	%	11.36	31.71	14.39	34.55	17.58	38.09
$>$ 600m	%	7.80	26.83	7.80	26.83	7.80	26.83
coast	%	32.25	46.77	32.25	46.77	32.25	46.77

3.4 Results and Discussion

The econometric models are estimated for the whole sample, including all crop farms as well as mixed livestock and crop farms, which are assumed to be directly (yields) or indirectly (fodder, pasture) affected by climate in order to examine the impacts of climate on the entire agricultural sector and to account for the full range of adaptation options. We correct for spatial correlation by clustering the error terms for the LS and the LD model at the NUTS 2 level. The spatial lag model can capture more complex spatial dependence, but is assumed to be inconsistent if not correctly specified (Seo & Mendelsohn, 2008). The results for our three models are given in Table 3.2 and 3.3 and graphically represented in Fig. 3.1.

The variation of the climate coefficients between the cross-sectional and the novel long differences approach is of particular interest. The linear temperature terms are positive and significant, whereas the quadratic terms are negative, suggesting an inverted U-shape response of land value to temperature, which is in line with findings in previous research. Although the climate coefficients do not change signs between the models, the responsiveness of land value to temperature delivers significantly different estimates in the cross-sectional and long differences approach, suggesting different temperature thresholds for the cross-sectional and the long differences models. Previous research has only shown a small or insignificant impact of precipitation on land value (e.g. Seo

& Mendelsohn, 2008). Our results also suggest an insignificant effect of precipitation in the three models. The final specifications do not include an interaction term of temperature and precipitation, because it had an insignificant effect on the temperature and precipitation coefficients and the models.

Table 3.2: Cross-sectional regression results

	Least Squares		**Spatial lag**	
Variable	**Coeff.**	**S.E.**[a]	**Coeff.**	**S.E.**
t30	6,824***	(2,657)	5,814**	(2,489)
$t30^2$	-236.2***	(92.93)	-196.7**	(87.04)
p30	-23.30	(12.31)	-18.29	(11.54)
$p30^2$	0.0231	(0.0164)	0.0182	(0.0153)
hoc	18,259	(6,961)	15,058**	(6,521)
moc	5,805***	(1,819)	4,769***	(1,704)
hwc	7,175***	(2,007)	5,739***	(1,880)
mwc	121.7	(2,491)	542.9	(2,333)
> 600m	-2,755	(3,837)	-1,271	(3,594)
coast	3,612*	(1,759)	3,683**	(1,648)
Constant	-37,905**	(18,733)	-44,368**	(17,547)
Obs.	824		822	
R^2	0.050			
ρ			0.978***	(0.0223)
σ			19,113***	(472.0)

Note: Standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% * significant at the 10%level. [a]Standard errors are clustered at the NUTS 2 level.

In addition, several control variables have a significant impact on land value. The organic content of the topsoil has a large and significant impact on land value, where a high organic content has an approximately three times larger impact than a moderate organic content. A moderate water capacity has no significant effect whereas a high water capacity of the topsoil considerably increases the value of land. Mountainous regions, defined as regions above 600m a.s.l., have a negative but insignificant influence on land value. Furthermore, coastal regions have a significantly higher land value, than land-locked regions. This may be due to competition for available land in coastal regions (e.g. tourism, settlement, fishery, agriculture), favourable environmental conditions (e.g. excellent soil or climatic conditions), or better infrastructure (e.g. roads, distance to ports, access to markets).

Table 3.3: Long differences regression results

Variable	Coeff.	S.E.[a]
$\Delta t30_{t>0}$	7,278*	(3,839)
$\Delta t30^2_{t>0}$	-1,920*	(1,040)
$\Delta p30_{p>0}$	49.54	(31.21)
$\Delta p30^2_{p>0}$	-0.0957	(0.0679)
$\Delta p30_{p<0}$	-65.99	(80.29)
$\Delta p30^2_{p<0}$	0.161	(0.579)
Constant	-3,416	(3,193)
Obs.	834	
R^2	0.022	

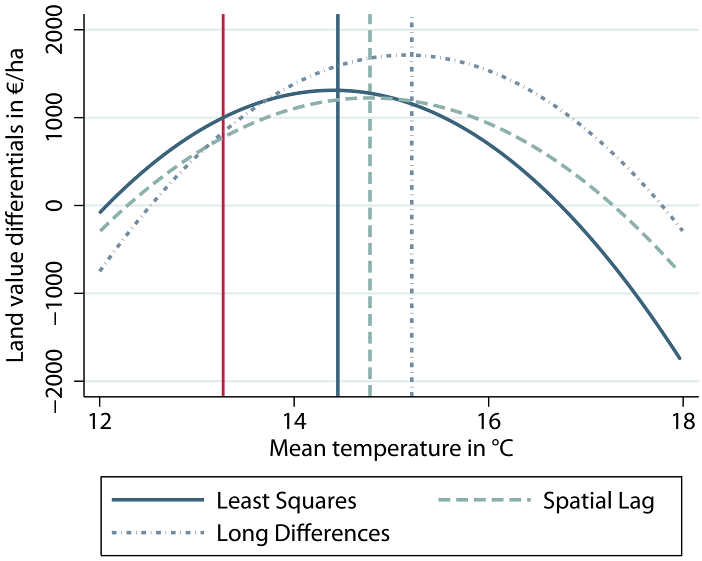
Note: Standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. [a]Standard errors are clustered at the NUTS 2 level.

Ricardian analyses can estimate the temperature at which the average land value is maximised, hereinafter called the optimal temperature. We suggest that the LD approach reduces short-term variability, whereas purely cross-sectional approaches examine a smaller sample, and therefore, are more likely to be biased by short-term variability. We find that the optimal temperature (t^*) differs considerably between the conventional cross-sectional and the long differences approach, as indicated in Fig. 3.1. While the LS model ($t^*_{LS} = 14.45°C$) and the SP model ($t^*_{SP} = 14.78°C$) show lower optimal temperatures, the LD model reveals a comparatively high optimal temperature ($t^*_{LD} = t_a + t^*_{dev} = 15.21°C$). These differences would lead to considerably different welfare impacts when assessing temperature changes.

We suggest that these differences result from a weather-related bias in the land value. The Ricardian method builds on the assumption that long-term climate variations (e.g. climate change) are exploited via cross-sectional variation in the land value. We assume that long-term climate is not isolated from short-term changes in purely cross-sectional approaches, because land value, defined as farmers' expectations about future streams of profits, are partly determined by current profit, which is influenced by short-term weather variability (e.g. droughts, heat waves, heavy precipitation events).

In the short-run, for example, farmers remain with established seed varieties and production technologies that are most productive for current climatic conditions. A sudden temperature increase, for example, can reduce the productivity when lacking intra-annual adaptation options (e.g. irrigation), but can increase profits when markets are not adjusted. Thus, current profits do not necessarily reflect long-run productivity because fixed production factors in the short-run may limit adaptation. The estimated optimal temperature in cross-sectional approaches, is therefore lower than in the long differences model and maximum land value is higher due to adaptation restrictions in the short-run.

Figure 3.1: Marginal temperature impacts and land price differentials by model



Previous research, using repeated cross sections, had mixed results for the climate coefficients and often could not replicate the results from one year to the next.[6] The climate coefficients, as well as the welfare effects, changed year by year Massetti & Mendelsohn (2012). By averaging the land value over a longer period, the long differences approach can separate longer term processes (e.g. climate change) from short-term events in a single year (e.g. relatively strong deviations of annual temperature from the climate) and this way reduces uncertainty (e.g. farmers' uncertainty about future profits) and weather-related fluctuations in farmers' expectations about future streams of profits.

The temperature difference due to weather bias between the LS and LD model is about $+0.76°$C. This corresponds to an average difference of the land value of 259 €ha^{-1} or 1.3 bn€ in total for the agricultural sector in the EU-12.

[6]Repeated cross-sections are estimated separately on each year of data.

3.5 Projection of Climate Change Impacts using a Regional Climate Model

Our last empirical exercise builds projections of the impacts of future climate change on agricultural outcomes in the EU-12 in order to test for bias in long-term projections. We combine econometric estimates with temperature and precipitation projections from the regional climate model REMO for the A2 and B1 IPCC emission scenarios. The projections demonstrate the potential benefits and damages from climate change under high-emission (A2) and low-emission (B1) scenarios. By using two diverse scenarios, some of the uncertainty associated with future climate change can be depicted.

Table 3.4 summarises future average temperature and precipitation changes and the associated land value differentials for the period 2071-2100. Under the A2 scenario, for example, the LS model suggests a decrease in the land value of approximately 64% which is equivalent to 98bn€ compared to a situation without climate change. As expected, the damages of climate change projected by the LD model (−17%) are considerably smaller than the damages projected by the conventional cross-sectional models (−44 to −64%) in the high emission scenario. In the low emission scenario, in contrast, projections with the LD model show considerable gains for farmers and a small increase of land value using the SP model (3%). In contrast, the LS model shows also negative impacts in the B1 scenariothan for the cross-sectional models (15 to 17%), which is due to the shift of the optimal temperature when reducing weather-related bias. Multiplying the damages and benefits for the utilised agricultural area in the EU-12 gives the total welfare impact. The aggregated welfare reduction amounts to −35bn€ in the LS model. On the other hand the LD model based damages are around 30% lower compared to the cross-sectional approaches.

In Fig. 3.2 to 3.4, we project average changes in land values by 2100 for two IPCC scenarios and the three different models for the combined effect of temperature and precipitation changes. All scenarios show a significant reduction of welfare in southern Europe. The results of the conventional cross-sectional models show a generally negative trend for land prices in southern Europe and a generally positive trend for northern Europe with some variance, whereas the LD model shows a more consistent picture with less variance. Moreover, the conventional models project larger welfare losses in southern Europe (−92%) and smaller welfare gains in northern Europe (+7%) compared to the LD model, which projects losses of up to 84% in southern Europe and welfare gains of 12% in northern Europe. The B1 scenario projects net benefits for agriculture in the

Table 3.4: Land value differentials under climate change[a]

	Period	**A2**	**B1**
Δ(temperature)[b]	2071-2100	+3.19°C	+2.01°C
Δ(precipitation)[b]	2071-2100	−92mm	−34mm
Least squares approach	2100	−64.45%	−9.34%
	ΔW^c	−98bn€	−14bn€
Spatial lag approach	2100	−43.87%	+3.32%
	ΔW^c	−67bn€	+5bn€
Long differences approach	2100	−17.04%	+26.98%
	ΔW^c	−26bn€	+41bn€

[a]Land values are weighted by region size. [b]Absolute change compared to sample climate (1979-2008). [c]Values in 2008€.

EU-12, but the A2 scenario indicates a division into two parts with benefits in the North and losses in the South, suggesting that Europe comprises of two to three agro-climatic zones that could be affected differently. Even though the net loss for the EU-12 is relatively small, the damages for the Mediterranean regions are substantial, suggesting that Mediterranean farmers will require assistance for more effective adaptation, improved technologies or even occupational redeployment.

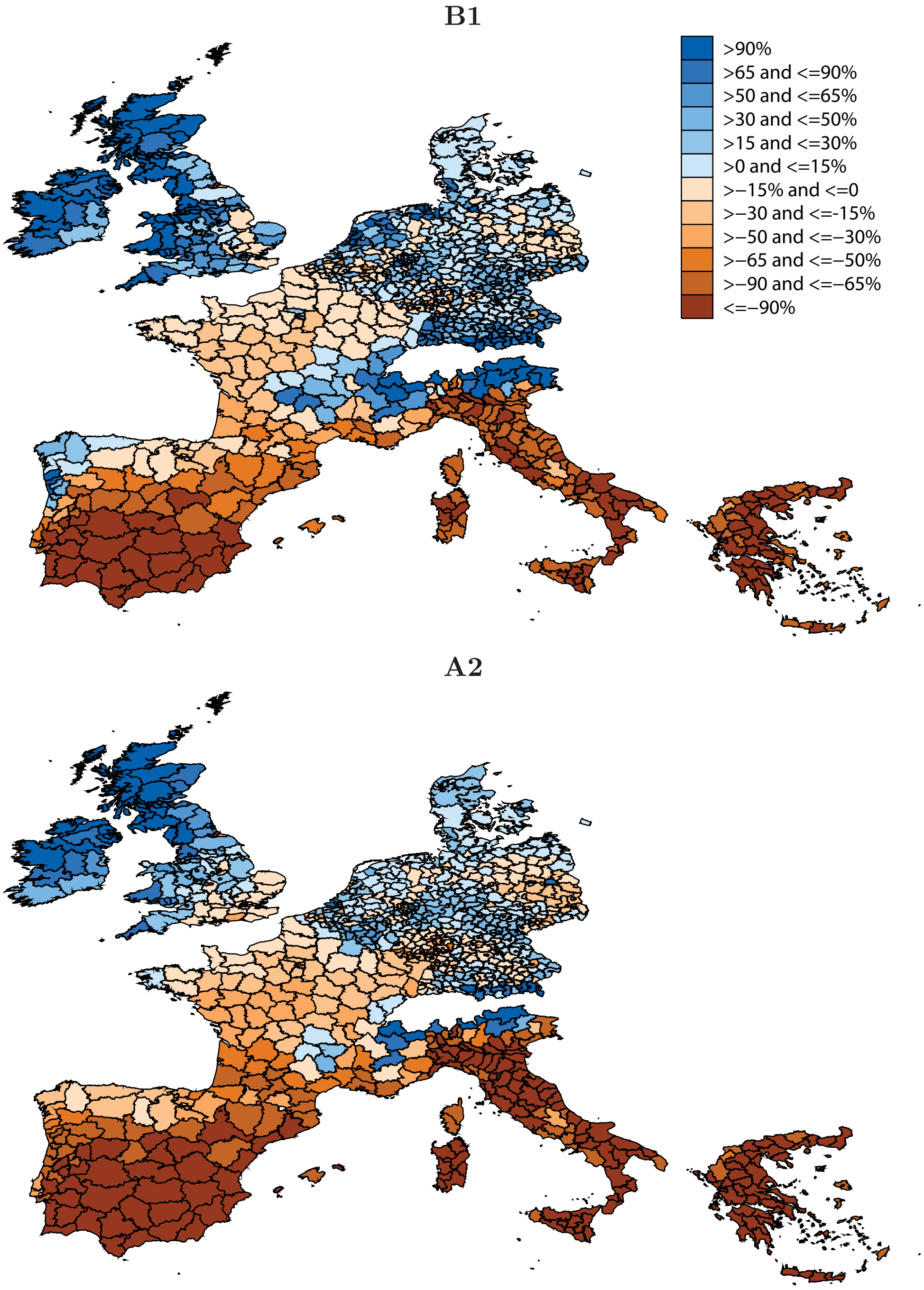
3.6 Conclusion

Quantitative assessments of future climate change impacts on various economic outcomes provide essential input into policy making. These analyses can assist in investment decisions aiming at reducing emissions, assessing mitigation efforts as well as in deriving and prioritising adaptation policies. This study uses a set of Ricardian models to assess the impacts of future climate change on the welfare of European farmers.

A common concern about many existing Ricardian analyses is the inconsistency of climate coefficients in cross-sectional approaches which often lead to ambiguous welfare assessments. These studies typically rely on single or repeated cross-sectional models. We exploit a larger range of variation in land value, temperature and precipitation trends across the EU-12 to investigate how farmers' welfare responds to longer-run trends in the climate. We argue that land value does not only reflect farmers' expectations about discounted future profits, but that land value is also driven by current profits which are amongst others determined by annual weather variability. Using a novel approach, we show that the optimal long-term temperature is about $+0.76°C$ higher when reducing the weather-related bias. The weather-related bias results in considerably different climate impact assessments and welfare projections, because a "low" optimal temperature shifts damages closer to the present and as a consequence reduce the available time with benefits, whereas a "high" optimal temperature is more likely to render positive net present values. Accordingly, the results suggest that the long differences approach can improve the accuracy of climate estimates.

Using climate change scenarios from a regional climate model, we project potential impacts on farmers' welfare by 2100. Our impact estimates suggest an average reduction in welfare of $17-64\%$, with current technologies and continuing adaptation efforts. This corresponds to a loss of GDP in the EU-12 by $1-3.3\%$ in 2008€. This is considerably smaller than the predicted losses for the US (e.g. >50%: Schlenker & Roberts, 2009) or for Africa (e.g. 75%: Seo & Mendelsohn, 2008). Even though the net impact of climate

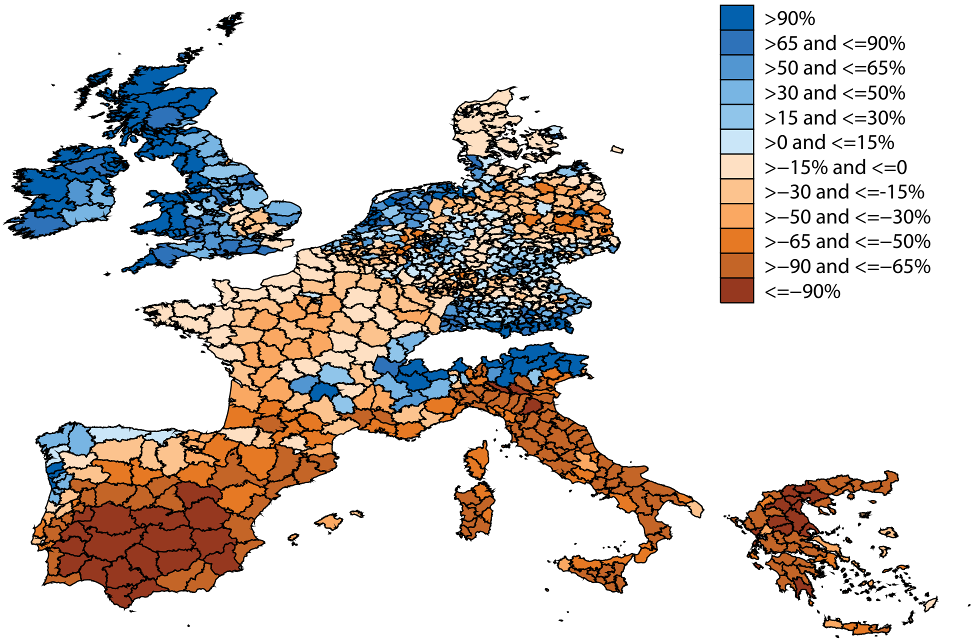
Figure 3.2: Change of land value in 2100 in %/ha (least squares approach)



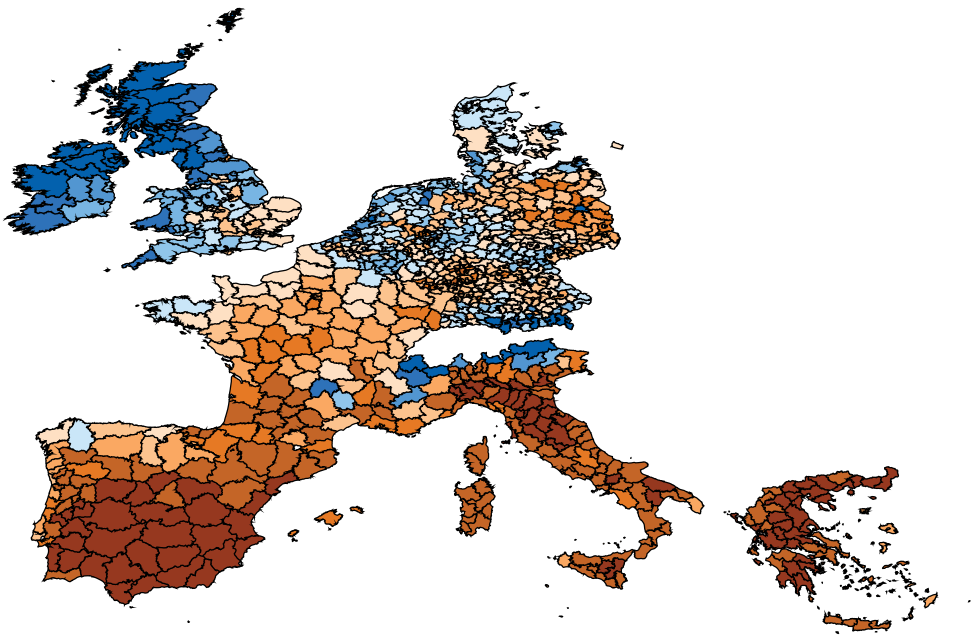
Note: The scales refer to percentiles. The largest and smallest value correspond to the 90th and 10th percentile, respectively.

Figure 3.3: Change of land value in 2100 in %/ha (spatial lag approach)

B1

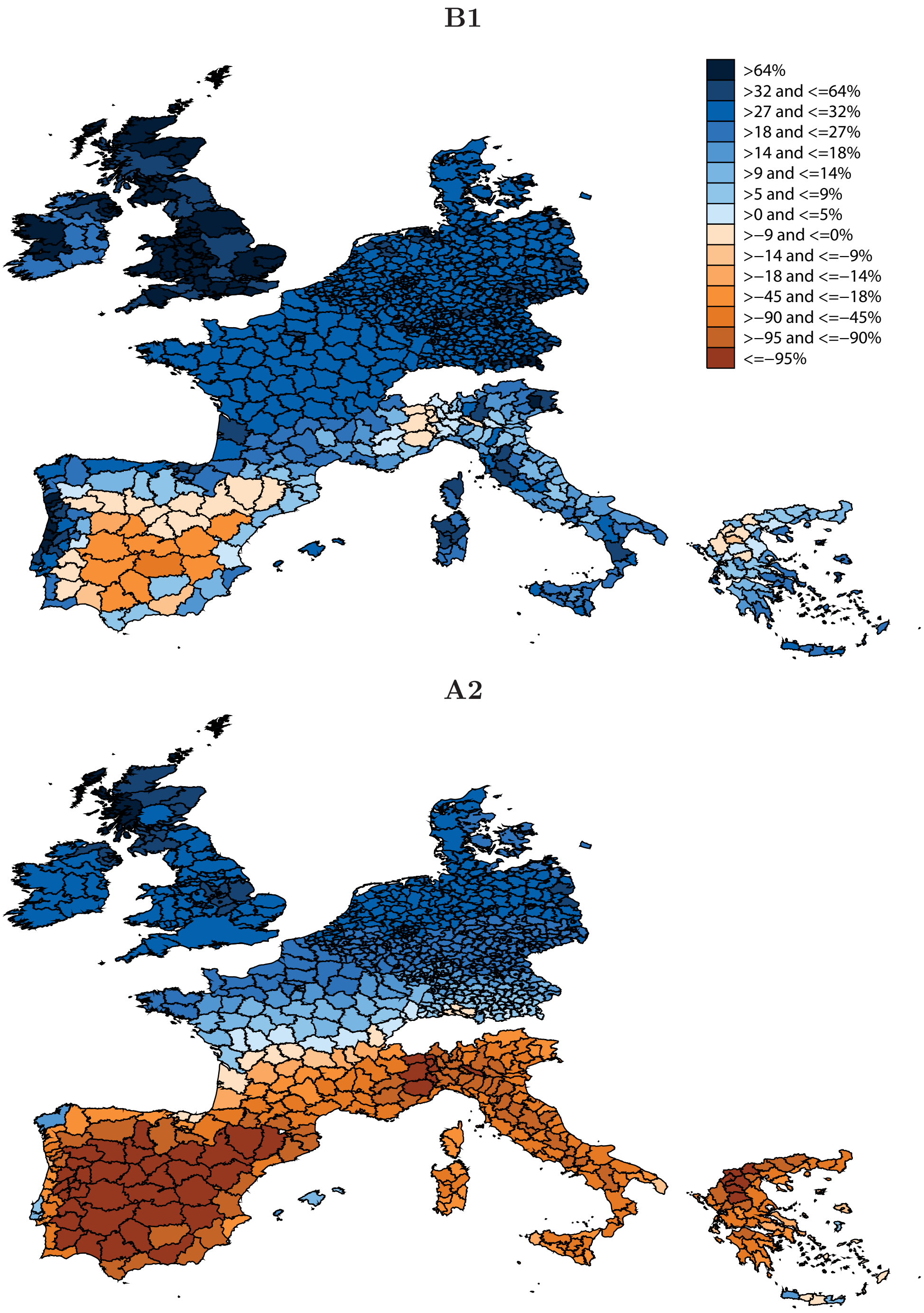


A2



Note: The scales refer to percentiles. The largest and smallest value correspond to the 90$^{\text{th}}$ and 10$^{\text{th}}$ percentile, respectively.

Figure 3.4: Change of land value in 2100 in %/ha (long differences approach)



Note: The scales refer to percentiles. The largest and smallest value correspond to the 90^{th} and 10^{th} percentile, respectively.

change is relatively small, the models predict a contrary effect for southern and northern Europe. Southern farmers will be substantially more harmed by temperature increases (−84 to −92%), while northern European farmers benefit from warmer temperatures (+7 to +12%).

It should be noted that these projections do not consider the full range of damages or benefits of climate change. An important limitation of the projections is that all other variables are held constant. A change in the climatic conditions, however, is also likely to alter the soil quality, the carbon content of soil, the water capacity and other important factors (e.g. increasing salinity in coastal areas). Accounting for soil changes, requires more complex approaches. Moreover, the models ignore possible changes in weather variability (e.g. increase in number of droughts or heat waves), which could increase with changing climatic conditions as well as the CO_2 concentration which could have a fertilisation effect on plants. These projections, therefore, cannot capture the full range of damages and benefits from climate change but give an indication of the direction of climate change impacts. Nevertheless, the results illustrate how harmful warming can be for European farmers by 2100 and in particular for southern European agriculture.

Given the large magnitude of the weather-related bias, we need a better distinction between weather and climate variability. While gradual temperature increases seem to be less damaging, but are more persistent and thus reflect constant damages and benefits, sudden short-term temperature changes (e.g. heat waves, extreme weather events) are only temporarily, but seem to be significantly more damaging. Global warming, however, will not be limited to marginal changes of temperature and precipitation alone, so that the full range of climate change damages is likely to be higher.

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3A Appendix

Testing for spatial correlation

In order to formally test for spatial error and spatial lag in the ordinary least squares (OLS) regression, we conduct three diagnostic tests for spatial dependence: (i) Moran's I, (ii) the Breusch-Pagan Lagrange multiplier test for spatial error and for spatial lag, and (iii) a robust Breusch-Pagan Lagrange multiplier test for spatial error and spatial lag. Table I summarises the results of the spatial dependence tests. We find both, spatial error and spatial lag in the OLS regression, so that the assumption of uncorrelated error terms is violated as well as the assumption of independent observations. As a result, the estimates are biased and inefficient.

Table I: Diagnostic tests for spatial dependence in least squares regression

Test	Statistic	p-value
Spatial error		
Moran's I	25.996	0.000
Lagrange multiplier	260.560	0.000
Robust Lagrange multiplier	41.591	0.000
Spatial lag		
Lagrange multiplier	229.834	0.000
Robust Lagrange multiplier	10.865	0.001

Distance-based (inverse distance) weights matrix.
Weights matrix is row-standardised.

Indirect Impacts of Climate Variability on European Farms and Options for Adaptation

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Abstract

This study empirically assesses (i) the impacts of climate variability on efficiency and (ii) options for adaptation. For this purpose, an output-oriented distance function is employed using a unique 19-year panel of more than 100,000 farms in 12 EU member states. Modelling the inefficiency term as a function of farm characteristics and a proxy variable for climate-related experience allows for an evaluation of indirect climate impacts on agricultural output. The results show an average efficiency level of 76% for the 12 EU member states, but a lack of climate-related experience significantly reduces the efficiency of farms, confirming the hypothesis that temperature also indirectly affects crop yields. Although, the results suggest that adaptation through input adjustments (e.g. increased use of fertiliser) or crop choice (e.g. higher share of fruits) is possible to a certain degree, a lack of climate-related experience reduces the efficiency significantly. By 2100, the efficiency could be reduced by up to 50% in the Mediterranean area and increased by up to 17% in Northern Europe.

Keywords: Agriculture, climate, EU, efficiency, parametric approach
JEL-Classification: Q12, Q51, L25, Q54, O52

Chapter 4

Indirect Impacts of Climate Variability on European Farms and Options for Adaptation

4.1 Motivation

Two fundamental goals for policy-making are to minimize damages associated with climate change as well as to justify expenditures for mitigation policies. The quantification of climate risks in different locations is fundamental for reaching this goal. The agricultural sector is one of the most vulnerable sectors, because climate and weather are direct inputs into agricultural production. Therefore, efficient policies require studies that link future changes in climatic conditions and weather patterns with agricultural production. Most previous research assessed the direct impacts of climate change, for example, on yields (e.g. Roberts & Schlenker, 2010; Schlenker & Roberts, 2009) or land rents (e.g. Schlenker & Lobell, 2010; Mendelsohn et al., 1994; Lang, 2007; Lippert et al., 2009; Deschênes & Greenstone, 2007), but only few studies examined the indirect impacts (e.g. efficiency: Demir & Mahmud, 2002). Changing climate and weather variability are also likely to affect production technologies (e.g. inputs) or to alter management practices (e.g. diversification, education), and therefore, the efficiency of farms. Moreover, if the indirect impacts are not random, they may be confounded with direct climate impacts, so that the climate coefficients may be biased. Hence, in this study, we evaluate the impact of climate variability on the efficiency of farms.

The technical efficiency refers to farmers' ability to transform physical inputs into outputs. Inefficiency is present if more (the same) output could be produced with the same level of (less) inputs. Previous research found that these variations are due to, for example, different management practices, size or type of the farm or the educational level. Most of these analyses primarily focus on the impact of farm-specific characteristics (Battese & Coelli, 1995; Battese et al., 1996; Battese & Tessema, 1993; Dawson et al., 1991; Kalirajan, 1991). Climatic conditions or other environmental factors, such as temperature, precipitation patterns or soil quality are usually ignored due to the assumption that they are random and captured by the stochastic error term. This assumption, however, has been questioned by Demir & Mahmud (2002), who argue that climate should not be treated as a purely random factor, because historical differences in agronomic and climatic conditions across large regions are known. They find that the omission of precipitation from the efficiency model affects the relative efficiency estimates and hence could lead to inaccurate interregional farm efficiency comparisons.

We hypothesise that farmers have experience of certain climatic conditions. Using the deviation of medium-term seasonal temperature average from a long-term seasonal temperature, defined as a 30-year average seasonal temperature, we construct a proxy for the climate-related experience of farmers. The greater the deviation of the medium-term temperature from the long-term temperature, the less experienced a farmer will be and the more training he will need to adjust the production. This increases the probability for inefficient management. In order to control for the effects of weather variability on the production technology, we add seasonal temperature averages and precipitation totals to the production function, which are assumed to affect the production directly, for example, by increasing the nutrient uptake of plants through more moisture.

In order to reveal potential efficiency gains or losses of European farms and to derive accurate policy implications, the determinants of levels of inefficiency need to be correctly specified and assessed. Ignoring the influence of farmer's climate-related experience may lead to bias in the assessment of climate impacts and could eventually lead to inefficient policies. This study simultaneously estimates an output-oriented stochastic production frontier following Battese & Coelli (1995) using maximum likelihood techniques to examine the influence of climate-related experience on efficiency levels of European farms.

The remainder of the paper is structured as follows: In section 4.2, we describe the methodology including the theoretical framework, the econometric specification and the estimation procedure. Section 4.3 describes the data and introduces the variables. This is followed by the regression results in section 4.4 and a conclusion in section 4.6.

4.2 Theoretical Framework

4.2.1 The Stochastic Production Frontier

Deterministic production frontiers for cross-sectional data following Kumbhakar & Lovell (2000) assume that a single-output is produced with N inputs. It consists of a production function $f(\cdot)$ and a technical efficiency term $e^{(-u_i)}$ for farm i:

$$Y_i = f(X_i, \beta)e^{(-u_i)} \tag{4.1}$$

where Y_i denotes the production of the ith farm, X_i is a $(1 \times k)$ vector of exogenous variables (e.g. inputs) of the ith farm and β is the $(k \times 1)$ corresponding vector of unknown parameters. u_i is a non-negative random variable associated with the technical inefficiency of the ith farm, which is assumed to be independently and normally distributed with the truncation at zero. The technical efficiency of each farm i can be defined as

$$TE = \frac{Y_i}{f(X_i, \beta)} \tag{4.2}$$

where technical efficiency is the ratio of observed output Y_i to the corresponding frontier output depending on the amount of inputs used by the farm. Viz. $e^{(-u_i)} = 1$ indicates perfect technical efficiency which allows the farm to achieve its maximum feasible output, whereas $e^{(-u_i)} < 1$ denotes production inefficiencies that are allowed to vary among all farms. Furthermore, we assume, holding all inputs constant, that

$$\frac{\delta f(X_i, \beta)e^{(-u_i)}}{\delta e^{(-u_i)}} > 0 \tag{4.3}$$

$$\frac{\delta^2 f(X_i, \beta)e^{(-u_i)}}{\delta x_i \delta e^{(-u_i)}} > 0 \tag{4.4}$$

technical efficiency increases production (4.3) and the marginal product of inputs (4.4). In order to incorporate farm-specific random shocks (e.g. shocks due to variation in labour or machinery performance) Aigner et al. (1977) and Meeusen & van Den Broeck (1977) extended the model to a stochastic production frontier, as follows

$$Y_i = f(X_i, \beta)e^{(\nu_i - u_i)}, \tag{4.5}$$

where $f(X_i, \beta)e^{(-u_i)}$ denotes the deterministic part of the production frontier which is common to all farms. ν_i is the stochastic error term and is assumed to be independently and identically distributed $N(0, \sigma_{\nu^2})$. Consequently, random variation in yields due to factors that are beyond the farmer's control but affect crop yields (e.g. farm-specific random shocks) are embedded in the stochastic error. The error term u_i is the one-sided inefficiency term, assumed to be half-normally distributed $N^+(\mu_i, \sigma_u^2)$ with a truncation point at zero, and it represents farm-specific technical inefficiency in the production.[1] The idea behind this composed error specification is to enclose any deviation from the frontier that is under the control of the farmer, such as the educational level, the size or type of the farm. In a stochastic framework, the technical efficiency can be formulated as

$$TE = \frac{Y_i}{f(X_i, \beta)e^{\nu_i}} \tag{4.6}$$

where technical efficiency is defined as the ratio of observed output Y_i to the corresponding value of the frontier output conditional on the environment characterized by e^{ν_i}. Consequently, a technically efficient farm produces on the production frontier with random fluctuations embedded in ν_i.

4.2.2 The Stochastic Output-Oriented Distance Function

In order to account for the multiple-input, multiple-output production structure of European farms, we additionally adopt Shephard (1953, 1970) distance functions. Distance functions provide a methodology that account for multi-input, multi-output production technologies without specifying a behavioural objective (e.g. profit-maximisation,

[1] There are three main distributional assumptions that have been proposed: (i) a normal distribution truncated at zero, $N^+(\mu_i, \sigma_{u^2})$ (Aigner et al., 1977); (ii) a half-normal distribution truncated at zero, $N^+(0, \sigma_u^2)$ (Jondrow et al., 1982) and (iii) an exponentially distributed u_i with variance σ_u^2.

cost-minimization). Distance functions can be classified into input-oriented and output-oriented distance functions. Input-oriented distance functions measure the distance between a given input vector and a representative input vector as a factor by which the inputs could be reduced, but remain feasible to produce a given output vector. The output-oriented distance function is defined as the distance between a given output vector and a benchmark output vector as a factor by which the output vector can be proportionally expanded with the input vector being held constant. In the multiple output case, the single output production frontier is simply replaced by an output oriented distance function. Accordingly, the stochastic production frontier in a single-output case $y_i = f(x_i, \beta)e^{(\nu_i - u_i)}$ is simply reorganized as

$$\frac{y_i}{f(x_i, \beta)} = e^{(\nu_i - u_i)}. \tag{4.7}$$

The multiple output version can be formulated as

$$D_o(x_i, y_i; \beta) = e^{(\nu_i - u_i)}. \tag{4.8}$$

Rearranging the last equation gives the output-oriented distance function model in a stochastic framework

$$1 = D_o(x_i, y_i; \beta)e^{(u_i - \nu_i)}, \tag{4.9}$$

where $D_o(x_i, y_i; \beta)$ is the multi-output distance function. Following Kumbhakar & Lovell (2000) equation (4.9) can be converted into an regression model by exploiting the linear homogeneity property of D_o which states that $D_o(x_i, \lambda y_i; \beta) = \lambda D_o(x_i, y_i; \beta)$, $\lambda > 0$. Setting $\lambda = |y_i|^{-1} = (\sum_m y_{mi}^2)^{-\frac{1}{2}}$, generating $D_o(x_i, \frac{y_i}{|y_i|}; \beta) = |y_i|^{-1} D_o(x_i, y_i; \beta)$, which leads to $D_o(x_i, y_i; \beta) = |y_i| \cdot D_o(x_i, \frac{y_i}{|y_i|}; \beta)$. Substituting this into equation (4.9) and dividing both sides by $|y_i|$ yields the regression model

$$|y_i|^{-1} = D_o(x_i, \frac{y_i}{|y_i|}; \beta)e^{(u_i - \nu_i)}. \tag{4.10}$$

The dependent variable is the reciprocal of the norm of the output vector and the covariates are the production inputs and normalized outputs. The error term consists of the two known components: (i) the symmetric error term ν_i, which captures random noise, and (ii) the one-sided error component u_i representing a reciprocal measure of the output-oriented technical efficiency. Equation (4.10) can be estimated like the stochastic production frontier with a change in the sign of the error term u_i as follows

$$\ln y_i = -\ln D^o + \nu_i - u_i, \tag{4.11}$$

provided that a sufficiently flexible form such as the transcendental logarithmic production function is applied.[2] To allow for a decomposition of technical efficiency effects we extend the Shephard (1953, 1970) distance function and define the inefficiency term u_i following Battese & Coelli (1995)

$$u_i = \phi(z_i) + w_i \tag{4.12}$$

where z_i is a $(NJ \times 1)$ vector of variables affecting technical inefficiency (e.g. size, type and management). ϕ is a $(m \times 1)$ vector of unknown coefficients. The random variable w_i is *i.i.d.* and defined by the truncation with mean zero and variance σ_w^2, so that $w_i \geq \phi(z_i)$. Accordingly, technical efficiency is defined as

$$TE_i = \frac{Y_i}{f(X_i, \beta)} e^{(\nu_i)} = e^{(-\phi z_i - w_i)}. \tag{4.13}$$

4.2.3 Empirical Specification

We estimate the stochastic output-oriented distance function with a transcendental-logarithm specification as follows

[2] The Cobb-Douglas form is inappropriate for an output distance function, because it has the wrong curvature in $\frac{y_i}{|y_i|}$ space Kumbhakar & Lovell (2000).

$$
\begin{aligned}
0 &= \alpha_0 + \sum_{m=1}^{M} \beta_m \mathrm{ln} y_{mit} + \sum_{k=1}^{K} \beta_k \mathrm{ln} x_{kit} + \sum_{n=1}^{N} \beta_n \mathrm{ln} c_{nit} + \sum_{\widetilde{m}=1}^{M} \sum_{m \neq \widetilde{m}}^{M} \beta_{m\widetilde{m}} \mathrm{ln} y_{mit} y_{\widetilde{m}it} \\
&+ \sum_{\widetilde{k}=1}^{K} \sum_{k \neq \widetilde{k}}^{K} \beta_{\widetilde{k}k} \mathrm{ln} x_{kit} \mathrm{ln} x_{\widetilde{k}it} + \sum_{n=1}^{N} \sum_{n \neq \widetilde{n}}^{N} \beta_{n\widetilde{n}} \mathrm{ln} c_{nit} \mathrm{ln} c_{\widetilde{n}it} + \sum_{k=1}^{K} \sum_{m=1}^{M} \beta_{km} \mathrm{ln} x_{kit} \mathrm{ln} y_{mit} \\
&+ \sum_{n=1}^{N} \sum_{k=1}^{K} \beta_{nk} \mathrm{ln} x_{kit} \mathrm{ln} c_{nit} + \sum_{n=1}^{N} \sum_{m=1}^{M} \beta_{nm} \mathrm{ln} c_{nit} \mathrm{ln} y_{mit} + \sum_{f=1}^{F} \beta_f g_{fit} + u_i - \nu_i
\end{aligned}
\tag{4.14}
$$

with M outputs, K inputs, N climate variables and F exogenous variables for i farms and t years. y_{mit} is a vector of logarithmic crop yields, x_{kit} denotes a matrix of logarithmic input variables, c_{nit} indicates logarithmic climate variables, and g_{fit} indicates a set of exogenous variables, such as soil characteristics. The constant is denoted by α_0; β are vectors of the corresponding parameters to be estimated. We impose linear homogeneity by normalising with respect to one of the outputs $y^*_{mit} = \frac{y_{mit}}{y_{1it}}$ and rearrange equation (4.14) to obtain

$$
\begin{aligned}
\mathrm{ln} D^o_{it} &= -(\alpha_0 + \sum_{m=1}^{M} \beta_m \mathrm{ln} \left(\frac{y_{mit}}{y_{1it}} \right) + \sum_{k=1}^{K} \beta_k \mathrm{ln} x_{kit} + \sum_{n=1}^{N} \beta_n \mathrm{ln} c_{nit} \\
&+ \sum_{\widetilde{m}=1}^{M} \sum_{m \neq \widetilde{m}}^{M} \beta_{m\widetilde{m}} \mathrm{ln} \left(\frac{y_{mit}}{y_{1it}} \right) \mathrm{ln} \left(\frac{y_{\widetilde{m}it}}{y_{1it}} \right) + \sum_{\widetilde{k}=1}^{K} \sum_{k \neq \widetilde{k}}^{K} \beta_{\widetilde{k}k} \mathrm{ln} x_{\widetilde{k}it} \mathrm{ln} x_{kit} \\
&+ \sum_{n=1}^{N} \sum_{n \neq \widetilde{n}}^{N} \beta_{n\widetilde{n}} \mathrm{ln} c_{nit} \mathrm{ln} c_{\widetilde{n}it} + \sum_{k=1}^{K} \sum_{m=1}^{M} \beta_{km} \mathrm{ln} x_{kit} \mathrm{ln} \left(\frac{y_{mit}}{y_{1it}} \right) \\
&+ \sum_{n=1}^{N} \sum_{k=1}^{K} \beta_{nk} \mathrm{ln} x_{kit} \mathrm{ln} c_{nit} + \sum_{n=1}^{N} \sum_{m=1}^{M} \beta_{nm} \mathrm{ln} c_{nit} \mathrm{ln} \left(\frac{y_{mit}}{y_{1it}} \right) \\
&+ \sum_{f=1}^{F} \beta_f g_{fit} + u_i - \nu_i)
\end{aligned}
\tag{4.15}
$$

Here, y_{1it} refers to cereals, and y_{mit} denotes other crops. The interaction of climate with farm variables allows for an examination of the impact of management adjustments (e.g. crop mix, input adjustments, irrigation) along with changes in the temperature or precipitation patterns on farm output. The technical efficiency term u_i is a function dependent on the determinants of levels of inefficiency. Coelli & Perelman (1999) suggest two alternative approaches to account for environmental factors in stochastic frontier models. The first approach assumes that environmental conditions affect the shape of the technology and therefore environmental parameters should be introduced into the production function. The second approach assumes that environmental conditions change the degree of technical efficiency directly, and therefore, should be introduced in the efficiency model. In this study, we examine the impact of climate-related experience by considering two alternative efficiency models: (i) in the first model we assume that climate deviation affects the production structure directly, and hence the technology of each farm by ignoring climate deviation in the efficiency model, and (ii) in the second model, we assume that the technical efficiency levels of farms are directly influenced by climate deviation; hence we presume that the production technology is the same for each farm and climate-related experience is a source of inefficiency (compare Appendix 4A for simple theoretical example). Accordingly, we estimate

$$u_i = \sum_{l=1}^{L} \delta_l z_{lit} + w_i \text{ (Model 1)} \tag{4.16}$$

$$u_i = \sum_{l=1}^{L} \delta_l z_{lit} + \sum_{j=1}^{J} \delta_j d_{jit} + w_i \text{ (Model 2)}, \tag{4.17}$$

where z_{lit} is a set of farm characteristics and d_{jit} is the proxy for climate-related experience[3]. The parameters δ_l and δ_j are the corresponding parameters and indicate the impact on inefficiency.

Due to the translog specification, we use the distance function to examine farm performance parameters as well as technical parameters (Paul & Nehring, 2005; Paul et al., 2000; Reidsma et al., 2009) that give us information on climate impacts on production and allow us to assess the influence of adaptation strategies (Reidsma et al., 2009). These parameters include the output, input and climate elasticities $\epsilon_{y_1,m}$, $\epsilon_{y_1,k}$, $\epsilon_{y_1,n}$.

The output elasticities $\epsilon_{y_1,m}$ represent the percentage change in total output following a 1% change in y_{mit} or the trade-off between different products along the production possibility frontier. Due to the homogeneity restriction, the elasiticity is calculated as $\epsilon_{\mathrm{D^o},1} = -\left(1 + \sum_m^M \epsilon_{\mathrm{D^o,m}}\right)$ (Reidsma et al., 2009). The interaction terms of y_m with cli-

[3]Climate-related experience is defined as the deviation of seasonal temperature from the precedent 30-year average seasonal temperature

mate variables are used as indicators for climate adaptation as in Reidsma et al. (2009). The mean output elasticties can be estimated as

$$\epsilon_{D^o,m} = \frac{\partial \ln D^o}{\partial y_{mit}} = \beta_m + \sum_{m \neq \tilde{m}}^{M} \beta_{m\tilde{m}} y_{\tilde{m}it} + \sum_{k=1}^{K} \beta_{km} x_{kit} + \sum_{n=1}^{N} \beta_{nm} c_{nit} \tag{4.18}$$

The elasticity $\epsilon_{D^o,n}$ measures the change in total output resulting from a 1% change in c_n. While, the elasticity of y_m and c_n represent output-oriented adaptation (e.g. land-use change or change of the crop mix), which is considered a major adaptation strategy of farmers (see Olesen & Bindi, 2002), the interaction-terms of x_k and c_n represent input-oriented adaptation (e.g. increase in irrigation water). The mean impact of climatic factors on total production is measured by the elasticity

$$\epsilon_{D^o,n} = \frac{\partial \ln D^o}{\partial c_{nit}} = \beta_n + \sum_{n \neq \tilde{n}}^{N} \beta_{n\tilde{n}} c_{\tilde{n}it} + \sum_{k=1}^{K} \beta_{nk} c_{nit} + \sum_{m=1}^{M} \beta_{nm} y_{mit} \tag{4.19}$$

The input elasticities give insight into the relative impact of input intensities on output. The mean elasticity is measured as follows

$$\epsilon_{D^o,k} = \frac{\partial \ln D^o}{\partial x_{kit}} = \beta_k + \sum_{k \neq \tilde{k}}^{K} \beta_{k\tilde{k}} x_{\tilde{k}it} + \sum_{m=1}^{M} \beta_{km} y_{mit} + \sum_{n=1}^{N} \beta_{nk} c_{nit} \tag{4.20}$$

4.3 Data and Variables

In order to examine the impact of climate-related experience of the farmer on the efficiency of farms and options for adaptation, we paired highly disaggregated farm data with a gridded weather dataset and a soil database.

4.3.1 Agricultural Data and Variables

Farm-level panel data from 1990 to 2008 for the 12 European member states (Belgium, Denmark, Germany, Greece, Spain, France, Ireland, Italy, Luxembourg, Netherlands, Portugal and United Kingdom) was provided by the *Farm Accountancy Data Network* (FADN) of the European Commission, and enables us to analyse the impact of climate-related experience of farmers on inefficiency while controlling for farm-specific determinants and the dynamics of inefficiency. The FADN annually collects harmonised micro-economic data from a sample of agricultural holdings, currently covering approximately 80,000 farms, which were selected according to homogeneity criteria and to obtain a representative sample for the European agricultural sector with respect to region, economic size and type of farming. Some of the farms are mainly livestock farming, and therefore, omitted from the dataset. For confidentiality reasons, the highest resolution available is the NUTS 3 level.[4]

The panel data structure allows us to exploit the cross-sectional variation to estimate climate impacts whereas the time-series variation allows us to examine weather effects. Seasonal temperature and precipitation data from 1961-2008 are drawn from the *European Climate Assessment and Dataset*. The E-OBS dataset contains daily information on a 0.25 degree regular grid. In order to pair the farm with climate information, the temperature and precipitation data are averaged over the NUTS 3 regions.[5] The average temperature and precipitation data cover the main growing period of various crops in numerous regions in Europe.[6] We follow Trapp & Schneider (2013) and construct the seasonal averages according to four main regions (Table 4.1). Soil information controls for the original growing conditions and is taken from the *European Soil Database*.

Table 4.1: Regions

Region	**Countries**	**Growing Season**
North Atlantic	United Kingdom and Ireland	May-August
Central Europe	Belgium, Denmark, Germany, Luxembourg and The Netherlands	April-August
North Mediterranean	France	March-June
South Mediterranean	Greece, Italy, Portugal and Spain	March-June

The dependent variable (y_{cer}) is the natural logarithm of cereal yield[7] measured

[4] NUTS is a geographical nomenclature for subdivisions of the European Union.

[5] We allocate temperature and precipitation information to each NUTS 3 region by calculating the average of all raster fields lying within each polygon shape using ArcGIS (http://eca.knmi.nl/).

[6] The original data contain daily land station observations. The station series are blended with station series from nearby stations in order to perform a basic quality control. The blended station series are then used to create the gridded dataset. For more detail: `http://www.ecad.eu/`.

[7] Cereals include oats, rye, rape, barley, soft wheat and hard wheat.

in tons per hectare (tha^{-1}). In order to control for the multi-output structure of farms and output-related adaptation strategies, we added fruits[8] (y_{fru}) and vegetables[9] (y_{veg}) as alternative or supplemental land-use options.[10]

We use farm input data from the FADN dataset to control for the expenditure on fertilisers (x_{fert}), which add nutrients to the plants, expenditures on crop protection (x_{prot})[11], which reduce the impact of pests, animals or weather phenomena, and the expenditure on machinery (x_{mach}), which ranges from tractors, cars and lorries to irrigation equipment. Labour (x_{lab}) is a control variable for the number of working hours spent during one year. Using working hours rather than expenditure on labour has the advantage that paid as well as unpaid work (e.g. spouse of a farmer) is included. Furthermore, we add the share of irrigated farmland (x_{irr}) to examine the effects of adapted production. Altitude variables control for farms lying below 300m a.s.l. (reference group), farms located 300 to 600m a.s.l. ($g_{3\text{-}6}$) and above 600m a.s.l. (g_{gt6}).

Soil conditions are exogenous influences that can affect crop growth through the nutrient content, moisture conditions or the overall soil texture. Therefore, we control for the water capacity (g_{wat}) and the organic content (g_{org}) in the top soil.

We follow the literature and represent climate by constructing temperature and precipitation variables. For this purpose, we average temperature (c_t) and calculate precipitation totals (c_p) for the period which characterizes the growing season for most crops. Temperature and precipitation are included in a linear and quadratic form to allow for a curvilinear response of yields. Furthermore, we include an interaction term with management variables, which allows us to assess the effects of management adjustments (e.g. crop mix, irrigation).

In order to account for temporal and spatial differences, we added a time trend (t) representing technological progress and binary variables for four climatic regions (g_{AtNo}, g_{Cen}, g_{MedNo}, and g_{MedSo}) as defined in Table 4.1. The translog form of the frontier model allows for non-monotonic responses and does not impose any a priori restrictions on the input or climate elasticities. Therefore, all output, input and climate variables of the frontier model are logged.

Beside the examination of climate-related experience of farmers in the efficiency model, we control for different farm characteristics and management practices. Special-

[8]Fruits include fruits, berries, orchards, citrus fruits, pome fruit, stone fruit, table grapes, wine grapes, tropical and subtropical fruits, lemons, oranges, and tangerines.

[9]Vegetables include cabbage, leaf vegetables, mushrooms, and roots.

[10]Major non-livestock output can be covered with the three crop groups.

[11]Crop protection includes pesticides, anti-hail shells, frost protection, bird scarers, and fences.

isation, for example, can increase the efficiency through a better knowledge of farmers. Therefore, we add z_{crop} to control for farms specialised in field crops. Farm size (z_1 - z_{10}) is defined by European Size Units (ESU)[12] ranging from less than 2 ESU up to more than 250 ESU; the latter indicates the reference group.

We expect efficiency differences between rented and non-rented farmland, assuming that rent represents the opportunity cost of not owning the land. This means that farmers need to be more productive in order to pay for the rent and uncertainty increases, because lease agreements are limited in time. In order to control for different ownership structures, we add a variable for the share of rented farmland (z_{ren}). Moreover, we introduce binary variables for organic farms (z_{org}) and farms converting to organic production (z_{corg}) to compare them to conventional farm management (reference group). This allows us to analyse the impacts of non-conventional farm management. It should be noted that organic farmers choose different management practices, and therefore, may have lower production possibilities. However, estimating a joint production technology allows for an estimation of the distance of organic farm output to the best practice output. This may be important in terms of policy formulation, especially, for setting incentives for organic production. The age of the holder and manager (z_{age}) serves as a proxy for education. We hypothesize that younger farmers learn more modern farm management practices than older farmers and therefore should be more efficient. In 2003, the Common Agricultural Policy (CAP) was reformed to reduce environmental pressure and decouple subsidies from production. To control for possible impacts on the efficiency, for example, production technologies needed to be adjusted to reduce pesticide or fertiliser applications, we add a binary variable for the CAP reform (z_{CAP}). In addition, we add a proxy for the climate-related experience of the farmer [13]. We assume that a farmer needs approximately 10 years in order to have enough experience of the farms climatic conditions. Climate fluctuations over the past suggest that a climate oscillation takes around 30 years (e.g. Scafetta, 2010). In order to estimate the impact of climate-related experience, we construct a variable which represents the deviation of the 10-year average seasonal temperature from the 30-year average seasonal temperature for each year. We distinguish between positive temperature deviation (d) and negative temperature deviation (d_n). Due to the upward trend of the average seasonal temperature since 1961 as well as during the sample period, we assume that farmers have less experience of

[12]The value of one ESU is defined by the EU Commission as a fixed number of €/ECU of Farm Gross Margin. For details view `http://ec.europa.eu/agriculture/rica/methodology1_en.cfm`.

[13]For simplicity we only consider temperature in this empirical example, because farmers can more easily adjust the production technology to precipitation variability (e.g. irrigation).

positive temperature deviations than of negative temperature deviations. Large temperature rises may shift the farmer into “unknown climatic conditions”, while farmers in “constant or cooling climatic conditions” are more experienced and thus better trained. All variable definitions and the units are summarised in Table 4.2[14].

4.4 Results and Discussion

The output-oriented distance function and the efficiency model are estimated in a single stage approach as suggested by Battese & Coelli (1995). Maximum Likelihood techniques are used to simultaneously estimate the frontier and technical efficiency function so that asymptotically efficient estimates for all the parameters can be obtained. The regression results of the two model specifications are given in Table III. The first column contains the results for the model without climate-related experience (Model 1); in the second column the model accounts for climate-related experience of the farmer (Model 2). The latter is the preferred model according to likelihood ratio tests.

4.4.1 Frontier Function

Climate

The cross-climate elasticities of production can give an indication of the impact of climate variability on production[15] and enable us to examine adaptation strategies. The climate elasticities as well as the mean elasticities $\epsilon_{\mathrm{y_1,c_t}}$ and $\epsilon_{\mathrm{y_1,c_p}}$ are given in Table 4.3 and show a highly significant and strong impact.

The mean elasticities represent the percentage change in output following a 1% change in the temperature or precipitation variables when holding all other variables constant (e.g. no adaptation). A 1% increase in temperature ($\mathrm{c_t}$) reduces yields by up to 3%, and a 1% increase in precipitation $\mathrm{c_p}$ reduces cereal yields by up to 0.7%. However, the marginal effects suggest that taking farm management (e.g. inputs, irrigation, crop mix) into account, reduces the influence of temperature and precipitation. Hence, a 1% increase in temperature reduces yields by 1.6%, and a 1% increase in precipitation increases yields by up to 0.65%. A simultaneous increase of $\mathrm{c_t}$ and $\mathrm{c_p}$ by 1%, holding all

[14] Data on subsidies were not available, but Reidsma et al. (2009) show that the effects of temperature and precipitation are much stronger in relation to subsidies.

[15] The cross-sectional variation of temperature and precipitation allows an examination of climate variability.

Table 4.2: Summary statistics

Notation	Unit	Description	Mean	SD
Frontier Model Variables				
y_{cer}	tha^{-1}	Cereals	5.28	2.52
y_{fru}	tha^{-1}	Fruits	8.26	0.49
y_{veg}	tha^{-1}	Vegetables	10.51	0.62
x_{fert}	€ha^{-1}	Fertilisers and soil improvers	105.13	0.95
x_{prot}	€ha^{-1}	Crop protection	78.45	1.57
x_{mach}	€ha^{-1}	Machinery	1152.22	1.09
x_{lab}	hha^{-1}	Labour including paid and unpaid labour	192.15	1.39
x_{irr}	ha^{-1}	Share of irrigated farmland	0.05	0.18
c_t	°C	Growing season temperature	15.64	1.76
c_p	mm	Growing season precipitation	289.87	126.59
t	trend	Technological progress	9.92	5.33
g_{AtNo}	1, 0 otherwise	North Atlantic	0.06	0.44
g_{Cen}	1, 0 otherwise	Central Europe	26.87	0.41
g_{MedNo}	1, 0 otherwise	Northern Mediterranean	20.97	0.23
g_{MedSo}	1, 0 otherwise	Southern Mediterranean (reference group)	46.16	0.50
g_{gt6}	1, 0 otherwise	Farms above 600 m a.s.l.	0.12	0.43
$g_{3\text{-}6}$	1, 0 otherwise	Farms 300 to 600 m a.s.l.	0.25	0.32
$g_{3\text{-}6}$	1, 0 otherwise	Farms below 300 m a.s.l. (reference group)	0.63	0.48
g_{wat}	1, 0 otherwise	High water capacity	0.77	0.42
g_{org}	1, 0 otherwise	High organic content of the topsoil	0.64	0.48
Efficiency Model Variables				
z_{age}	years	Age of farmer	50.82	12.11
z_{ren}	ha	Share of rented farmland	0.01	0.39
z_{crop}	1, 0 otherwise	Specialisation on field crop production	0.16	0.37
z_{org}	1, 0 otherwise	Organic production	0.01	0.10
z_{corg}	1, 0 otherwise	Converting to organic production	0.01	0.07
z_{CAP}	1, 0 otherwise	CAP reform in 2003	0.30	0.46
z_1	1, 0 otherwise	Less than 2 ESU	0.01	0.02
z_2	1, 0 otherwise	2 to 4 ESU	0.01	0.12
z_3	1, 0 otherwise	4 to 6 ESU	0.03	0.17
z_4	1, 0 otherwise	6 to 8 ESU	0.04	0.18
z_5	1, 0 otherwise	8 to 12 ESU	0.08	0.27
z_6	1, 0 otherwise	12 to 16 ESU	0.06	0.24
z_7	1, 0 otherwise	16 to 40 ESU	0.29	0.45
z_8	1, 0 otherwise	40 to 100 ESU	0.30	0.46
z_9	1, 0 otherwise	100 to 250 ESU	0.15	0.36
z_{10}	1, 0 otherwise	Greater than 250 ESU (reference group)	0.04	0.44
d	°C	Positive temperature deviation from previous 30 year average	0.30	0.04
d_n	°C	Negative temperature deviation from previous 30 year average	-0.01	0.02

Note: Means and standard deviation calculated from dataset based on the Farm Accountancy Data Network, the European Climate Assessment & Dataset, and the European Soil Database.

other factors constant, can even enhance yields by up to 0.28%. This may be due to the protection of the plant from additional heat through additional moisture. In general, Model (1) and Model (2) have significantly different temperature coefficients, suggesting that ignoring climate-related experience in the efficiency model may introduce a bias in the temperature elasticities.

The interaction terms with x_k and y_m can give more information on how inputs and outputs influence the effects of temperature and precipitation changes. Interactions with x_k enable us to examine input-related adjustment strategies, and interactions with y_m allow us to analyse the relative vulnerability of crops and indicate land-use preferences dependent on current climatic conditions and technologies.

A simultaneous increase in x_k and c_t or c_p can enhance or reduce the total impact on output. For example, a larger share of irrigated farmland and a more intensive usage of labour can significantly reduce negative impacts resulting from a temperature rise, and therefore may serve as an adaptation strategy. In fact, at higher temperatures more fertilisers increase the positive effect on output. Higher temperatures may accelerate the photosynthesis process, which accelerates the uptake of nutrients. In contrast, a larger share of irrigated farmland along with higher precipitation totals, has a significant negative impact on output. This implies that irrigated areas may be more vulnerable to precipitation changes. In addition, an increased x_{fert}, x_{prot} or x_{mach} amplifies negative impacts of more precipitation.

The y_m and c_t or c_p interaction variables give information about the relative climate vulnerability of different crops. Our results suggest that fruits are more vulnerable to temperature increases than cereals. Therefore, the proportion of y_{fru} decreases relative to cereals with increasing temperature. Vegetables, on the other hand seem less vulnerable to changes in the temperature. y_{veg} increases with rising temperatures. Accordingly, a higher share of vegetable production may reduce the risk of yield losses with increasing temperatures. This could affect the crop choice of farmers, and hence, relative land-use preferences in the future. Precipitation patterns also have a significant influence on crop choice. More c_p, for example, increases fruits and vegetables relative to cereals. Farms with larger shares of fruits and vegetables, thus, can significantly benefit from rising precipitation.

In addition to direct climate impacts, we find that farms lying between 300 and 600m a.s.l. have on average lower yields compared to the reference group, and farms above 600m a.s.l. on average have the lowest output. As expected, farms with a higher water capacity and a higher organic content of the topsoil show significantly higher yields. Furthermore, yields on average are amongst the lowest in the Southern Mediterranean countries and amongst the highest in the North Atlantic countries and Northern Mediterranean regions, which may as well be due to the more favourable environmental conditions or other region specific time-invariant factors.

Lastly, technological progress (e.g. machinery, improved seed varieties) over the sample period has significantly increased the output of farms, but the quadratic term suggests that technological progress is slowing down. This may reduce future options for adaptation in the long-term.

Inputs

The own-input, cross-input and mean elasticities of the production function can be obtained from Table 4.3 and enable us to assess the impact of input intensities on output.

The input elasticities are generally expected to be positive, which implies an increase in the output with higher input application. All mean elasticities are significant and show a positive impact, except for fertilisers in Model (2). The fertilisers coefficient as well shows a negative impact, suggesting that fertilisers are used in abundance. Unexpectedly, labour also has a negative impact. Labour enables us to investigate technological development of farms (e.g. labour intensity of technologies). A high labour intensity suggests that the farm has less machinery equipment and as a result a lower output.

Furthermore, an increase in crop protection or machinery has a significant positive impact on yields. When using more fertilisers in addition to more crop protection, yields may as well be increased. Fertilisers may support the growth of weeds or pests which can be reduced by increased crop protection. However, if fertiliser and machinery, crop protection and labour or labour and machinery are simultaneously increased, yields are reduced. Machinery assists in the application of fertilisers, but fertilisers may be used in abundance.

Farms with a higher share of irrigated farmland show a lower output than farms with a smaller share of irrigated farmland. This is surprising, but may indicate a small impact of irrigation on output. In addition, farms that need to irrigate may have unfavourable environmental conditions so that the output level is commonly lower. However, if the share of irrigated farmland and fruit production increases, total output can be increased. This suggests that irrigation can assist in building up more resilience. Fruits are more intensively cultivated in Southern Europe, where precipitation often is scarce and average temperatures are amongst the highest. Those farmers, may be able to use the environmental conditions in favour of agricultural production. On the contrary, farms that increase the share of irrigated farmland in addition to vegetable

Table 4.3: Parameter estimates of the Stochastic Production Frontier

Variable	**Without climate-related experience**		**With climate-related experience**	
	Coefficient	**SE**	**Coefficient**	**SE**
Frontier Model				
c_t	-3.543***	(0.174)	-3.558***	(0.174)
c_t^2	0.298***	(0.0247)	0.300***	(0.0247)
c_p	-0.693***	(0.0373)	-0.693***	(0.0373)
c_p^2	0.0230***	(0.000667)	0.0229***	(0.000665)
$c_t * c_p$	0.278***	(0.0122)	0.278***	(0.0122)
$c_t * x_{fert}$	0.102***	(0.00644)	0.102***	(0.00644)
$c_t * x_{prot}$	-0.0331***	(0.00423)	-0.0336***	(0.00423)
$c_t * x_{lab}$	0.0715***	(0.00530)	0.0713***	(0.00530)
$c_t * x_{mach}$	-0.0823***	(0.00406)	-0.0818***	(0.00405)
$c_t * x_{irr}$	0.599***	(0.0226)	0.601***	(0.0226)
$c_t * y_{fru}$	-0.0730***	(0.0122)	-0.0727***	(0.0122)
$c_t * y_{veg}$	0.0376***	(0.00818)	0.0377***	(0.00818)
$c_p * x_{fert}$	-0.00868***	(0.00155)	-0.00860***	(0.00155)
$c_p * x_{prot}$	-0.0330***	(0.00106)	-0.0331***	(0.00106)
$c_p * x_{lab}$	0.0198***	(0.00129)	0.0198***	(0.00129)
$c_p * x_{mach}$	-0.0155***	(0.000945)	-0.0154***	(0.000944)
$c_p * x_{irr}$	-0.0877***	(0.00705)	-0.0869***	(0.00706)
$c_p * y_{fru}$	0.0303***	(0.00275)	0.0305***	(0.00275)
$c_p * y_{veg}$	0.0239***	(0.00188)	0.0237***	(0.00188)
$g_{3\text{-}6}$	-0.145***	(0.00144)	-0.145***	(0.00144)
g_{gt6}	-0.241***	(0.00218)	-0.241***	(0.00218)
g_{org}	0.0138***	(0.00164)	0.0139***	(0.00164)
g_{wat}	0.0690***	(0.00131)	0.0689***	(0.00131)
g_{Cen}	0.0186***	(0.00199)	0.0181***	(0.00199)
g_{MedNo}	0.0922***	(0.00200)	0.0916***	(0.00200)
g_{AtNo}	0.109***	(0.00316)	0.109***	(0.00316)
t	0.0145***	(0.000444)	0.0146***	(0.000444)
t^2	-0.000547***	(2.19e-05)	-0.000552***	(2.19e-05)
Constant	7.154***	(0.329)	7.180***	(0.329)
Climate elasticities				
ϵ_{y_1,c_t}	-1.5815***		-1.5891***	
ϵ_{y_1,c_p}	0.6475***		0.6480***	
Observations	403,150		403,150	
Number of farms	105,806		105,806	
γ	0.9808		0.9804	
σ^2	3.9714		3.0451	

Note: Standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10%level.

production have on average a lower output level. Vegetable farmers are more often located in moderate climatic regions, such as Germany or the Netherlands, with moderate precipitation.

Table 4.3 (continued): Parameter estimates of the Stochastic Production Frontier

Variable	Without climate-related experience		With climate-related experience	
	Coefficient	**SE**	**Coefficient**	**SE**
Frontier Model				
x_{fert}	-0.281***	(0.0224)	-0.283***	(0.0224)
x_{prot}	0.394***	(0.0150)	0.397***	(0.0150)
x_{lab}	-0.200***	(0.0184)	-0.199***	(0.0184)
x_{mach}	0.317***	(0.0138)	0.315***	(0.0138)
x^2_{fert}	0.0176***	(0.000399)	0.0176***	(0.000399)
x^2_{prot}	0.00557***	(0.000248)	0.00558***	(0.000248)
x^2_{lab}	0.00322***	(0.000415)	0.00323***	(0.000415)
x^2_{mach}	0.00425***	(0.000172)	0.00426***	(0.000172)
$x_{fert} * x_{prot}$	0.00173***	(0.000495)	0.00171***	(0.000494)
$x_{fert} * x_{lab}$	0.000242	(0.000722)	0.000283	(0.000721)
$x_{fert} * x_{mach}$	-0.00208***	(0.000513)	-0.00208***	(0.000513)
$x_{prot} * x_{lab}$	-0.0171***	(0.000458)	-0.0171***	(0.000458)
$x_{prot} * x_{mach}$	-0.000235	(0.000336)	-0.000260	(0.000336)
$x_{lab} * x_{mach}$	-0.00256***	(0.000410)	-0.00258***	(0.000409)
x_{irr}	-0.985***	(0.0864)	-0.995***	(0.0865)
x^2_{irr}	0.980***	(0.0150)	0.978***	(0.0150)
$x_{irr} * x_{fert}$	-0.00727*	(0.00415)	-0.00740*	(0.00415)
$x_{irr} * x_{prot}$	-0.131***	(0.00289)	-0.131***	(0.00289)
$x_{irr} * x_{lab}$	0.0248***	(0.00356)	0.0252***	(0.00357)
$x_{irr} * x_{mach}$	-0.0347***	(0.00212)	-0.0346***	(0.00212)
Constant	7.154***	(0.329)	7.180***	(0.329)
Mean input elasticities				
$\epsilon_{y_1,x_{fert}}$	0.0969***		-0.0215***	
$\epsilon_{y_1,x_{prot}}$	0.0738***		0.0738***	
$\epsilon_{y_1,x_{mach}}$	0.0378***		0.0378***	
$\epsilon_{y_1,x_{lab}}$	0.0404***		0.0402***	
Observations	403,150		403,150	
Number of farms	105,806		105,806	
γ	0.9808		0.9804	
σ^2	3.9714		3.0451	

Note: Standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10%level.

Outputs

Note that elasticities with respect to production should be negative to be consistent with trade-offs along the production possibility frontier (Reidsma et al., 2009). Negative coefficients denote a greater contribution of y_m to total output, because an increase in other land-uses can only be attained, if the production of the other crops increases or cereal production decreases.[16] The negative output elasticities, for both fruits and vegetables, confirm this trade-off (Table 4.3). Despite that, a more diversified output structure can reduce the risk of losses resulting from changes in the weather patterns or climatic conditions (compare 4.4.1).

The changes in input in conjunction with different crop mixes on total farm output vary across inputs and outputs. These impacts are represented by the interaction terms of $\mathrm{y_m}$ and $\mathrm{x_k}$. For example, fruit production in combination with and increased use of fertilisers increases total output, whereas a higher share of vegetable production in combination with an increased use of fertiliser reduces total output. As already noted, $\mathrm{x_{lab}}$ and $\mathrm{x_{mach}}$ reflect technological differences between farms. The interaction terms of $\mathrm{y_m}$ and $\mathrm{x_{lab}}$ have a significant negative coefficient while the interaction terms of $\mathrm{y_m}$ and $\mathrm{x_{mach}}$ are significantly positive, suggesting that more technically developed farms have significantly higher total output.

4.4.2 Technical Inefficiency

Recall that we consider two alternative approaches:

Model (1) ignores "climate-related" experience in the efficiency specification
Model (2) includes "climate-related" experience in the efficiency specification,

to examine the influence of climate variability on technical efficiency. Many coefficients are indeed significantly different when accounting for climate-related experience of the farmer. But before looking at the efficiency variables, it is interesting to examine $\ln\sigma^2$ and γ.[17] The terms $\ln\sigma^2$ and γ are both positive and significant at the 1% level. γ represents the estimated share of the inefficiency in the variance of the composed error term. For Model (1) γ is insignificantly higher than for Model (2) and implies that 98.27% of the difference between observed and maximum feasible output can be explained by technical inefficiencies in our model specification. The mean technical efficiency level across Europe is around 76.75% for Model (1) and 76.84% for Model (2). This suggests that the efficiency can still be significantly increased. Furthermore, we find that the efficiency varies across the EU-12 (compare Figure 4.1). Farms in the Benelux reached the highest efficiency levels, implying that more farms are managed efficiently. Regions

[16] $\mathrm{y_1} \downarrow \ \Rightarrow \ \ln\left(\frac{\mathrm{y_m}\uparrow}{\mathrm{y_1}\downarrow}\right)\uparrow$

[17] $\gamma = \frac{\sigma_u^2}{(\sigma_u^2+\sigma_\nu^2)}$

Table 4.3 (continued): Parameter estimates of the Stochastic Production Frontier

Variable	Without climate-related experience		With climate-related experience	
	Coefficient	**SE**	**Coefficient**	**SE**
Frontier Model				
y_{fru}	-0.0973**	(0.0427)	-0.0994**	(0.0427)
y_{veg}	-0.229***	(0.0282)	-0.229***	(0.0282)
y^2_{fru}	-0.0232***	(0.000560)	-0.0232***	(0.000560)
y^2_{veg}	-0.00775***	(0.000347)	-0.00775***	(0.000347)
$y_{fru} * y_{veg}$	0.0290***	(0.00162)	0.0290***	(0.00162)
$y_{fru} * x_{fert}$	0.0279***	(0.00164)	0.0280***	(0.00164)
$y_{veg} * x_{fert}$	-0.0134***	(0.00120)	-0.0134***	(0.00120)
$y_{fru} * x_{prot}$	-0.0425***	(0.00112)	-0.0425***	(0.00112)
$y_{veg} * x_{prot}$	0.0181***	(0.000851)	0.0182***	(0.000851)
$y_{fru} * x_{lab}$	-0.000467	(0.00142)	-0.000498	(0.00142)
$y_{veg} * x_{lab}$	-0.0220***	(0.000938)	-0.0221***	(0.000937)
$y_{fru} * x_{mach}$	-0.00108	(0.000944)	-0.00105	(0.000944)
$y_{veg} * x_{mach}$	0.00325***	(0.000767)	0.00332***	(0.000767)
$x_{irr} * y_{fru}$	0.0225***	(0.00623)	0.0231***	(0.00624)
$x_{irr} * y_{veg}$	-0.0407***	(0.00470)	-0.0406***	(0.00471)
Constant	7.154***	(0.329)	7.180***	(0.329)
Mean output elasticities				
$\epsilon_{y_1, y_{fru}}$	-0.1683***		-0.1683***	
$\epsilon_{y_1, y_{veg}}$	-0.0655***		-0.0656***	
Observations	403,150		403,150	
Number of farms	105,806		105,806	
γ	0.9808		0.9804	
σ^2	3.9714		3.0451	

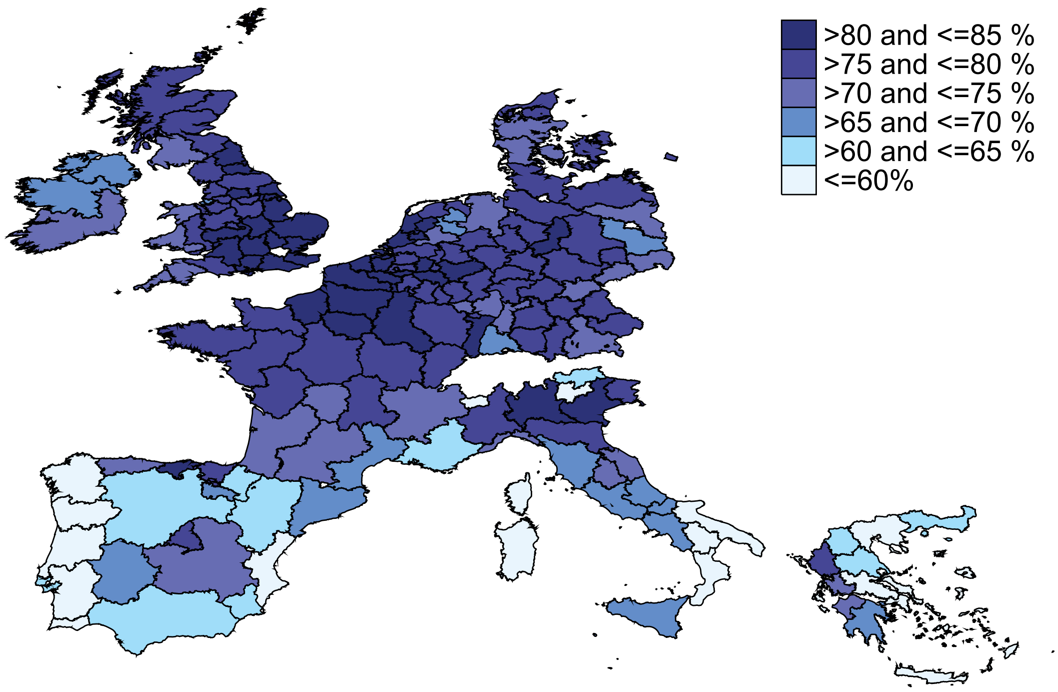
Note: Standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10%level.

with lower efficiency levels indicate that more farms are further away from the frontier, or more specifically, the 'best practice' in the region. Especially, Portugal and other southern Mediterranean countries could improve.

The results for the technical efficiency coefficients can be obtained from Table 4.4. It should be noted, that when reading the results, the estimated coefficients show the impact on *inefficiency* in the model. Therefore, the determinants with a positive coefficient reduce the efficiency level, while a negative coefficient indicates that the variable enhances the efficiency level.

Age is used as a proxy for education. The positive coefficient indicates that younger farmers are more efficient than older farmers, suggesting that younger farmers may have

Figure 4.1: Spatial distribution of average technical efficiency scores in the EU12



Note: Model (1) and (2) show the same spatial distribution among the NUTS-2 regions.

a better education or learn more modern management practices.[18]

Organic farms and farms converting to organic production are significantly less efficient than conventional farms, but farms converting to organic production are more efficient than fully organic farms. Organic farms do not employ chemical products, and therefore, are expected to produce below the production possibility frontier. This result, however, indicates that with lower efficiency and output levels, farmers have less incentive to shift towards organic farming. As a result, the development of the organic sector may decelerate, despite positive externalities on the environment (Stolze et al., 2000). The low efficiency levels of organic farms call for better education in organic production and farmers wanting produce organically, should become more experienced before switching to organic production methods.

Previous research found conflicting results for the link between farm size and effi-

[18]The quadratic term was insignificant in all model specifications and hence is omitted from the final models.

ciency. While some studies find that small farms are the most efficient (e.g. Nehring et al., 1989; Bravo-Ureta & Rieger, 1990; Kumbhakar, 1993), other studies find the opposite (e.g. Hadri & Whittaker, 1999). The lack of consensus is not surprising, because those studies use different data sources covering various countries, regions and commodities and reflect different technologies. Different methodologies or specification of the production technologies may also affect the results. In this study, we find a hill-shaped response of farm size and efficiency levels, where small farms are less efficient than very large farms and medium to large farms are more efficient than very large farms.

The results indicate that farms with higher shares of rented farmland are more efficient. This is in line with previous findings. Feng (2008), for example, finds that the direct cost of the rent and the opportunity cost of owning the land may create an incentive to produce more efficiently.

The CAP reform in 2003, reduced intervention prices for cereals by 50% and aimed at reducing negative externalities on the environment. Our results suggest that this reform reduced farms' efficiency levels. Policy changes aiming at agricultural production, require an adjustment of production technologies in order to correspond with the new policies. This could have caused a temporary reduction in efficiency.

Climate change is very likely to raise the mean temperature in Europe. This could shift farmers to unknown climatic conditions, requiring increased learning and adaptation to reduce negative impacts. Temporarily, a temperature shift could create inefficiencies, because farmers are inexperienced. Our results suggest that a temperature rise significantly reduces the efficiency level. Hence, the more the temperature deviates from the long-term average, the higher the probability that the farmer is inexperienced, and that climate change induces inefficiency. These effects, however, can vary between regions, farm types or management. Organic farms, for example, respond particularly negatively to a rise in temperature. A temperature increase by more than 0.5 °C could reduce the efficiency by up to 6%, whereas conventional farms only lose around 1% in efficiency. On the contrary, a temperature decrease is likely to improve the efficiency. This may indicate that farmers are more experienced and better trained for 'colder' climates due to the warming trend in Europe during the past years.[19] This way a temperature reduction by 0.5 °C can increase the efficiency of both management types, organic (5%) and conventional farming (7%). In addition, the results suggest that other efficiency variables are likely to be biased when ignoring the climate-related experience of farmers, because climate-related experience may be correlated with other influences.

[19]The average temperature has increased by 0.8 °C over the past century (IPCC, 2007).

Hence, the model may suffer from an omitted variable bias, confirming the hypothesis that the omission of environmental variables can introduce a bias in the estimation of agricultural production functions.

Table 4.4: Parameter estimates of the Efficiency Model

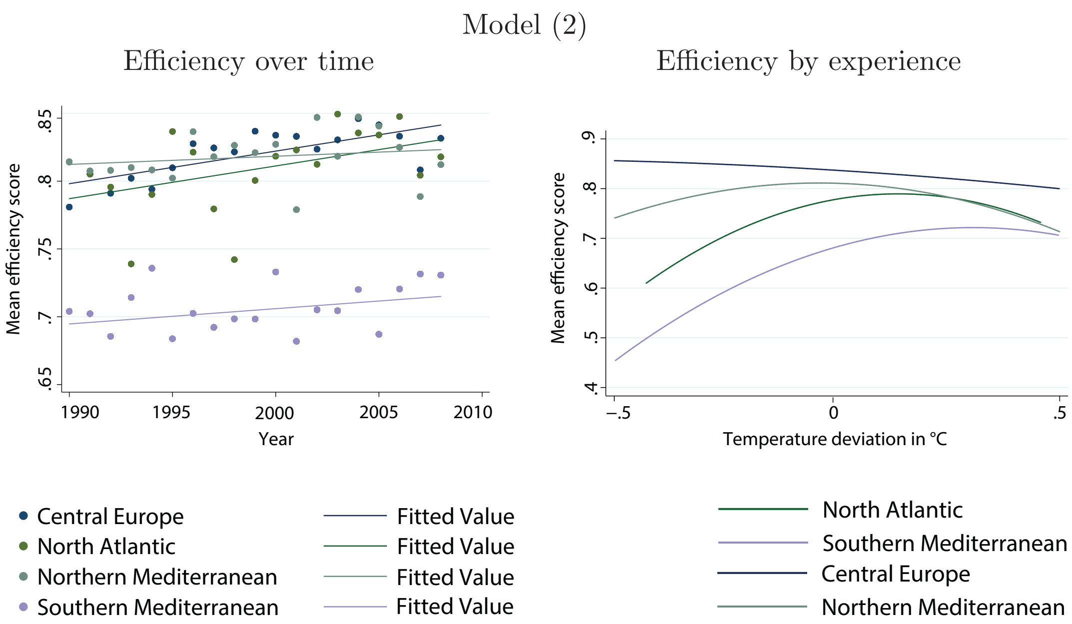
Variable	**Without climate-related experience**		**With climate-related experience**	
	Coefficient	**SE**	**Coefficient**	**SE**
Efficiency Model				
z_{age}	0.0363***	(0.00285)	0.0353***	(0.00273)
z_{org}	3.560***	(0.264)	3.462***	(0.253)
z_{corg}	2.156***	(0.260)	2.093***	(0.252)
z_{crop}	-2.314***	(0.166)	-2.266***	(0.159)
z_1	10.18***	(0.725)	9.992***	(0.697)
z_2	7.856***	(0.551)	7.714***	(0.530)
z_3	7.213***	(0.511)	7.081***	(0.491)
z_4	6.858***	(0.490)	6.736***	(0.471)
z_5	6.577***	(0.471)	6.463***	(0.454)
z_6	6.050***	(0.441)	5.949***	(0.425)
z_7	4.007***	(0.321)	3.970***	(0.312)
z_8	-0.671***	(0.189)	-0.594***	(0.183)
z_9	-3.085***	(0.295)	-2.984***	(0.284)
z_{ren}	-1.273***	(0.0968)	-1.246***	(0.0931)
z_{CAP}	0.188***		0.237***	(0.0519)
d			-6.945***	(1.031)
d^2			4.783***	(0.670)
d_n			16.61***	(3.030)
d_n^2			8.742***	(3.282)
Constant	-13.32***	(0.996)	-13.00***	(0.953)
Observations	403,150		403,150	
Number of farms	105,806		105,806	
γ	0.9808		0.9804	
σ^2	3.9714		3.0451	

Note: Standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10%level.

Even though, efficiency has increased over the sample period in all regions, the lack of climate-related experience can reduce the efficiency level in all regions of Europe (compare Fig. 4.2). Especially in the southern Mediterranean regions, where the average efficiency is at a relatively low level, a temperature rise could profoundly reduce efficiency. This has important policy implications. Regions with less capital intensive farms and higher expected temperature rises, for example, may require support in order to increase efficiency. Education programs or creating networks between farmers, for example, could assist in reaching higher efficiency levels despite temperature increases.

Policy makers also have to anticipate future climatic changes when formulating policies aiming at increasing the efficiency. If the technical performance can be improved, environmental damage could be reduced while, at the same time, economic performance and productivity can progress. Therefore, decision makers should assist in the successful transition to a more sustainable and efficient agriculture.

Figure 4.2: Mean technical efficiency scores dependent on time and climate-related experience



4.5 Sensitivity to Climate Change

The final empirical example assesses the sensitivity of efficiency to long-term changes of temperature by combining the regression results with weather simulations obtained from the regional climate model REMO for the A1B, A2 and B1 scenarios (Jacob, 2001, 2005a,c,b).[20] The Ensemble data (air temperature, TEMP2) are stored in NetCDF and have a 0.5 degree resoultion. We use ArcGIS to approximate the average temperature for each NUTS 3 region by creating 50 central points for each grid cell and calculating a mean over all central points lying within the NUTS shape. Then we convert absolute temperature values into Centigrade. It should be noted that these scenarios do not represent the efficiency development by 2050 and by 2100, but only indicate the efficiency sensitivity to long-term temperature changes holding all other variables constant.

We compare the temperature deviation in the three climate change scenarios for the periods 2031-2050 and 2081-2100 and predict the average efficiency change compared to 1990-2008 for each scenario in Table 4.5. Scenario A2 shows the largest temperature change with an average increase of 1 °C. The smallest increase in the average temperature is given in the B1 scenario. Surprisingly, the average efficiency decreases significantly in all three scenarios, with the largest reduction in scenario A2 ($\Delta\text{te} = -28.37\%$) and the smallest reduction ($\Delta\text{te} = -23.92\%$) in the B1 scenario. The difference in the efficiency reduction between the scenarios is relatively small. Note, that the change of efficiency is the difference between the reference efficiency for the period 1990-2008 and the predicted efficiency under the climatic conditions in 2021-2050 and 2071-2100.

Accordingly, we also only observe a small difference in the spatial response of efficiency to temperature changes as shown in Fig. 4.3-4.5. In the Benelux, Southern UK as well as in Western Germany, efficiency remains constant or even increases in all three scenarios. In the Mediterranean regions, Eastern Germany as well as in Ireland, efficiency declines in most regions and especially in the A2 scenario. In Spain, however, the efficiency sensitivity is more heterogeneous. This may be due to the REMO predictions, which show great temperature variability between the NUTS regions of Spain and the already diverging efficiency level today (compare Fig. 4.1). Consequently, we cannot draw clear conclusions about the sensitivity of efficiency in these regions.

[20]The A1B scenarios depicts a future with fast economic and population growth until 2050 and a decline thereafter (IPCC, 2007). This scenario is also associated with a rapid introduction of novel and more efficient technologies as well as an equal use of fossil and non-fossil energy resources. The A2 scenario describes a heterogeneous world with a constantly growing population, a regionally oriented economic development and slow technological progress (IPCC, 2007). The scenario B1 depicts a convergent world with a population growth similar to the A1B scenario, but a fast changing economy towards more service products and less material intense products as well as the usage of clean, resource-efficient technologies (IPCC, 2007).

Table 4.5: Sensitivity of the Efficiency to climate change

Scenario	Period	A1B	A2	B1
Mean seasonal temperature	1990-2008	15.4 °C	15.2 °C	15.2 °C
	2031-2050	16.0 °C	16.5 °C	16.5 °C
	2081-2100	17.6 °C	18.8 °C	18.8 °C
$\overline{\text{te}}$	2031-2050	52.06%	51.51%	51.89%
	2081-2100	49.85%	47.51%	51.78%
Δte	2031-2050	-24.20%	-24.28%	-23.81%
	2081-2100	-25.98%	-28.37%	-23.92%

Note: $\overline{\text{te}}$ denotes the average efficiency level for the base period and a comparable period; Δte denotes the change of the efficiency level compared to the base period

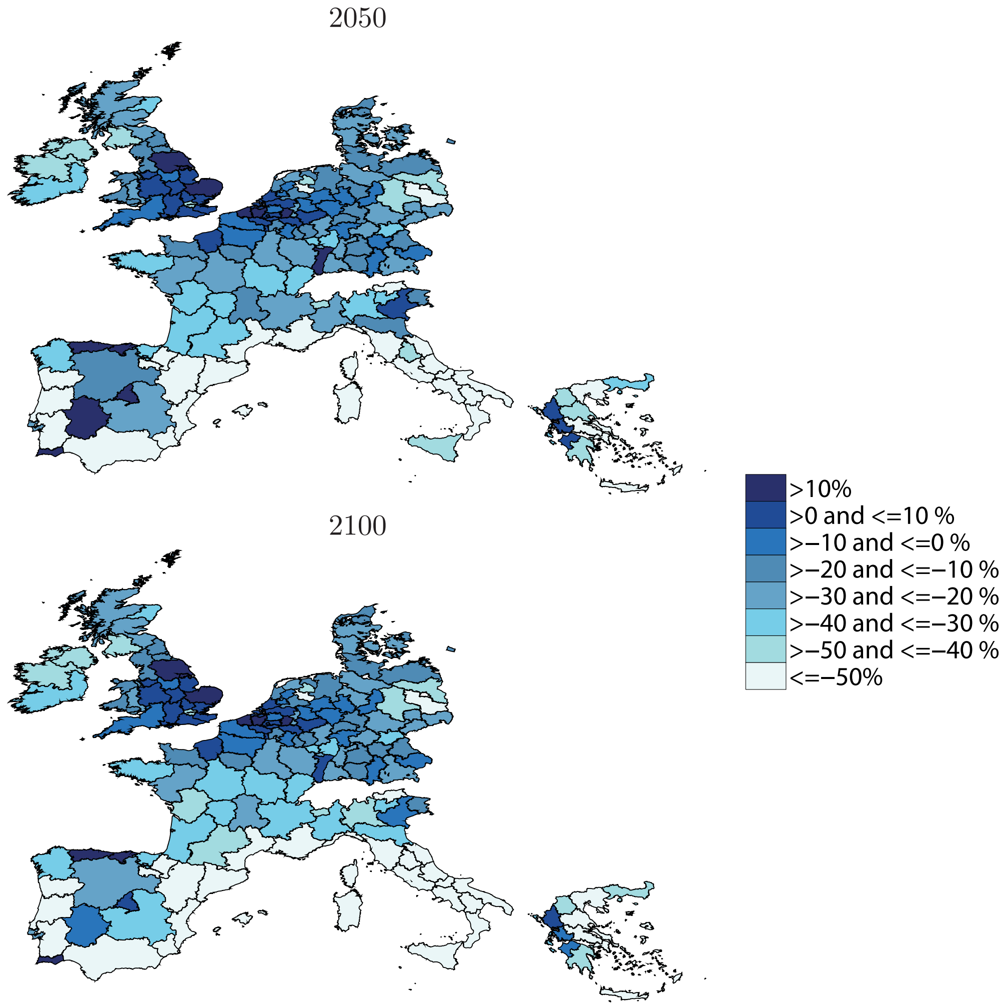
4.6 Conclusion

This study estimates the indirect impacts of climate variability on the technical efficiency of agriculture, using a 19-year sample of European farms. We empirically assess (i) the role of climate-related experience and (ii) options for adaptation using a multi-output, multi-input production technology via a stochastic distance function.

We find an average efficiency level of 76% for the 12 EU member states, which is in line with previous findings (e.g. Zhu & Lansink, 2010; Hadley, 2006; Bravo-Ureta et al., 2007). Even though the overall efficiency has increased between 1990 and 2008, this analysis shows that climate-related experience of the farmer significantly affects the efficiency and thus the output. If farmers are exposed to “unknown” climatic conditions and hence become inexperienced, the efficiency level decreases. Regions with larger temperature deviations, therefore, are expected to lose in terms of efficiency, while regions with constant temperatures are more likely to preserve current efficiency levels or even gain with regard to efficiency. Temperature changes, could therefore, lead to a structural change, where farms with little experience and larger temperature changes lose in terms of efficiency, and raise the pressure to adopt more flexible technologies and for increased adaptation.

Moreover, a sensitivity analysis reveals that climate change can have indirect im-

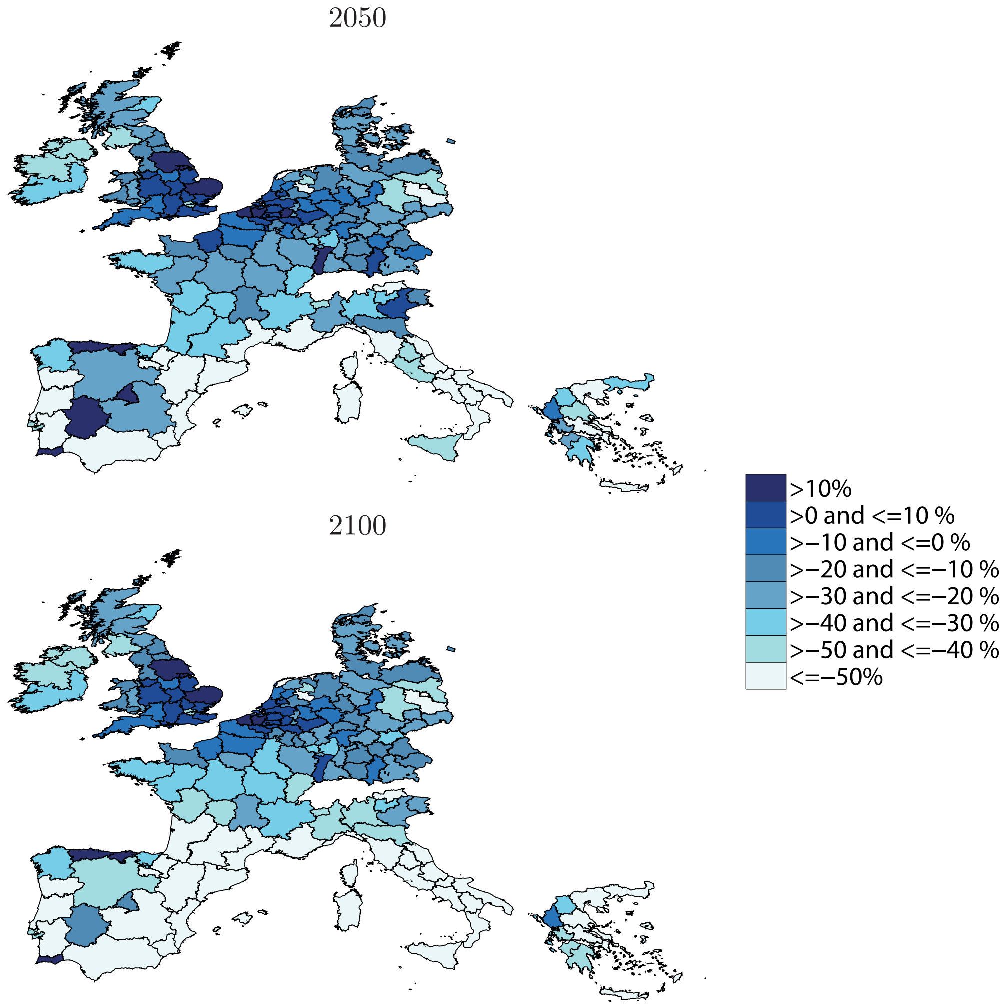
Figure 4.3: Efficiency sensitivity in the A1B scenario



Source: Simulations based on REMO scenario data. Average efficiency level for 1989-2008 compared to the predicted average efficiency level for 2081-2100.

pacts on agriculture. The A2 scenario, for example, shows an average efficiency loss for Europe of more than 28%, and of up to 55% for some Mediterranean regions when holding all other variables constant. In some northern European countries, such as the Netherlands, efficiency may increase by up to 17%. The sensitivity of efficiency to future warming suggests that under new climatic conditions, untrained or inexperienced farmers will have lower output levels compared to experienced farmers. Hence, climate benefits and damages in the agricultural sector may be underestimated, and policies

Figure 4.4: Efficiency sensitivity in the A2 scenario

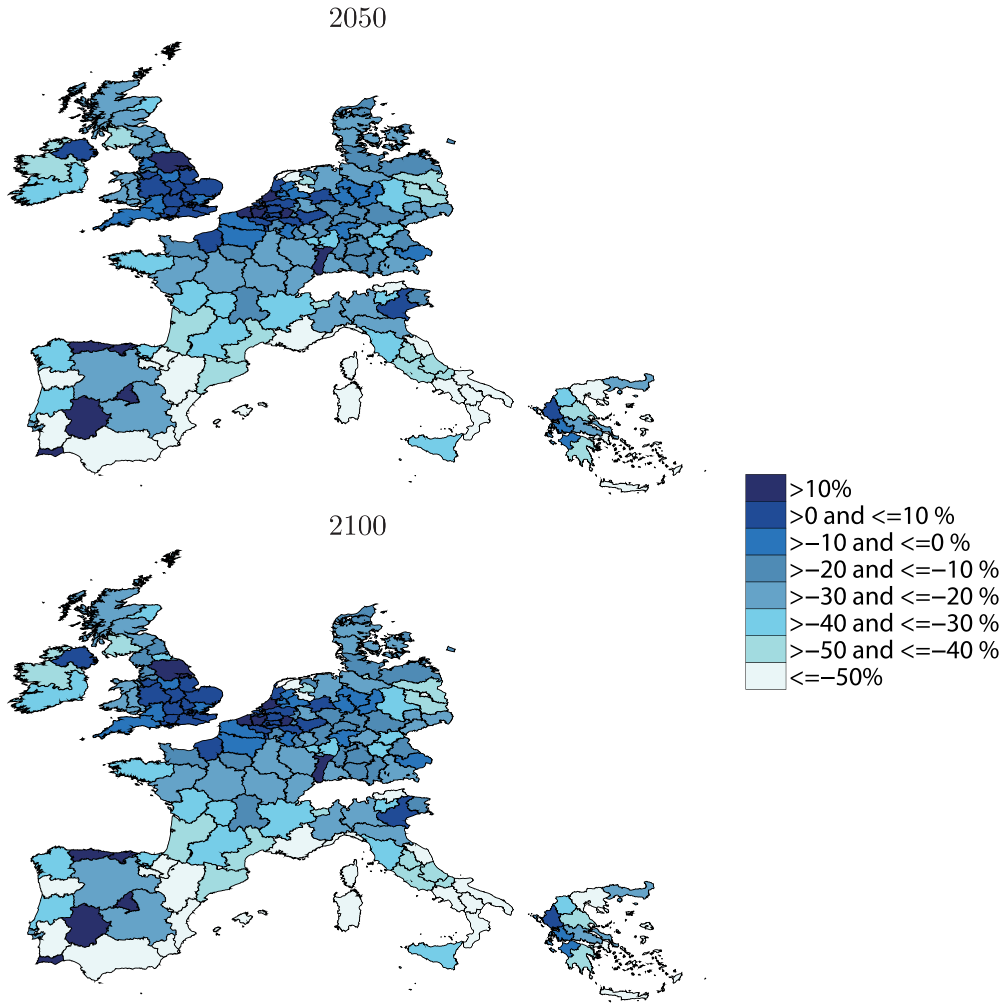


Source: Simulations based on REMO scenario data. Average efficiency level for 1989-2008 compared to the predicted average efficiency level for 2081-2100.

aiming at increasing the efficiency may be less beneficial when ignoring changes in the environmental conditions and the needs of vulnerable regions (e.g. adaptation, training for farmers).

Furthermore, the frontier model reveals that autonomous adaptation in the realm of current technologies can considerably enhance the output. We consider two possible adaptation options: (i) adjustment of inputs and (ii) crop choice. Firstly, we find input adaptation strategies that reduce negative impacts of climate change as well as strategies

Figure 4.5: Efficiency sensitivity in the B1 scenario



Source: Simulations based on REMO scenario data. Average efficiency level for 1989-2008 compared to the predicted average efficiency level for 2081-2100.

that enhance positive impacts. Particularly, a higher share of irrigated farmland or more labour can significantly reduce negative impacts, while fertilisers can intensify positive impacts of a temperature rise. Secondly, the output composition is influenced by climatic conditions, and thus, can give an indication on the climate vulnerability of crops. When temperature rises, farmers planting more fruit crops, for example, are likely to have lower output if temperature increases, relative to farmers planting more cereals, while farmers planting more vegetables are likely to benefit, relative to cereal farmers. On the other hand, when precipitation increases, planting a higher share of fruits or vegetables leads to a higher total output relative to planting a higher share of cereals. It should be noted that the level of aggregation in this analysis may conceal differences within regions and crop groups (e.g. citrus fruits vs. apples).

Even though, this study shows that farm adjustments can alleviate negative impacts of climate change to a certain extent, ignoring indirect impacts of climate change (e.g. technical efficiency, resource efficiency, substitution elasticities) could overestimate or underestimate future climate change impacts. In order to improve the consideration of indirect impacts and adaptation options in assessment studies, more reliable data and a better integration of biophysical processes in economic models are fundamental.

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4A Appendix

For simplification we assume constant climate change, where farmer's experience follows a function

$$u_t = u_1 n^{\lambda}$$

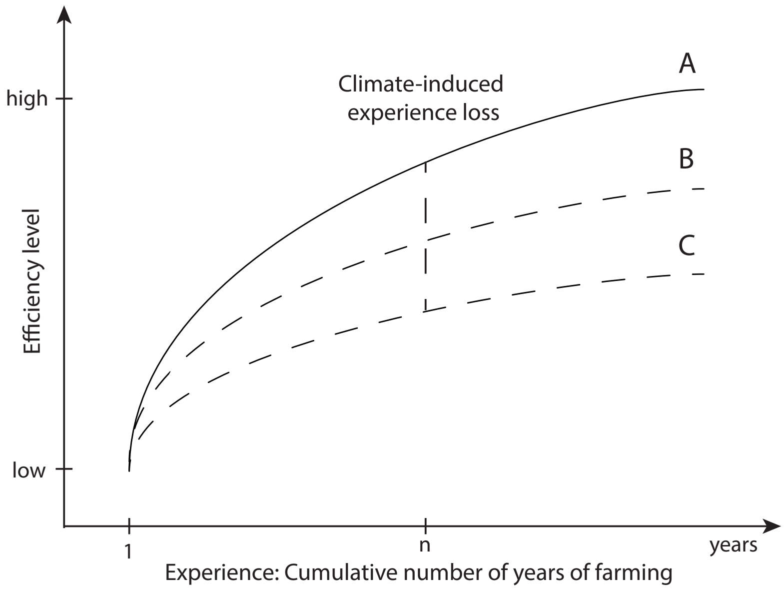
where u_t is the efficiency level of the tth year of farming, u_1 is the efficiency level of the first year, n is the cumulative number of years (experience), and λ is the elasticity coefficient with respect to cumulative years.[21] In the case of climate change, we assume that the experience effect is slowed down by a shift to unfamiliar growing conditions as follows

$$u = \delta u_t n^{\lambda} \text{ where } \delta < 1$$

where δ is a slowing factor induced by climate change. To further illustrate the impact of climate change on the shape of the experience curve, we depict three different cases in Fig. A.1. The first case (curve A) indicates the experience effect without climate change. Cumulative experience increases at a constant rate when climate conditions are stable. As a result, farmer's efficiency is more likely to increase with more experience, and thus, also the production. The alternative case (curve B) denotes the experience effect with moderately changing climate conditions. Assuming that climate conditions are part of the production technology, the technologies need to be continuously adjusted to changing climate conditions, hence, farmers need to learn continuously, so that the experience effect is slowed. This learning process increases the probability of inefficiency. The third case (curve C) indicates severe climate change. The change in temperature or precipitation shift farmers to unknown climate conditions, so that efficiency is significantly reduced. These cases are very simplified illustrations of our hypothesis that farmers' efficiency may be affected indirectly by climate change. We test this hypothesis by constructing a novel variable to approximate the experience and the impacts of changes in the climatic conditions on efficiency. It should be noted that not all conceivable cases are illustrated or discussed here (e.g. climate tipping points).

[21] Alternatively, u_t could denote efficiency level the tth time of harvest of a specific crop.

Figure 4A.1: Hypothetical climate-related experience curve



Case A: Stable climate conditions

Case B: Uniform moderate climate change

Case C: Uniform severe climate change

Agricultural Adaptation to Climate Change in the European Union

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Abstract
This study assesses the impacts of climate change on agriculture and the value of major adaptation strategies at the farm and policy levels. It extends previous research by (i) using an integrated approach which combines statistical models with a partial equilibrium model, (ii) linking detailed farm level data for the entire European Union to international agricultural commodity markets of global scope and (iii) simulating trade and biomass policies simultaneously in order to gain insight into potential interdependencies and land use feedbacks.

The model demonstrates that negative impacts of climate change can be largely mitigated by a combination of different adaptation strategies and by shifting food crop production to Northern Europe. However, large-scale bioenergy production, as targeted by the EU, induces competition between food and bioenergy crops for scarce land: up to 30% less of the agricultural area is used for food commodities. In the scenarios, welfare increases substantially if trade is liberalised under the assumption that bioenergy does not generate negative environmental externalities (e.g. carbon emissions from land use change). To approximate the external costs of bioenergy production, a net import quota is implemented. The results from this trade policy experiment show much stronger welfare impacts.

Keywords: Agriculture, EU, partial equilibrium, bioenergy, trade
JEL-Classification: Q12, Q54, Q24, F10, C61

Chapter 5

Agricultural Adaptation to Climate Change in the European Union

5.1 Motivation

Food production is fundamental to human well-being, economic prosperity and to achieve greater sustainability. Despite technological advancements in European agriculture (e.g. genetically modified crop types for higher heat resistance) and due to cost considerations, food production is highly dependent on climate conditions and weather patterns. Changes in the climate or weather variability alter growing conditions and production capacities and therefore can make the adaptation of management practices, production technologies and policies crucial for preserving agricultural productivity and availability of food. For this purpose, a detailed assessment of the heterogeneous agricultural sector is needed, which combines diverse resource and technical conditions and farm characteristics with international commodity market adjustments, and so allows for an evaluation of the impacts of different adaptation and policy strategies on crop production and land use decisions.

5.1.1 Mathematical Programming Models

Mathematical programming models have increasingly been used to investigate climate change, policy impacts and future pathways for the agricultural sector in greater detail.

A major advantage of these models is that they explicitly represent production technologies (Schneider et al., 2008a; Arndt et al., 2011; Robinson et al., 2012) which can be adapted to environmental or policy changes and therefore can depict shifts in the economy (e.g. farm income, price shifts). Mathematical programming models can therefore simulate the impacts of policy actions. These models can be categorised into (i) general equilibrium models, (ii) partial equilibrium models, and (iii) farm level decision models.

(i) Computable General Equilibrium models (CGE) represent a complete economy as a system in which the agricultural sector is linked to non-agricultural sectors (e.g. Golub et al., 2009; Jorgensen et al., 2004; Darwin et al., 1995, 1996; Winters et al., 1998). CGE models use relatively coarse information on climate and resources but are able to depict macroeconomic feedbacks through changes in prices of inputs and sectoral income levels whereas trade provides a link to the rest of the world. The main advantage of CGE models is the consistent depiction of income changes. They are especially important for economies where the agricultural sector has a large share of total GDP (e.g. low income countries) and/or where policy has a strong impact on agricultural income.[1] However, CGE models are often criticised for their over-simplification and their poor econometric specification (Mendelsohn & Dinar, 2009). Moreover, there is a great loss in detail of the agricultural sector and regional climate impacts (Mendelsohn & Dinar, 2009) because of the high level of aggregation in sectors and regions, which inhibits a deeper insight into the adaptation potential and farmers' behaviour.

(ii) Partial equilibrium (PE) models represent parts of a whole economy thereby ignoring effects on other sectors in the economy (e.g. Tobey et al., 1992) or assuming that income shifts in the modelled sector have insignificantly small impacts on other sectors in the economy.[2] Linkages to technology equations can depict the impacts of policy actions by simulating changes in the equilibrium for the market that is directly affected, whereas linkages to other economic sectors via resource supply functions (e.g. land, energy) and factor demand curves (e.g. labour) can account for constraints imposed by other economic sectors.[3] In addition, PE models often include detailed land use and agricultural market characteristics and thus simulate local economic or environmental impacts and

[1] Partial equilibrium models are more suitable in economies where the agricultural sector has only a small share of total GDP and/or policy has a small impact on agricultural income.

[2] CGE models commonly depict agriculture as an aggregated sector, whereas PE models depict agriculture as an disaggregated sector at different levels. Consequently, PE models can distinguish between production technologies, crop species or livestock species and therefore depict adaptation potential in more detail.

[3] For example, an emission tax can increase the costs of fertilisers and other inputs.

complex policy decisions (e.g. ESIM[4], FAPRI-CARD[5], MISS[6], CAPRI[7]). These models are particularly suitable to capture the likely response of the agricultural sector to climate change (Kokoski & Smith, 1987), because they depict changes on a highly disaggregated and detailed level. In contrast to CGE models, PE models do not represent a complete economy, and therefore, cannot depict how large supply and demand shifts can alter prices (Mendelsohn & Dinar, 2009). Severe climate change, large-scale mitigation or adaptation policy actions, however, are not limited to the agricultural sector, but can affect the whole economy and change both input and output prices. For example, increased expenditure for research and development in order to adapt production technologies to changing climatic conditions could lead to technological progress which can increase the output or decrease the cost per unit output (e.g. high yielding or pest resistant seed varieties). As a result, consumer expenditure decreases or producer profit increases and the disposable income rises which can induce further increases in consumption (Schneider, 2014b). On the other hand, mitigation policies (e.g. emission tax) increase the production costs and consumer prices, which can in turn reduce the disposable income. Although such income shifts can only be depicted by CGE models, the economic significance is assumed to be negligible for the European economy when accounting for the small share of agriculture in relation to the total GDP.

Equilibrium models often fail to model farm-specific characteristics and therefore ignore possible interactions between farm types in product and factor markets (Roebeling et al., 2000). (iii) Farm level decision models portray a higher degree of spatial resolution and incorporate farm specific characteristics to provide policy evaluation at a higher resolution (e.g. APORAj: Baranger et al. (2008), FAMOS: Schmid (2006), RAUMIS[8], EU-EFEM[9], Roe et al. (2005)). These models depict farm-specific agricultural production, factor input and/or agricultural income and can illustrate regional adaptation to changing agricultural or environmental policies. Farm-level models often treat prices exogenously, and therefore, overestimate the effectiveness of policy measures (Baranger et al., 2008). This study combines the farm level scales (high resolution data) with a representation of global markets (partial equilibrium model).

[4]European Simulation Model (Banse et al., 2004)

[5]Food and Agricultural Policy Research Institute-Centre for Agricultural and Rural Development (Devadoss et al., 1989)

[6]Modèle International Simplifié de Simulation (Mah & Moreddu, 1987)

[7]Common Agricultural Policy Regionalized Impact Modelling System (`http://www.capri-model.org/dokuwiki/doku.php?id=start`)

[8]`http://www.ti.bund.de/de/startseite/institute/lr/forschungsbereiche/politikfolgenabschaetzung/vti-modellverbund/raumis.html`

[9]`https://opus.uni-hohenheim.de/volltexte/2011/610/`

5.1.2 Econometric Models

Another commonly used approach for climate change impact assessments on agriculture are econometric models which are based on economic theory and use real observations to investigate linkages between agriculture and environmental characteristics. These models can be categorised into (i) empirical yield models which are based on production function theory and use crop yield data (e.g. Schlenker & Roberts, 2008; Trapp & Schneider, 2013; Gbetibouo & Hassan, 2005; Onyeji & Fischer, 1994), and (ii) Ricardian models which are based on the Ricardian theory (Ricardo, 1817) and use land value data (e.g. Mendelsohn et al., 1994; Schlenker et al., 2005; Deschênes & Greenstone, 2007; Lang, 2007; Lippert et al., 2009; Van Passel et al., 2012; Fezzi & Batemen, 2012; Trapp, 2013). Both approaches allow for a consideration of weather or climate effects in an actual context and are relatively precise because they use real observations and have a sound theoretical foundation. However, empirical yield models estimate climate impacts on current and past production technologies and do not account for farmers' adaptation of crop choices and management practices. Hence, empirical yield models tend to overestimate the impacts of climate change. Ricardian models try to overcome this shortcoming by estimating the impacts of climate on land values using cross-sectional data, which implicitly considers farmers' behaviour and adaptation strategies to observed variations in climate. On the other hand, Ricardian models do not explicitly represent production and so do not give any insight into the production technologies or adaptation strategies.[10] Furthermore, prices are assumed to remain constant (Cline, 1996) which is problematic given that agricultural prices are largely determined by policies (e.g. subsidies). Another criticism of Ricardian models is the negligence of adjustment costs from one equilibrium to another (Kaiser et al., 1993). The Ricardian approach is a comparative-steady state analysis and not able to capture short-term weather effects or transaction costs between the two long-term equilibria.

Furthermore, econometric models depict relationships from the past and so have a limited forecasting potential and are constrained by the available data with the consequence that the dynamics or effects of unobserved political decision-making (e.g. bioenergy production targets, trade policies) or behavioural change (e.g. cropland expansion) cannot be taken into account. Political change in the EU, however, becomes increasingly

[10] The Ricardian models cannot be linked to equilibrium models.

important in the face of climate change mitigation, adaptation and unrestricted trade.[11] More sophisticated models that depict the complete agricultural sector are required in order to examine future political activities and changes in agriculture.

5.1.3 Objectives

This brief review reveals important shortcomings for both approaches, mathematical programming models and econometric models. Although, empirical yield models are accurate tools for studying short-term effects, methods are required that capture medium and long-term impacts, such as mathematical programming models. These models in turn often lack empirical specification and are based on strong assumptions with little empirical justification. This study attempts to overcome some of the limitations of independently used methods by integrating econometric estimations for the European Union (EU) into a partial equilibrium framework. This allows us to investigate the impacts of climate change on land use decisions and crop production more consistently at different adaptation levels and for different political strategies.

By combining an econometric yield function (Trapp & Schneider, 2013), an econometric input function and a partial equilibrium model (Schneider et al., 2008a), we

(i) assess the medium to long-run impacts of climate change on crop production,

(ii) examine the role of trade, technologies and cropland expansion, and

(iii) investigate the impacts of bioenergy production on land use competition.

Firstly, we econometrically estimate productivity changes at the NUTS2 level in the European Union for different climate change scenarios and use the partial equilibrium approach to assess the net impact of climate change on European agriculture after farm and market adjustments.

Secondly, we examine the role of trade and adaptation strategies. The EU currently follows protectionist trade policies (e.g. domestic support, export subsidies, tariff rate quota utilisation) that impose restrictions on international trade (WTO, 2013). Protectionist trade restrictions can reduce information on global market developments

[11] Many EU countries have adopted programmes, policies or strategies aimed at (i) reducing GHG emissions (e.g. `http://www.eea.europa.eu/themes/climate/policy-context`), (ii) reducing the vulnerability of key sectors (e.g. `http://ec.europa.eu/clima/policies/adaptation/what/index_en.htm`) and (iii) increasing trade (e.g. `http://ec.europa.eu/trade/policy/in-focus/ttip/`).

(Rosenzweig & Parry, 1994) or lower the import volume which can lead to excess demand or increased domestic production. Such developments are often associated with increased land use and reduce economic efficiency. Moreover, a well functioning trade system is responsive to price signals so that agricultural production can shift to regions with comparative advantages for farming and may compensate for losses in other regions (Juli & Duchin, 2007). On the other hand, there are three major arguments against free trade: (i) protection of infant industries, (ii) prevention of dumping and (iii) protection of environmentally regulated industries. Both arguments may play an important role with future climate change. (i) Agricultural production may emerge in new regions due to changing climatic conditions. Farmers may encounter high production costs per unit crop and are at a cost disadvantage compared to more established agricultural regions. These regions may need protection in the short-term to become more competitive on the international agricultural market and to promote farming efficiency. (ii) Dumping may need to be prevented if certain regions can export products at a lower price than other regions due to changing comparative advantages as a result of changing climatic conditions. (iii) Countries which impose stringent environmental regulations in order to internalise negative externalities can reduce the competitiveness of their pollution-intensive industries and hence weaken their comparative advantage (Van Beers & Van Den Bergh, 1997; Jug & Mirza, 2005). Trade barriers, for example, can assist in protecting the domestic industry by increasing the costs of foreign products (e.g. import tariff) or by limiting the import quantities (e.g. import quota). Accordingly, agriculture needs to be considered within a global perspective and the role of trade needs to be recognized in order to consistently investigate the economic impacts of climate change on agriculture. Furthermore, we assess the effects of different adaptation strategies in order to compare the impacts of adaptation on climate impact assessments. Firstly, farmers can adjust their production technology by adopting irrigation technologies. Irrigation can reduce the vulnerability of agricultural production or enable farmers to produce in dry regions. Secondly, farmers can change their choice of crops and adjust their crop portfolio. Farmers, for example, can move to crop types that grow better in warmer or arid climates. And thirdly, farmers can acquire additional land from areas currently dedicated to other uses to compensate for lower productivity. More generally, farmers can increase cropland areas in some regions and/or decrease areas in other regions. We introduce all three adaptation mechanisms that allow for an assessment of policy feedbacks on adaptation and the effectiveness of each strategy.

Finally, we investigate the impacts of bioenergy production on land use competition. Despite a controversial debate about its efficiency (e.g. Searchinger et al., 2008), bioenergy continues to receive political support as a component in the transition from fossil to renewable energy systems and an option to mitigate greenhouse gas emissions. While climate change poses challenges for agricultural production, bioenergy production poses challenges for the demand of agricultural resources and commodities. In the case of limited resources (e.g. fertile land) and climate change, bioenergy can shift land and other resources away from food production and cause competition between bioenergy and food crops (Rathmann et al., 2010; Johansson & Azar, 2007; Schneider et al., 2008b; Da Silva et al., 1978). Therefore, this study considers different scales of bioenergy production and its interdependencies with climate change adaptation and trade policies.

These investigations enable us to gain more insight not only into the costs and benefits of climate change, but also into the value of adaptation and its importance in climate impact assessments.[12]

The remainder of the paper is organised as follows: section 5.2 introduces and combines a partial equilibrium model and econometric models. Section 5.3 presents several farm-level adaptation strategies, bioenergy and trade policy scenarios that allow for a more comprehensive assessment of climate change impacts on agriculture. In section 5.4 we discuss the simulation results and conclude in section 5.5.

5.2 Theoretical Framework

In order to assess the impacts of climate change on European agriculture, we modify an existing partial equilibrium model for the European agricultural sector (EUFASOM: Schneider et al., 2008a) and increase the resolution from a combination of nations and homogeneous response units to an explicit depiction of NUTS2 regions and farming characteristics related to farm type, farm size and altitude level. Forestry and livestock are only implicitly considered in this study.

The agricultural market equilibrium of EUFASOM is computed by choosing regionally available land management systems in order to maximize welfare (i.e. the sum of consumer and producer surplus) subject to resource, technology, and policy constraints. Commodity demand, resource supply, international trade flows, crop areas, crop mix and biomass activities are determined endogenously, whereas other parameters, such as

[12]This study additionally extends previous research by using a modified version of the European Forest and Agricultural Sector Optimization Model (EUFASOM) on a higher resolution (NUTS-2 level) than previous EUFASOM studies and by using detailed farm data from the Farm Accountancy Data Network (FADN) which allow for the consideration of different farm characteristics (e.g. altitude, farm size, specialisation, management practices) in climate impact assessments.

input intensities for different crop types or climate-specific yields, are exogenous. Furthermore, we integrate econometrically estimated impacts of climate change on crop productivity and input requirements. In the following, we give a brief overview of the modified version of the EUFASOM used for this study.

5.2.1 Partial Equilibrium Model

The modified EUFASOM model is a regional model that depicts 273 NUTS 2 regions in 27 EU member states and represents agricultural markets in 28 international regions as indicated in Table 5.1.[13] The model consists of six key components: An objective function (Equation 1), regional commodity balance equations linking domestic and foreign production and consumption (Equation 2), regional resource balance equations for land (Equation 3), and physical resource constraints (Equation 4), regional crop mix equations (Equation 5), biomass production constraints (Equation 6), and non-negativity conditions (Equation 7). Producer adaptation to climate change is incorporated into the management and includes crop portfolio adjustments, cropland expansion and alternative management practices. The objective function maximises social welfare subject to a set of constraining equations and finds the optimal level of all endogenous variables. Social welfare is defined as the areas underneath the demand functions minus the areas underneath the resource supply functions minus the sum of all production and trade cost. By maximising social welfare, the model yields the competitive market equilibrium, where producers are price-taking profit maximisers and consumers maximise utility under given economic, political and technological conditions. Hence, social welfare is maximised as follows

$$
\begin{aligned}
(1)\ \text{Max} \quad W = & \sum_{r,y} \left[\int_0^{Q^*_{r,y}} p_{r,y}\left(Q_{r,y}\right) dQ_{r,y} \right] - \sum_{r,u} \left[\int_0^{Q^*_{r,u}} p_{r,u}\left(Q_{r,u}\right) dQ_{r,u} \right] \\
& - \sum_{r,f,c,m} \left(c_{r,f,c,m} \cdot A_{r,f,c,m}\right) - \sum_{r,\widetilde{r},y} \left(c_{r,\widetilde{r},y} \cdot T_{r,\widetilde{r},y}\right)
\end{aligned}
$$

[13] The definition of regions is consistent with the Global Biosphere Management Model (GLOBIOM) (Schneider et al., 2011) which is based on 11 regions that are used in energy and pollution abatement models and smaller regions from the Prospective Outlook on Long-term Energy Systems (POLES model) (Criqui et al., 1999). This facilitates a linkage of the EUFASOM model to energy models for detailed climate energy sustainability assessments.

$$
\begin{aligned}
\text{s.t.}\quad &(2)\ -\sum_{f,c,m}(o_{r,f,c,m,y}\cdot A_{r,f,c,m})+Q_{r,y} \\
&\qquad +\sum_{\widetilde{r}}T_{r,\widetilde{r},y}-\sum_{\widetilde{r}}T_{\widetilde{r},r,y}\le 0 && \forall r,y \\
&(3)\ \sum_{f,c,m}(i_{r,f,c,m,u}\cdot A_{r,f,c,m})-Q_{r,u}\le 0 && \forall r,u \\
&(4)\ Q_{r,u}\le b_{r,u} && \forall r,u \\
&(5)\ \sum_{f,c_b,m}(A_{r,f,c_b,m})-\sum_{f,c_f,m}\left(A_{r,f,c_f,m}\right)\le 0 && \forall r \\
&(6)\ \sum_{m}(A_{r,f,c,m})-\sum_{t}h_{r,c,t}\cdot X_{r,f,t}=0 && \forall r,f,c \\
&(7)\ Q_{r,y},Q_{r,u},A_{r,f,c,m},T_{r,\widetilde{r},y}\ge 0
\end{aligned}
$$

where variables are endogenous and denoted by capital letters (Q, A, T, B, X) and parameters are exogenous and represented by small letters (c, o, i, h).

Eq. (1) is the objective function which maximises the sum of consumer and producer surplus. The first integral is the area below the inverse demand function for all commodities and regions. The second integral is the area underneath the resource supply function. The third term is the marginal cost for crop production for all regions, management practices, crop types and all combinations of farm characteristics which are summarised in the index f and include the farm type, the farm size and the altitude of the farm.[14] The last term refers to the marginal cost of trade activities.

Eq. (2) links agricultural activities to commodity markets and gives the supply demand balance for all regions and commodities, i.e. for each region and product, commodity demand $(Q_{r,y})$ and the sum of all exports $(\sum_{\widetilde{r}} T_{r,\widetilde{r},y})$ cannot exceed the sum of imports $(\sum_{\widetilde{r}} T_{\widetilde{r},r,y})$ and the total supply of crop production. Trade between European regions and outside of European regions is allowed for food commodities, subject to transportation and trade policy costs (Schneider et al., 2008a). Land use management is linked to crops c through input $(i_{r,f,c,m,u})$ and output $(o_{r,f,c,m,y})$ coefficients, such that $i_{r,f,c,m,u}$ identifies input requirements and $o_{r,f,c,m,y}$ identifies output requirements. The factor requirements are given in Eq. (3), which ensures that the total use of each production factor to produce food and bioenergy crops cannot exceed the supply of resources $Q_{r,u}$ for all regions and resources. The agricultural commodities, food and bioenergy, are produced with the explicit resources land, labour, and water (u), whereas

[14]For a better illustration, all combinations of farm characteristics are summarised in one index. In the model, each farm characteristic is represented by an individual index.

other production factors, i.e. energy, pesticides, and fertilisers, are embedded in the production cost parameters. The production costs related to resource use or factor requirements are depicted by the supply function $Q_{r,u}$ in Eq. (1). Agricultural resource usage is constrained by an upward sloping supply function, whereas food demand faces a downward sloping function (Schneider et al., 2008a). Both, supply and demand, are specified as constant elasticity functions.

Scarce and immobile resources limit the agricultural production. For example, agricultural land or irrigation water are typically limited by regional endowments. These physical constraints are represented by Eq. (4), which ensures that resource supply $Q_{r,u}$ cannot exceed given regional resource endowments $b_{r,u}$ for all regions and resources.

We include a restriction to the allocation of resources to biomass production in Eq. (5). This equation simply forces the total use of resources allocated to biomass production to be at or below 50% of the total use of resources allocated to food production.

Crop rotation plays a critical role in the maintenance of soil quality (e.g. Larkin, 2008), in reducing soil erosion (e.g. Jankauskas & Jankauskiene, 2003), in adding nutrients to the soil (e.g. Houx et al., 2011) and in controlling pests and diseases (e.g. Brust & King, 1994). Modelling crop rotation, however, requires site-specific data on the history of land-use or even detailed analysis when the degree of soil erosion differs within a field (Antle & Stoorvogel, 2001). Therefore, we simplify crop rotation restrictions by a crop mix equation (Eq. 6) which limits all land management options for each region, crop and farm characteristics to a combination of historically observed crop decisions and crop mixes for each farm.

Lastly, we introduce non-negativity constraints which ensure that commodity demand, resource supply, land management, biomass production and trade are greater or equal to zero (Eq. 7). The model components are summarised in Table 5.2.

The model is calibrated in order to ensure that area-weighted average yields aggregated over all observed management options, farm types, and farm size in each NUTS 2 region equal the reported yield data from the Farm Accountancy Data Network (FADN, 2010) and that international trade flows equal the observed trade flows in the reference period (2003-2008) in the FAO database (FAO, 2007). The main challenge in the calibration of the model is the reproduction of the observed data (i.e. benchmark data) for the reference period. Common approaches often assign values estimated in the literature to parameters. Even though such calibration is somewhat arbitrary, it is argued that they are legitimate, because the deviations of a model are deviations from a hypothetical equilibrium and not from an actual economy. In order to reduce this arbitrariness, we

Table 5.1: Geopolitical regions of the basic EUFASOM

Model region	Included countries
ANZ	Australia, New Zealand
Brazil	Brazil
Canada	Canada
China	China
Congo Basin	Cameroon, Central African Republic, Democratic Republic of the Congo, Republic of the Congo, Equatorial Guinea, Gabon
Former USSR	Armenia, Azerbaijan, Belarus, Georgia, Kazakhstan, Kyrgyzstan, Moldova, Russian Federation, Tajikistan, Turkmenistan, Ukraine, Uzbekistan
India	India
Japan	Japan
Mexico	Mexico
Middle East North Africa	Algeria, Bahrain, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Qatar, Saudi Arabia, Syria, Tunisia, United Arabic Emirates, Yemen
Pacific Islands	Fiji Islands, Kiribati, Papua New Guinea, Samoa, Solomon Islands, Tonga, Vanuatu
Central America	Bahamas, Barbados, Belize, Bermuda, Costa Rica, Cuba, Dominica, Dominican Republic, El Salvador, Grenada, Guatemala, Haiti, Honduras, Jamaica, Antilles, Nicaragua, Panama, St. Lucia, St. Vincent, Trinidad Tobago
Rest of Central Europe	Albania, Bosnia Herzegovina, Croatia, Macedonia, Serbia, Montenegro
Rest of Western Europe	Gibraltar, Iceland, Norway, Switzerland
South America	Argentina, Bolivia, Chile, Colombia, Ecuador, Guyana, Paraguay, Peru, Suriname, Uruguay, Venezuela
Rest of South Asia	Afghanistan, Bangladesh, Bhutan, Maldives, Nepal, Pakistan, Sri Lanka
South East Asia other Pacific Asia	Brunei, Indonesia, Malaysia, Myanmar, Philippines, Singapore, Thailand
South East Asia	Cambodia, North Korea, Laos, Mongolia, Vietnam
South Africa	South Africa
South Korea	South Korea
Sub Saharan Africa	Angola, Benin, Botswana, Burkina Faso, Burundi, Cape Verde, Chad, Comoros, Ivory Coast, Djibouti, Eritrea, Ethiopia, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Martinique, Mauritania, Mozambique, Niger, Nigeria, Rwanda, São Tomé and Príncipe, Senegal, Seychelles, Sierra Leone, Somalia, Sudan, Swaziland, Tanzania, Togo, Uganda, Zambia, Zimbabwe
Turkey	Turkey
USA	USA
Baltic EU	Estonia, Latvia, Lithuania
Central East EU	Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia
Midwest EU	Austria, Belgium, France, Germany, Luxembourg, Netherlands
Northern EU	Denmark, Finland, Ireland, Sweden, United Kingdom
Southern EU	Cyprus, Greece, Italy, Malta, Portugal, Spain

Table 5.2: Model components

	Variables
Q	commodity demand or resource supply quantity
A	land management
T	trade
X	crop mix
	Parameters
c	marginal cost for production and trade activities
o	output productivity
i	resource / factor requirements
b	resource endowments
h	historical crop allocation decision
	Functions
p	inverse demand or supply function
	Sets
r	region
y	commodity
u	resource
f	farm characteristics (includes all combinations of farm type, farm size and altitude)
c	food crops (c_f) and bioenergy crops (c_b)
m	management
t	time
	Equations
(1)	Objective function
(2)	Commodity balance
(3)	Resource balance
(4)	Resource limits
(5)	Country-specific biomass constraint
(6)	Crop mix equations
(7)	Non-negative conditions

apply Schneider (2014a) novel downscaling calibration technique which uses a three step procedure. In the first step, the model is solved by maximising social welfare. The welfare results are then implemented into the second step that uses a standard econometric approach in which all the land use and trade parameters are chosen by minimizing the sum of the mean squared deviations from the observed values in the database subject to the welfare solution of the first step. We allow for a small deviation from the first solution by introducing a constraint to the minimization problem that the second welfare solution has to be equal or larger than 99.9% and smaller or equal to 100.1% of the first welfare solution. In the third step, the model is solved again by maximizing welfare subject to the chosen values of the second step.

5.2.2 Econometric Estimates

In order to improve the accuracy of the input and output parameters and their sensitivity to climate change, we implement two econometric models in the agricultural sector model: (i) an empirical yield model (Trapp & Schneider, 2013) and (ii) Just et al. (1990)'s behavioural input rules.

Output Parameters

Impacts of climate change on crop yields are obtained from the study of Trapp & Schneider (2013), which estimates an empirical yield model that links cereal yields to agricultural inputs and environmental conditions. Temperature and precipitation impacts are examined for existing practices. The production process of farm f in year t is defined by the production function y_{ft} follows

$$y_{ft} = g\left(i_{jft}, q_{kft}, v_{lft}, s_{mft}, p\right) \tag{5.1}$$

where y_{ft} are cereal yields, i_{jft}, q_{kft}, v_{lft} and s_{mft} are $FT \times J$, $FT \times K$, $FT \times L$ and $FT \times M$ matrices of agricultural inputs, weather variables, farm and soil characteristics respectively, and p represents technological progress.

The input matrices i_{jft} contain fertilisers, crop protection, machinery and labour and the farm matrix v_{lft} contains information about the economic farm size, crop management (conventional vs. organic) and the altitude of the farm for farm f in year t. The weather matrix q_{kft} contains seasonal temperature averages and precipitation sums and the soil matrix s_{mft} contains variables for the soil quality, type and moisture. These estimates are based on a farm panel dataset obtained from the Farm Accountancy Data Network[15], which was combined with the European Soil Database[16] and the European Climate Assessment & Dataset[17].

The empirical yield model is estimated using dynamic panel data regression methods which allow for the consideration of agricultural input variables. Subsequently, the regression results are combined with climate change scenarios of the regional climate model REMO (Jacob, 2001, 2005a,c,b) for IPCC SRES scenarios (A2, B1) to assess the crop sensitivity in 2100. The statistical results show only partial impacts of climate on crop yields. The integration into the partial equilibrium model allow for the examination of crop developments under climate change and adaptation.[18]

Input Parameters

Most European farms have multiple-input multiple-output production technologies. For example, the production of wheat requires a different amount of fertilisers than the production of corn. Farm datasets, however, typically contain aggregated information on input use and land allocation, whereas production data is often given on a more disaggregated level. Accordingly, most equilibrium models treat input parameters in an ad hoc manner or base them on the literature (e.g. Tol & Fankhauser, 1998). In order to treat the input parameters more consistently in this equilibrium framework, we apply Just et al. (1990)'s approach which allocates different inputs to different outputs based on behavioural rules. Just et al. (1990)'s approach describes variable input allocation in a region with a group of f farms ($f = 1, 2, ..., F$) producing c crops ($c = 1, 2, ..., C$) using i inputs ($i = 1, 2, ..., I$) over t years ($t = 1, 2, ..., T$) and allocates variable inputs among different crops. The input intensities $i^*_{c,i,f,t}$ are defined as the quantity of input i per unit of land used at time t by farm f in producing crop c, are estimated as follows

$$i^*_{cift} = \frac{I_{cift}}{L_{cft}} = \sum_{c=1}^{C} \left[\alpha_{ri} + \beta_{fr} + \gamma_{it}\right] L_{cft} + \epsilon_{ict} \text{ where } \epsilon_{ict} \sim N(\mu, \sigma^2) \tag{5.2}$$

[15] `http://ec.europa.eu/agriculture/rica/`
[16] `http://eusoils.jrc.ec.europa.eu/ESDB_Archive/ESDB/`
[17] `http://eca.knmi.nl/`
[18] The empirical yield model is estimated as a semi-translog function in which the coefficients represent semi-elasticities.

where α_{ri} is an average regional use of input i per hectare of land used for crop c throughout the sample period, β_{fr} denotes deviations by farmer f from the regional average for use of input r, and γ_{it} denotes deviations from the regional average for use of input i at time t. L_{cft} is the area allocated to the production of crop c by farmer f at time t and ϵ_{ict} denotes random variation associated with input i applied by farmer f in time t and is assumed to be i.i.d. The sum of the estimated parameters $\widehat{\alpha}_{ri}, \widehat{\beta}_{fr}$ and $\widehat{\gamma}_{it}$ gives the estimated allocation of input i to crop c at time t. The input allocation coefficients are estimated using the farm panel data of the FADN.[19]

Implementation of Econometric Data

Implementing statistical input and output parameters into the equilibrium model has two major advantages. Firstly, the econometric yield model assumes constant production technologies, and therefore, can only depict the sensitivity of yields and technologies to climate change but not the impacts of climate change on crop yields. Farmers can adapt by adjusting management practices (e.g. irrigation) or crop portfolios (e.g. heat resistant crop species) or by expanding cropland areas. Secondly, the parameters in equilibrium models often lack statistical specification and are subsequently less accurate. In order to analyse the impacts of climate change on adapted agriculture we incorporate the parameters into the EUFASOM as follows: The elasticity estimates $e_{r,f,m,y,j}$ depict the yield response of each region r, farm type f, management practices m, commodity y and weather j to weather parameters w as follows

$$e_{r,f,c,m,y,j} = \frac{\partial \ln(o_{r,f,c,m,y})}{\partial \ln(w_{r,j})} \tag{5.3}$$

where o represents the output productivity parameters, w denotes a set of weather parameters and j represents the weather parameter index. The yield response functions o are defined as translog production functions, specified as

$$o_{r,f,c,m,y} = Z_{r,f,c,m,y} \cdot \prod_j w_{r,j}^{e_{r,f,c,m,y,j}} \tag{5.4}$$

where the parameter $Z_{r,f,m,y}$ is approximated by observed yields and weather parameters

[19]Details on the estimation results are available from the corresponding author.

$$Z_{r,f,c,m,y} = \frac{(\widetilde{o}_{r,f,c,m,y})}{\prod_j \widetilde{w}_{r,j}^{e_{r,f,c,m,y,j}}}. \tag{5.5}$$

Accordingly, the output parameters are specified as

$$o_{r,f,c,m,y} = Z_{r,f,c,m,y} \cdot \prod_j w_{r,j}^{e_{r,f,c,m,y,j}} \tag{5.6}$$

where j represents a set of weather variables (i.e. temperature and precipitation). We additionally implement the input intensities determined with Just et al. (1990)'s behavioural approach. Factor and resource requirements are assumed to be only sensitive to regional climate observed during the sample period. Accordingly, the factor requirement functions are defined as follows

$$i_{r,f,c,m,u} = \sum_{c=1}^{C} \left[\widehat{\alpha}_{ri} + \widehat{\beta}_{fr} + \widehat{\gamma}_{i_{\overline{2003-2008}}}\right] L_{cf_{\overline{2003-2008}}} \tag{5.7}$$

where the sum of the estimated coefficients $\widehat{\alpha}_{ri}$,$\widehat{\beta}_{fr}$ and $\widehat{\gamma}_{it}$ denote the estimated allocation of inputs to food crop c for a group of farms f in the reference period $2003 - 2008$ and region r. The input intensities for each farm are then determined by the product of the estimated input allocations and the area L_{cf} allocated to the production of crop c by farm f in the reference period.

5.3 Scenarios

We simulate agricultural sector impacts by 2100 for 48 scenarios which result from a combination of two climate change projections (B1, A2), six bioenergy policy scenarios (0Mt up to 400Mt), two adaptation scenarios (CMAdapt, MaxAdapt) and two trade regimes (free trade, net import quota).

5.3.1 Climate Change Scenarios

This study considers the impacts of climate change on crop productivity by introducing an econometric yield model. We use two different scenarios in order to capture a range of possible future climate change impacts on Europe. The two climate change projections are based on a regional climate model (REMO) and correspond to the IPCC SRES scenarios (A2 and B1). The B1 scenario corresponds to a "low" emission scenario, whereas the A2 scenario corresponds to a "high" emission scenario. For each climate change scenario, we use the econometric yield model based on Trapp & Schneider (2013) to project changes in the area-weighted average crop yield for each NUTS-2 region, farm type, farm size, altitude and crop.

5.3.2 Non-food demand

A major aspect of this study is to extend the scope of purely econometric models in order to examine the feedbacks of novel land service (non-food) demands on agricultural production. Policies promoting bioenergy production or use affect the agricultural sector in multiple ways (Walsh et al., 2003; Rowe et al., 2009). Firstly, policies aiming at increasing the bioenergy production affect the agricultural areas allocated to food commodities and other agricultural resources. This leads to competition for land and other resources, especially if the resource is scarce (e.g. fertile land). In response to increased land competition between food and bioenergy crops, farmers, for example, can alter their production decisions, land use allocation or management practices. Secondly, policies promoting bioenergy production can have market feedbacks on agricultural producers as well as consumers via price adjustments.

In order to investigate variations in climate change impacts if non-food demand is added, we introduce different bioenergy production targets. Bioenergy production is only promoted in EU countries whereby resources for bioenergy can only be sourced from agricultural land activities. The bioenergy targets are implemented as exogenous demand targets. Starting from a baseline scenario of 0Mt (NoBioEng), bioenergy production targets are gradually increased by 80Mt (BioEng1 to BioEng4) up to a maximum production target of 400Mt (BioEng5). The different scales of bioenergy production targets are illustrative for different climate change mitigation. Bioenergy is represented by three biofuel and energy crops (i.e. miscanthus, poplar coppice and reed canarygrass plants). Data for the three crops are obtained from the European Non-Food Agriculture project (ENFA, 2008). Bioenergy production is constrained by a land use allocation rule, which limits land use for bioenergy production to 50% or less of total land endowments in each NUTS2 region.

5.3.3 Climate Change Adaptation

Effective response to climate change also requires that farmers adapt to changing climatic conditions in order to reduce the vulnerability of agriculture and damages of a long-term warming. Accordingly, farmers can adjust the crop portfolio (e.g. increasing the share of less vulnerable crop types) and management practices (e.g. irrigation) in order to reduce the vulnerability and risk of agricultural production or to increase agricultural productivity. Furthermore, cropland areas can be expanded, subject to resource endowments, in response to an increase in land use competition or declining productivity in order to offset areas allocated to other alternatives (e.g. bioenergy) or climate change-induced production declines.

We introduce three adaptation strategies into EUFASOM and assess the value of adaptation by comparing crop production and welfare changes for the different adaptation scenarios. The baseline scenario assumes that regions do not adapt to climate change (Base scenario). The reference resource and land use data are taken from the FADN (FADN, 2010). In order to assess the impacts of different adaptation strategies, we introduce crop portfolio adjustments within historically observed crop mix (CMAdapt scenario) and an adaptation scenario with cropland expansion and crop share restrictions but without crop mix restrictions (MaxAdapt scenario). Management practices are additionally determined endogenously and allow the farmers to adopt irrigation technologies.[20] The exogenous and endogenous adaptation decision parameters are summarised in Table 5.3.

5.3.4 Trade Scenarios

Trade increases the economic efficiency, and therefore, reduces agricultural production costs, food shortage or resource scarcity. Unrestricted trade, for example, tends to reduce water use in water scarce regions (Calzadilla et al., 2011) and consequently can indirectly resolve problems of water stress or accelerate the efficacy of climate change adaptation.[21] The model accounts for net trade between 28 regions that are exporters and importers of agricultural commodities. Trade is endogenously determined by the model within trade constraints as imposed by different trade policy scenarios. Three trade scenarios simulate different trade regimes and allow for an evaluation of the effects

[20]Irrigation is one of the major adaptation strategies and can increase the productivity, but raises the production costs per hectare.

[21]If externalities or inputs, however, are not internalised in markets (e.g. irrigation water is free of cost), unrestricted trade may countervail efficient adaptation.

Table 5.3: Adaptation scenario in EUFASOM

Management parameter	Adaptation strategy	Adaptation options
No adaptation[1]	BaseAdapt	
Irrigation alternatives	CMAdapt, MaxAdapt	No irrigation
	CMAdapt, MaxAdapt	Full irrigation
Crop choice[2]	CMAdapt	Crop choice within historically observed crop mixes
	MaxAdapt	Crop choice with crop share restrictions
Agricultural area	CMAdapt	Expansion with crop mix restrictions
	MaxAdapt	Expansion without restrictions

[1]Solution as in base period (2003-2008). [2]Crops in EUFASOM include wheat, barley, oats, rye, rice, corn, soya, sugarcane, sugarbeet and potatoes.

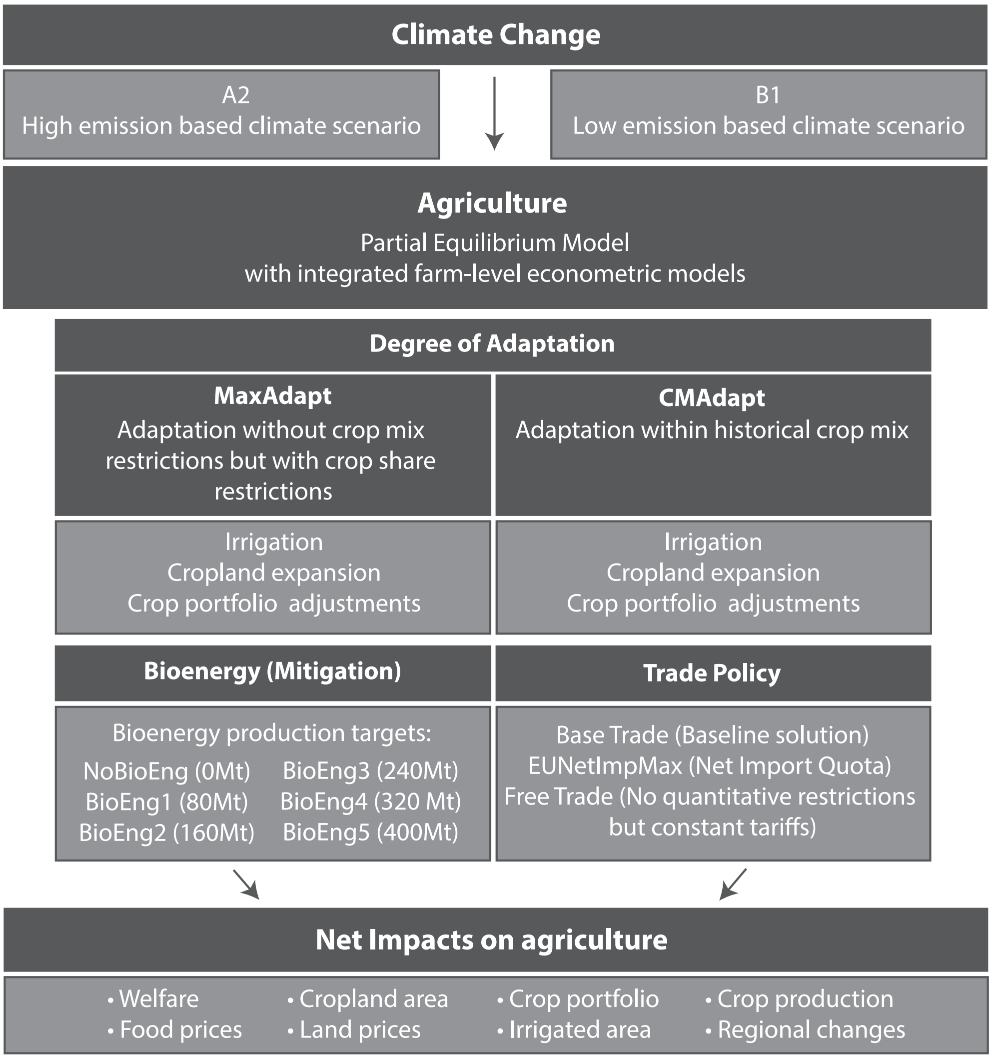
of unrestricted trade on crop production, commodity prices and welfare as well as the interdependencies with climate change, adaptation and mitigation (i.e. bioenergy production). The baseline scenario fixes trade volume to current import and export levels (Base Trade). In order to examine the importance of trade, we introduce two alternative scenarios and simulate (i) unrestricted trade (Free Trade) and (ii) the introduction of a net import quota (EUNetImpMax) which limits the sum of net imports (imports minus exports).[22] The net import quota restricts the volume of trade such that the sum of all imports minus the sum of all exports is smaller or equal to the net imports in the baseline scenario. The latter scenario represents a moderate trade regime which restricts the trade volume, while the first scenario (Free Trade) liberalises trade. A net import quota is conceivable, for example, to support local producers or domestic markets, to protect the health of the European population, to avoid shortage of commodities in the domestic market or to prevent anti-dumping regulations. Furthermore, import tariffs could be introduced to reduce carbon leakage and trade of high emission products (e.g. fertiliser intensive crops). Trade data (e.g. export and import quantity, price and export elasticity) and international market data (e.g. production, demand, supply, price) are

[22]EUFASOM is calibrated to observed trade quantities and determines total trade costs which lead to the observed trade quantities. Determining the contribution of tariffs (e.g. in order to simulate the effects of unrestricted trade) to total trade costs is complex and difficult, because there is great variation across countries and goods.

obtained from the FAOSTAT database (FAO, 2007).

A schematic representation of the modelling framework with all policy and adaptation scenarios is given in 5.1. The exogenous policy and adaptation parameters affect several important parameters in the modified EUFASOM. The model is solved for each scenario and we examine in particular (i) regional crop production, (ii) consumer welfare, (iii) the role of different adaptation strategies (farm-level, policy-level) and (iv) the role of bioenergy production.

Figure 5.1: Schematic representation of analysis



5.4 Simulation Results and Discussion

The objective of this study is to assess medium-term to long-term impacts of climate change on European agriculture under the consideration of different adaptation strategies, trade regimes and bioenergy policies. In order to evaluate the influence of different adjustment strategies and potential interdependencies between policies and adaptation, we examine regional production changes, welfare impacts as well as the influence of different adaptation strategies at the farm and policy-level. For this purpose, EUFASOM performs several experiments with political, farm and environmental changes. The experiments include unrestricted trade, a net import quota, bioenergy production (0 to 400 Mt), irrigation, cropland expansion, crop portfolio adjustments and climate change.

5.4.1 Impacts of Climate Change and Bioenergy Production on Regional Crop Production

Climate change is expected to have different impacts on regions with some being winners and others being losers of a long-term warming. Previous research confirms the expecation of a positive development in agriculture for Northern Europe and a decrease in productivity for Southern Europe (Lang, 2007; Lippert et al., 2009; Van Passel et al., 2012; Fezzi & Batemen, 2012; Trapp & Schneider, 2013; Trapp, 2013), but the overall net impacts of climate change in Europe are yet uncertain. Potential interdependencies between climate change and land use change add uncertainty to the assessment of climate change. Climate change can reduce agricultural productivity (Trapp & Schneider, 2013; Trapp, 2013) whereas increased demand for non-food agricultural products (e.g. bioenergy crops and policies) adds pressure to regional food production by increasing land use competition.

The combined effects of climate change and bioenergy on regional production by 2100 assuming no effective adaptation or trade adjustments are shown in Fig. 5.2.[23] The four scenarios (a-b) depict different climatic conditions and the influence of land use competition between bioenergy and food commodities on regional food production. As expected, food crop production shows a south-to-north gradient in the high emission based climate scenario (A2) due to changing climatic conditions. Thus production in most regions in Southern Europe decreases by 10 to 80% and increases in Northern

[23] Note that production changes are based on the assumption of no adaptation at the farm or policy-level.

Europe by up to 40%. In the low emission based climate scenario (B1) production declines significantly less in Southern European regions, but decreases significantly more in Northern Europe due to less favourable climatic conditions. The net impact of climate change on total crop production in Europe is negative in the A2 scenario (-4%) and positive in the B1 scenario (+2%).

Bioenergy production, in conjunction with climate change, has a significantly larger impact on regional crop production. EUFASOM allocates bioenergy production to regions that have a comparative advantage for bioenergy production (e.g. lower production cost), but maintains a minimum of 50% food crop areas in each NUTS2 region. Both scenarios, A2 and B1, suggest that bioenergy crop production increases in Central Eastern, Mid West and Baltic Europe and food crop production increases in Northern Europe and some regions in Southern Europe. In the B1 scenario, food crop production increases more in Southern and Mid West Europe. The net impact of large-scale bioenergy production on food production is negative for both scenarios.

Negative impacts of climate change and bioenergy production on food production and welfare, however, can be mitigated by adaptation at the farm-level (compare section 5.4.3) and at the policy-level (compare section 5.4.4).

5.4.2 Welfare Impacts

Consumer Welfare

This section examines the change in consumers' welfare for different scenarios in more detail.[24] Consumer welfare refers to the benefits derived from the consumption of agricultural commodities and is measured by the Marshallian consumer surplus. Consumer surplus and producer surplus can be calculated as follows

$$\text{Consumer surplus} = \int_0^{q^e} D(q)dq - p_e q_e = \int_0^{q^e} [D(q) - p_e]dq \tag{5.8}$$

$$\text{Producer surplus} = p_e q_e - \int_0^{q^e} S(q)dq = \int_0^{q^e} [p_e - S(q)]dq \tag{5.9}$$

where $D(q)$ and $S(q)$ are the demand and supply function of commodity q with the corresponding equilibrium price p_e and equilibrium quantity q_e. Consumer and producer surplus as well as the expected impacts of climate change on welfare are illustrated in Fig. 5.3.

[24] Producer welfare can be examined equivalently.

Figure 5.2: Regional changes in crop production by 2100 (in %) with (a) no bioenergy and (b) 400Mt bioenergy production assuming constant trade (i.e. baseline solution) and no effective adaptation (i.e. constant crop areas in the NUTS2 regions)

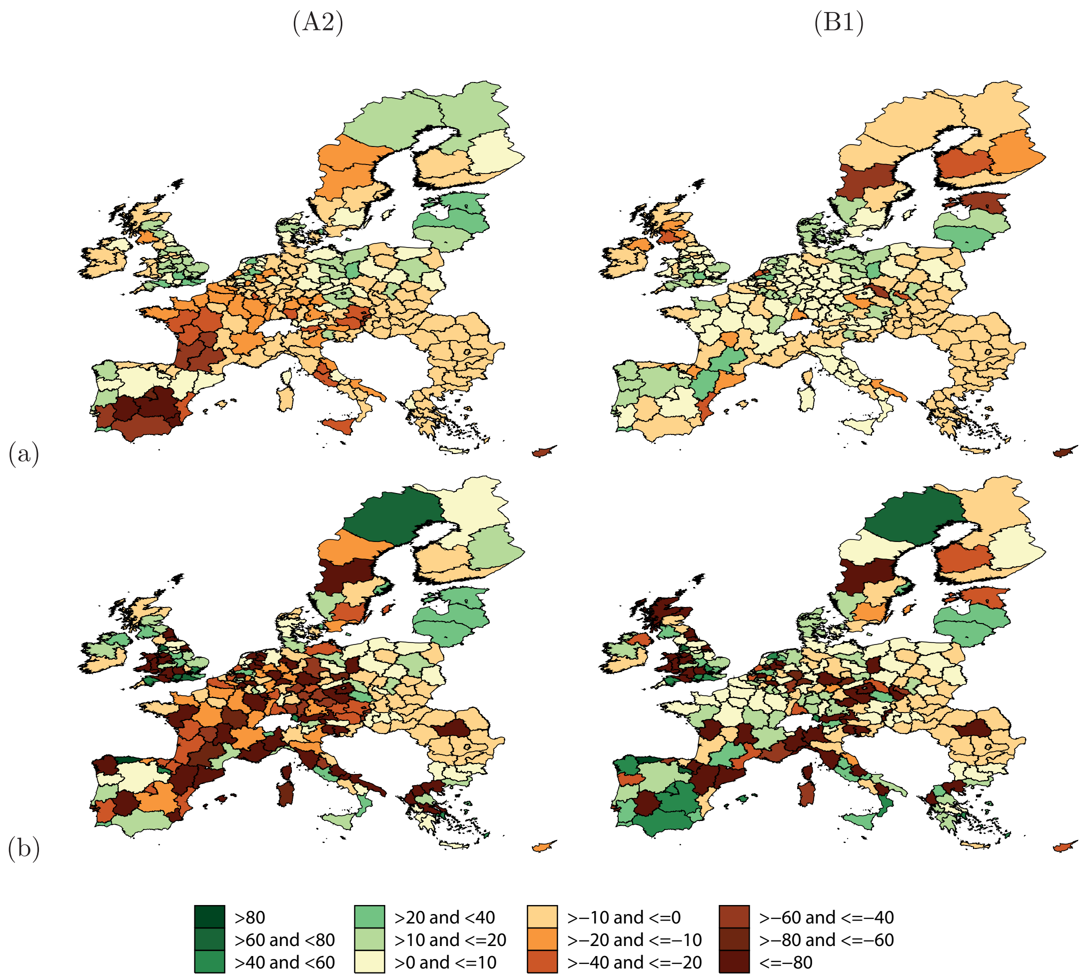
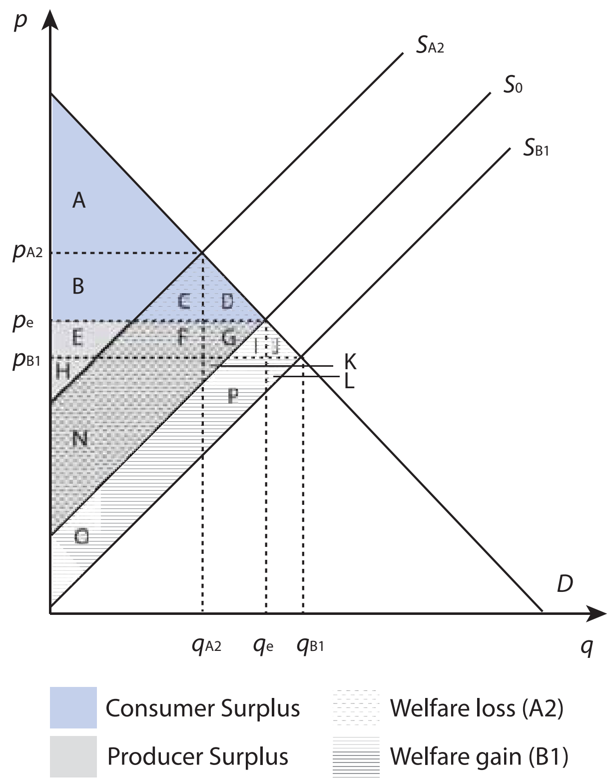


Figure 5.3: Climate change impacts on welfare



Marshallian consumer surplus is the area below the demand curve and above the equilibrium price $(A+B+C+D)$, whereas producer surplus is the area above the supply curve and below the equilibrium price $(E+F+G+H+N+K)$. Severe climate change (A2) is expected to reduce the productivity and, ceteris paribus, shifts the supply curve upwards from S_0 to S_{A2} and raises commodity prices to p_{A2}. Consumption declines to q_{A2} as a result of higher prices. Hence, consumer surplus decreases by $(B+C+D)$ and producers gain area (B) due to an increase in commodity prices, but producers also lose area $(F+G+K+N)$ as a result of lower demand and climate change impacts (i.e. lower productivity). The total welfare loss caused by climate change (A2) is equivalent to the area $(C+D+F+G+K+N)$. On the other hand, a low emission scenario (B1) is expected to increase agricultural productivity. Ceteris paribus, the supply curve shifts downwards from S_0 to S_{B1}. The higher level of output increases production to q_{B1} and reduces consumer prices to p_{B1} so that consumers and producers can gain from moderate climate change. Hence, consumer surplus increases by $(E+F+G+I+J)$ and producer surplus increases by area $(L+O+P)$ because of an increased demand, but producers also lose $(E+F+G)$ due to lower commodity prices. The total welfare gain as a result of moderate climate change is equivalent to the area $(I+J+L+O+P)$.

In the baseline scenario of EUFASOM, the EU implicitly controls the entry of cereals and other crops into the EU by issuing a standardised import license and payment of a variable or fixed import tariff (EU, 2014).[25] Furthermore, the EU is a net importer in the base scenario.[26] Fig. 5.4 and 5.5 depict the world market for agricultural commodities for the two climate change scenarios (A2 and B1) and illustrate the impacts of climate change, non-food demand and trade policies on consumer welfare. The corresponding model results for the change in EU and non-EU consumer welfare are summarised in Appendix 5A (Fig. 5.12).

Climatic conditions in a high emission based climate scenario (e.g. A2), for example, shift the supply curve upwards from S_0 to S_{neg} as a result of lower agricultural productivity (compare Fig. 5.4). The production decline in the EU ($q_{S,neg}$) increases import demand, and thus, shifts the import demand curve upwards to MD_{neg} which raises world market prices (p_{neg}). Ceteris paribus, domestic production increases to $q_{S,neg}$ and domestic consumption reduces to $q_{D,neg}$, whereas non-EU production increases to q_{S,neg^*} and non-EU consumption decreases to q_{D,neg^*}. The loss in consumer surplus as a result of climate change impacts on EU agriculture and raising commodity prices is equivalent to the area $(A + B + C)$, whereas consumers in non-EU countries lose area $(A^* + B^*)$.

On the other hand, in a low emission based climate scenario (e.g. B1), the supply curve shifts downwards from S_0 to S_{pos} (compare Fig. 5.5), because of a higher productivity under the growing conditions in the B1 scenario. A higher domestic production lowers import demand, and therefore, shifts the import demand curve downwards to MD_{pos} and reduces commodity prices to p_{pos}. The price reduction in turn increases consumption in the EU ($q_{D,pos}$) and in non EU countries (q_{D,pos^*}) but reduces domestic ($q_{S,pos}$) and non-EU production (q_{S,pos^*}). Consequently, EU consumers gain area $A + B + C + D$ and non-EU consumers gain area $A^* + B^*$.

The degree to which the supply curve is shifted, however, is highly dependent on the adaptation strategy, the trade regime and the scale of bioenergy production. If farmers, for example, adapt to the new climatic conditions within the limits of historically observed crop mixes (CMAdapt) the supply curve would shift less upwards in the A2 scenario or even further downwards in the B1 scenario than in a scenario without any adaptation. As a result, the loss or gain in consumer welfare decreases or increases, respectively.

[25] Note that EUFASOM is calibrated to observed trade quantities, which are based on current trade policies of the EU and include a range of import barriers.

[26] Note that the EUFASOM model is based on data from 2003-2008. During this period, the EU was a net importer of major agricultural products. The EU has turned into a net exporter due to increasing commodity prices in 2010 (`http://ec.europa.eu/agriculture/trade-analysis/map/archive_en.htm`).

If adaptation options are unlimited (MaxAdapt) farmers' can specialise even more, and therefore, can adapt even better to climate change, because the production of less vulnerable crop types is increased and more vulnerable crop types are decreased. Ceteris paribus, the supply curve shifts upwards for some commodities and downwards for others. The net effect on consumer surplus is dependent on the degree and the direction to which the supply curves shift. The reasoning behind the diverging shift of the supply curve for different commodities can be derived from the production possibility frontier, which shifts towards crop species that grow better under the climatic conditions of a high or low emission based climate scenario (compare Fig. 5.6). The net impact of intensive adaptation on consumer surplus, therefore, highly depends on the change in the production possibility frontier of the EU.

The degree of specialisation in agricultural production also depends on the trade regime and agricultural non-food demand. In order to assess their impact on consumer welfare, we implement three additional experiments into EUFASOM.

In a first experiment, we assume that the EU imposes a net import quota (IQ) in a high emission based climate scenario (compare IQ in Fig. 5.4). An IQ affects trade similarly to a subsidy on exports plus a tariff on imports.[27] An IQ fixed to current levels drives a wedge between the import demand and export supply curve which raises the price for commodities in the EU (p_{IQ}) and reduces prices in non-EU countries (p_{IQ^*}). As a result of higher domestic prices, EU production increases ($q_{S,IQ}$) and domestic consumption decreases ($q_{D,IQ}$). Non-EU production, on the other hand, decreases (q_{S,IQ^*}) because producers obtain lower prices on the world market (p_{IQ^*}) whereas non-EU consumers increase demand as a result of lower commodity prices in non-EU countries. Accordingly, domestic consumers lose area ($D+E+F$) in the case of a negative supply shift whereas consumers in non-EU countries gain area (A^*+B^*). Even though domestic producers gain from higher domestic prices ($D+E$), the IQ results in deadweight losses ($I + J$) and reduces consumption and production efficiency.[28] Furthermore, domestic markets are expected to be more vulnerable to environmental and policy changes because trade adjustments to supply and demand changes are limited with an IQ. In the case of a positive supply shift, on the other hand, the IQ has no effect on the domestic or the world market, because the positive supply shift increases domestic production and reduces import demand. Hence, the equilibrium import demand lies below the initial

[27]It should be noted that this would violate the EU's commitments under the World Trade Organisation (WTO, 2013), but allows us to compare consumer surplus to the baseline scenario.

[28]If the export curve is steep enough, the terms-of-trade effect can be strong so that the EU can still gain.

import demand.

The market equilibria in a scenario with a net import quota are similar to the market equilibria of the baseline scenario, which restricts imports and exports to trade quantities which are optimal for conditions in the baseline scenario (i.e. no climate change, 0Mt bioenergy production, no trade barriers and no adaptation). Therefore, in a second experiment the EU liberalises trade by eliminating the trade restrictions of the baseline scenario. Unrestricted trade (FT) in a high emission based climate scenario (A2), ceteris paribus, reduces commodity prices in the EU to p_{FT}. Lower commodity prices increase domestic demand ($q_{D,FT}$) but reduce domestic production ($q_{S,FT}$) and consequently, import demand increases to q_{FT} and world market prices rise to p_{FT}. Due to the rise in world market prices, non-EU producers increase the production (q_{S,FT^*}), but non-EU consumers lower demand (q_{D,FT^*}). Accordingly, EU consumers gain compared to the baseline scenario ($D + E + F$) as a result of lower commodity prices, whereas domestic producers lose (D) as a result of lower commodity prices. The increase in consumer surplus, therefore, comprises a reduction of producer surplus and efficiency gains (I). Consumer surplus in non-EU countries decreases by $A^* + B^*$ and producer surplus in non-EU countries increases by $A^* + B^* + C^*$ in an unrestricted trade scenario because of the rise in world market prices. In a low emission based climate scenario (B1), unrestricted trade policies are less effective due to the positive supply shift, which increases domestic production and reduces import demand.

In a last experiment, we assume that the EU implements large-scale bioenergy production targets (compare Fig. 5.4). In EUFASOM, bioenergy production initiates competition for land and other resources between bioenergy crops and food crops resulting in lower domestic food production ($q_{S,neg}$). Lower domestic production increases import demand and shifts the import demand curve upwards to MD_{neg}. Prices on the world market increase to p_{neg} which reduces domestic consumption ($q_{D,neg}$) and non-EU consumption ($q^*_{D,neg}$). As a result, consumer surplus in the EU and non-EU decreases by $A + B + C$ and $A^* + B^*$, respectively. The degree to which consumer surplus is affected, therefore, highly depends on the scale of bioenergy production, the trade regime, the adaptation strategy as well as on the magnitude of climate change. For example, in a scenario (i) with large-scale bioenergy production, low adaptation efforts, severe climate change and trade barriers (i.e. IQ), consumer surplus will decrease significantly more than in a scenario (ii) with small-scale bioenergy production, intensive adaptation, moderate climate change and liberalised trade as a consequence of increased land use competition, reduced productivity and trade barriers. These results are confirmed by

EUFASOM (compare Appendix 5A Fig. 5.12) which shows that consumer surplus in the EU and non-EU decreases gradually by up to 3.3% in scenario (i) and increases by up to 0.1% in scenario (ii).

Producer welfare can be examined similarly to consumer welfare and is represented by the area above the supply curve and below the equilibrium price. The change in producer surplus, however, is highly dependent on the elasticity of demand. Fig. 5.7 exemplifies the influence of adaptation induced technological progress on the shift of the supply curve and the resulting change in producer surplus for a relatively elastic and inelastic demand function.

Food Prices and Market Adjustments

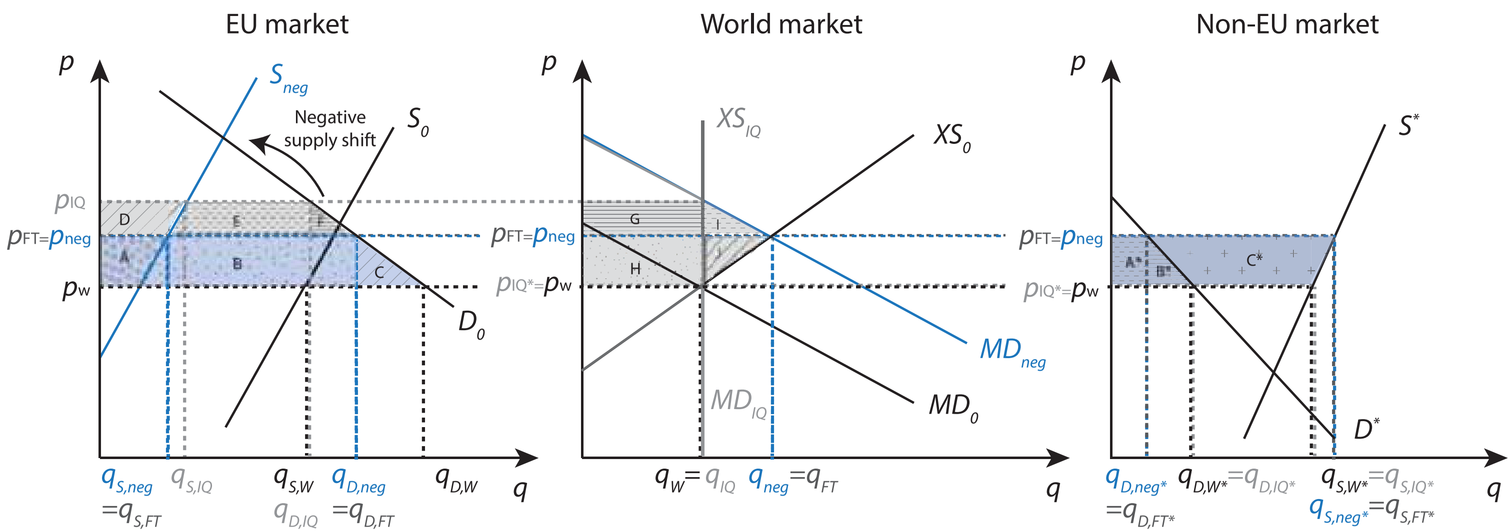
Agricultural markets respond to changes in food production via price adjustments. Price indices are used to measure price changes and allow for a comparison of price and consumption changes for different climate conditions, trade regimes, bioenergy regulations and adaptation strategies. For this purpose, we use the Fisher price index, because it is defined as the mean of the Laspeyres price index and the Paasche price index, and therefore, it is known as the "ideal" price index (Persons, 1921). The Laspeyres price index compares the price of a basket of crops c in the baseline scenario with a bioenergy production target t (i.e. 0Mt) with the prices of the same basket of crops in a scenario with a bioenergy production target $t+1$ (e.g. 40Mt), where prices are weighted by the quantity of crops in the baseline scenario with bioenergy production t. Accordingly, the Laspeyres price index is defined as follows

$$P_L = \frac{\sum_{c=1}^{n} P_c^{t+1} Q_c^t}{\sum_{c=1}^{n} P_c^t Q_c^t} \tag{5.10}$$

where P_c is the price for a crop c and Q_c is the quantity of crop c. The Paasche price index compares the cost of purchasing a basket of crops c in a scenario of a bioenergy production target $t+1$ with the cost of purchasing the same basket of crops in the baseline scenario with a bioenergy production target t, where prices are weighted by the quantity of crops in the scenario with bioenergy production targets $t+1$. Accordingly, the Paasche price index is defined by

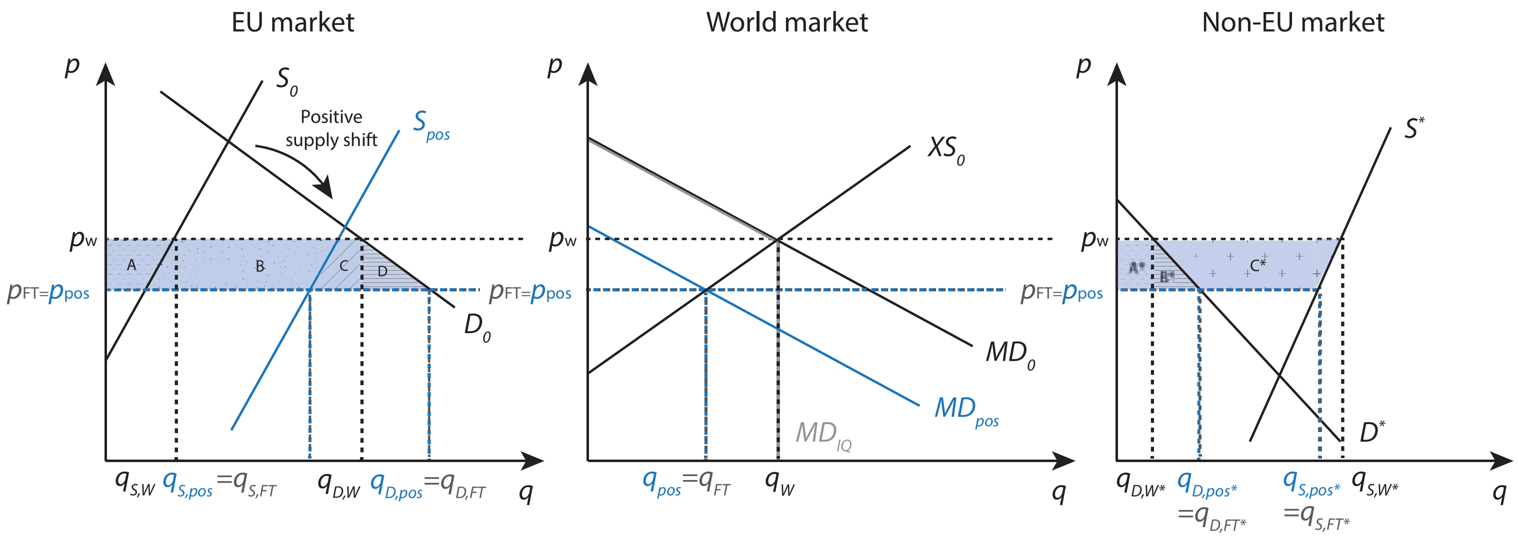
$$P_P = \frac{\sum_{c=1}^{n} P_c^{t+1} Q_c^{t+1}}{\sum_{c=1}^{n} P_c^t Q_c^{t+1}}. \tag{5.11}$$

Figure 5.4: Change in consumer surplus with a negative supply shift (e.g. A2 climate change scenario, bioenergy production), a net import quota (IQ) and unrestricted trade (FT)



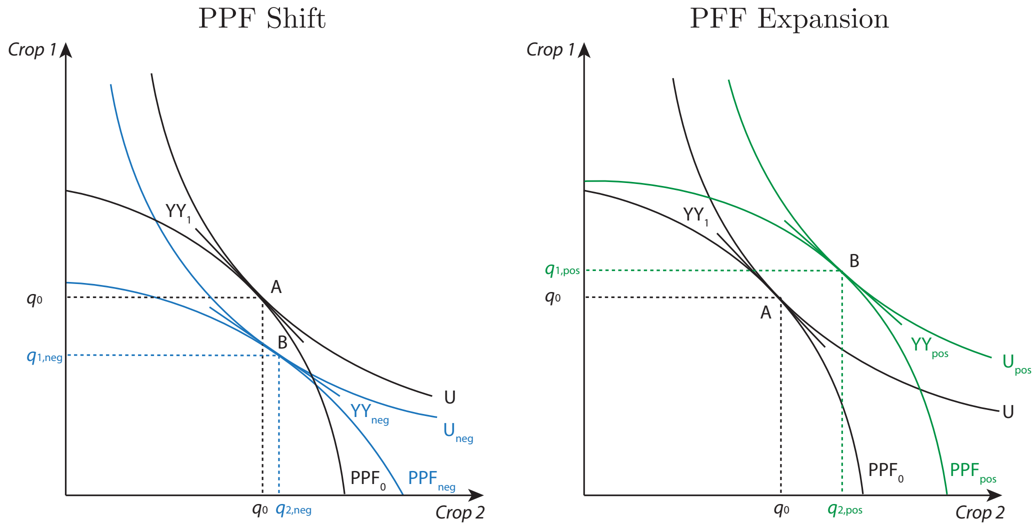
Note that consumption changes are only illustrated by changes along the demand function. A shift of the demand function, for example, due to population growth or a change in diets, is not considered in this analysis in order to depict the partial effects of climate change, adaptation mechanisms, trade policies and bioenergy production.

Figure 5.5: Change in consumer surplus with a positive supply shift (e.g. B1 climate change scenario, adaptation), a net import quota (IQ) and unrestricted trade (FT)



Note that consumption changes are only illustrated by changes along the demand function. A shift of the demand function, for example, due to population growth or a change in diets, is not considered in this analysis in order to depict the partial effects of climate change, adaptation mechanisms, trade policies and bioenergy production.

Figure 5.6: Climate change impacts on the production possibility frontier (PPF) of the EU



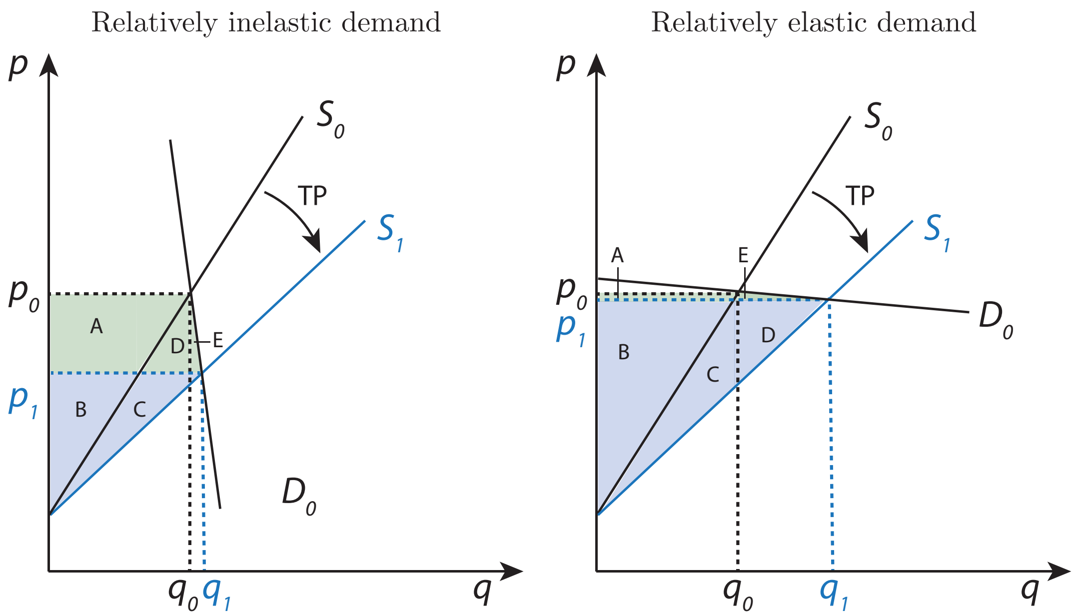
The figure illustrates the impacts of climate change on the production possibility frontier of the EU and the associated change in consumer surplus by depicting the difference in welfare between two consumption points, one without climate change (A) and one with climate change (B). For better illustration, we assume no tariffs, taxes or transportation costs and consider only two crops (crop 1, crop 2). The EU can either use all resources to produce crop 1 or crop 2 or a combination of both crops along the production possibility frontier (PPF). The indifference curve (U) represents the utility of European consumers for the combination of crop 1 and crop 2 whereas YY indicate the ratio of prices of crop 1 and crop 2. Climate change alters the growing conditions and shifts the production possibility frontier (PPF) from PPF_0 to PPF_{neg} in the left panel (e.g. high emissions) and to PPF_{pos} in the right panel (e.g. low emissions). In the left panel, crop 2 benefits from changing climatic conditions and the production of crop 2 increases from q_0 to $q_{2,neg}$ whereas the production of crop 1 decreases from q_0 to $q_{1,neg}$. In the right panel, both crops benefit from changing climatic conditions in which the production of crop 2 increases more ($q_{2,pos}$) than the production of crop 1 ($q_{1,pos}$). The gains and losses are depicted by the consumption points of crop 1 and crop 2 (A and B, respectively).

The Laspeyres and Paasche indices define the lower and upper bound of the Fisher index (Diewert, 1978), which is defined as

$$P_F = \sqrt{P_L P_P} \tag{5.12}$$

where P_L is the Laspeyres price index and P_P is the Paasche price index. An index (P_F) below 100 indicates that crop prices in a scenario with bioenergy production lie below the price levels in the baseline scenario, whereas an index above 100 indicates that

Figure 5.7: Impacts of adaptation induced technological progress and price elasticity of demand on welfare



$$\Delta PS = -A + C$$
$$\Delta PS < 0 \text{ if } -A > C$$
$$\Delta CS = A + D + E$$

$$\Delta PS = -A + C + D$$
$$\Delta PS > 0 \text{ if } -A < C + D$$
$$\Delta CS = A + E$$

The figure illustrates that the price elasticity of demand is decisive for the change in producer surplus. For example, adaptation of management practices and farming activities to changing climatic conditions could lead to technological progress (TP). Assuming that TP is reflected by a change in a supply shifting variable, TP leads to a rotation of the supply curve from S_0 to S_1. TP lowers production costs which decreases commodity prices to p_1, and consequently, increases demand (q_1). If the demand for food commodities is relatively inelastic, the net gain in producer surplus (PS) is negative due to the steepness of the demand curve. More specifically, farmers would gain an area C as a result of increased demand but lose area A due to a drop in commodity prices. Hence, the price effect is greater than the quantity effect if food demand is inelastic. Consumer surplus (CS), on the other hand increases significantly if the demand is inelastic and gain area $A + E + D$. If the demand for food commodities is relatively elastic, the net gain in producer surplus is more likely to be positive due to the flatness of the demand curve. The area A depicts the loss of producer surplus as a result of lower commodity prices, whereas the area $C + D$ depicts the gain in producer surplus as a result of increased demand. Hence, the quantity effect can be greater than the price effect if the demand for food commodities is elastic. Consumers gain significantly less if the demand for food commodities is elastic ($A + E$). Accordingly, the net impact of supply shifts - induced by technological, environmental or policy changes - on consumer and producer surplus, highly depends on the elasticity of food demand.

price levels in a scenario with bioenergy production lie above crop prices in the baseline scenario.

EUFASOM shows that commodity prices respond to changes in agricultural production and lead to adjustments in the demand and supply balance. The price adjustments are the net result of simultaneous environmental and market changes: (i) climate change, (ii) bioenergy production, (iii) trade regimes and (iv) adaptation mechanisms.[29] Fig. 5.8 depicts the model results of the Fisher price index and the demand and supply balance for each scenario.

(i) In a high emission based climate scenario (A2) agricultural productivity and production levels decrease if production technologies and management practices are not sufficiently adapted to the climatic conditions. The demand for food is relatively inelastic, and therefore, a production decline (e.g. 1% to 5% in the CMAdapt scenario) leads to a rise in food prices (7% to 10%) but only small adjustments in food demand (0% to -2%) as illustrated in Fig. 5.8. The degree of price adjustments though largely depends on the policy settings. In a low emission based climate scenario (B1), on the other hand, production is increased (e.g. 5% in the CMAdapt scenario), leading to a price decrease (1% to 3%). Although, climate change will affect agriculture and food prices globally, the price index for non-EU countries in EUFASOM depicts only the partial effects of political and environmental changes in European agriculture on the rest of the world. EU food prices, for example, influence non-EU food prices via trade flows. Therefore, climate change in the EU only affects non-EU food prices, if trade adjusts to production and consumption changes (e.g. free trade).

(ii) Growing crops for bioenergy increases competition for land and other resources, and therefore, can also affect food prices. EUFASOM only considers bioenergy which is produced on agricultural areas dedicated to food. Consequently, agricultural production decreases significantly if bioenergy production increases which raises commodity prices. Depending on the scale of bioenergy production and the trade regime, land use competition can have an even larger impact on production and commodity prices than climate change. If trade is additionally restricted, prices in the EU increase by up to 70% for

[29] EUFASOM is designed to examine medium-term to long-term price and production trends whereas short-term price fluctuations (e.g. annual, monthly), such as speculation induced price volatility or price peaks arising out of production losses in extreme weather, are not captured by the model. Other long-term developments, such as rising energy prices (e.g. fossil fuels), increases in agricultural costs of production (e.g. irrigation water), increasing demand due to population growth or global economic growth and the corresponding change in diets could put additional pressure onto food prices. Furthermore, adjustment and transaction costs (e.g. cost of transforming forests into agricultural land) are not taken into account.

large bioenergy production targets, whereas in a free trade scenario, much of the price increase is mitigated by trade. Consequently, prices increase significantly less (<11%).[30]

Accordingly, (iii) trade plays a moderating role by responding to supply or demand shifts. For example, in a scenario with large-scale bioenergy production and limited adaptation options, food production declines (12% to 21%) and in order to mitigate price increases, imports rise in a free trade scenario to balance supply and demand. If trade is limited (e.g. net import quota), supply can be more easily distorted by climate change and land use competition due to trade barriers which inhibit trade adjustments. As a result prices increase substantially more (50% to 70%) than in a free trade scenario and consumption levels adjust correspondingly. The experiments show that a free trade scenario has also important implications for non-EU countries and global commodity prices. On the one hand, unrestricted trade can even reduce commodity prices in non-EU markets (1% to 2%) if climate change in the EU is less severe. On the other hand, global commodity prices respond more strongly to policy change in the EU (i.e. bioenergy policies), because bioenergy production crowds out some of the domestic food production. In order to balance supply and demand in the EU, export supply declines or import demand rises which, ceteris paribus, leads to an increase in global commodity prices.[31]

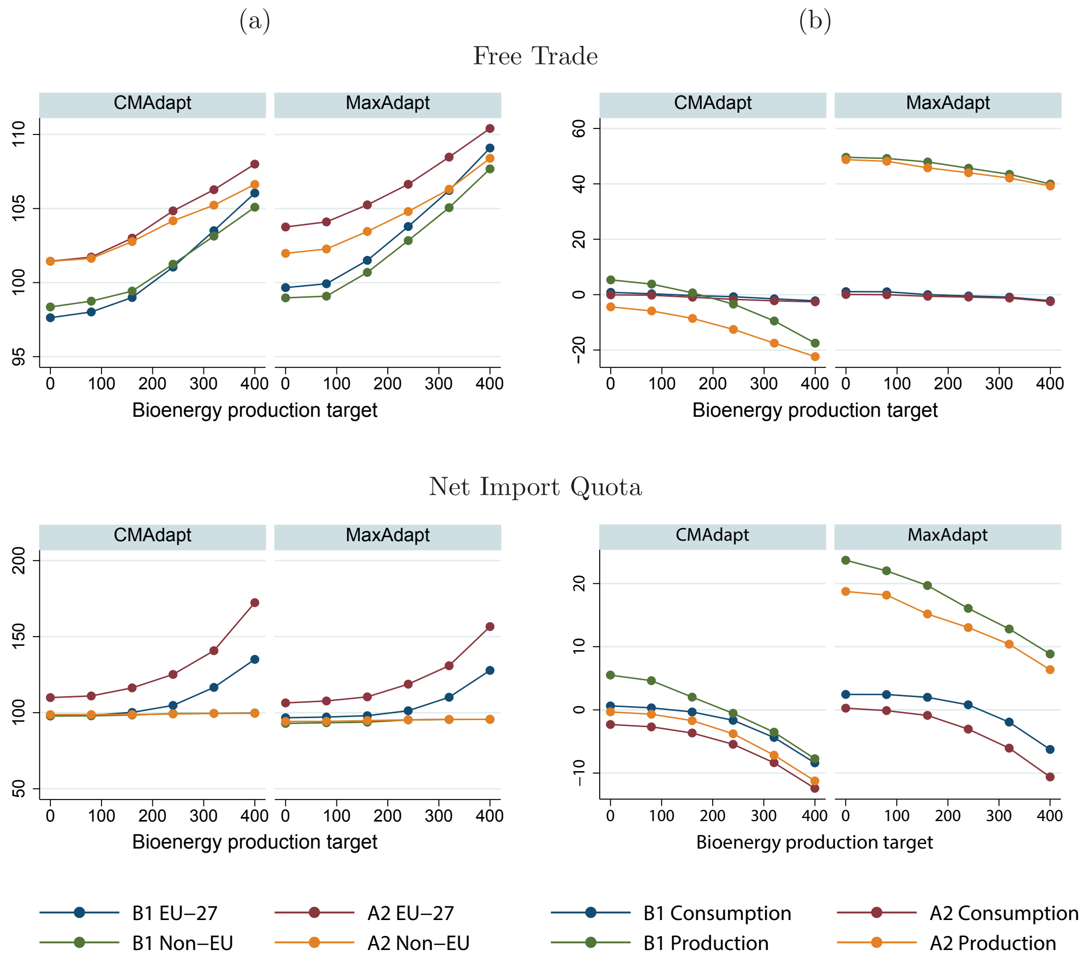
Furthermore, (iv) adaptation can play a moderating role by reducing the vulnerability of agricultural production to changes in the climatic conditions, and thus, assists in stabilising prices. For example, if trade is restricted (i.e. net import quota) adaptation can increase agricultural production in response to climate change. Especially, in a high emission based climate scenario (A2) adaptation can mitigate price increases by increasing the productivity through the adoption of irrigation technologies, crop portfolio adjustments or cropland expansion (MaxAdapt). Hence, price levels can be reduced by up to 15%. In a free trade scenario, the EU can specialise even more and adjust crop mixes to environmental changes. However, a high degree of specialisation also requires an increase in trade. In EUFASOM the total production in the rest of the world is assumed to be constant. Therefore, prices for crop types which are quantitatively less produced in the EU increase, whereas prices for crops that are quantitatively more pro-

[30]It should be noted that prices also vary greatly between the European regions and the different commodities (compare Appendix 5A Fig. 5.13 and Fig. 5.14), because some regions increase bioenergy production more than other regions or are more favourable for crop production in a high emission based climate scenario. The crop portfolios are also adjusted to changing climate conditions and bioenergy production or trade is increased due to more specialisation. For a more detailed discussion on crop developments and regional differences compare section 5.4.3 and section 5.4.1.

[31]The change in global commodity prices in EUFASOM is defined as $\Delta P_W = \Delta P_{EU} + \Delta P_{Non-EU}$, where all factors in non-EU countries are constant and prices are only influenced by changes in the EU.

duced decrease. The model suggests that the price increase of come crops outweighs the price reduction of other crops so the total price level increases more if adaptation is not restricted in a free trade scenario. Accordingly, adaptation mechanisms that allow for an increase in agricultural productivity or production (e.g. crop, expansion of agricultural areas) can increase food supply or reduce land use competition between bioenergy and food production but their impact on prices highly depends on the trade regime. It should be also noted that potential negative externalities of large-scale land use change and environmental feedbacks are not considered in the model.

Figure 5.8: Fisher price index (a) and change in supply and demand by 2100 in % (b)



The model results give some important insights. Firstly, agricultural systems are stressed by climate change, hence, commodity prices increase with great variations between commodities, regions and policy settings. The total impact of climate change on European commodity prices, however, is relatively small compared to policy influences. It should be noted that EUFASOM only shows the partial impacts of gradual temperature and precipitation changes on commodity prices. In order to assess the total impact on commodity prices, dynamic models are required which include short-term and long-term impacts of climate change and can account for price uncertainty. Secondly, the implementation of bioenergy and adaptation policies have a greater impact on food prices and the supply and demand balance than climate change. Adaptation can raise the productivity and production, increasing supply, whereas bioenergy crops compete for resources with food commodities, and so reduce supply. Accordingly, there is a trade-off between climate change adaptation, bioenergy production and food production. Thirdly, trade barriers (e.g. net import quota) raise prices in the EU significantly, but mitigate commodity price increases on the world market, for example, if the EU introduces bioenergy policies. Hence, a reduction of trade barriers reduces commodity prices in the EU market but marginally increases prices in the non-EU market, especially if the EU produces bioenergy on a large-scale. Bioenergy production increases EU's import demand for food commodities, and thus, the demand for land in the rest of the world. Without trade barriers, bioenergy production could therefore cause negative environmental externalities or generate carbon leakage (i.e. increase foreign GHG emissions) if land use change is involved. Fourthly, unrestricted trade and adapting to changing climatic conditions substantially reduces price increases, even if climate change becomes more severe or if bioenergy is produced on a larger scale.[32] Accordingly, not any key factor determines changes in commodity prices, but a combination of different factors can lead to rising or declining commodity prices. Some factors reflect the changes in agricultural productivity (i.e. climate change), whereas other factors reflect the response of food production to policy shocks (i.e. bioenergy production). Consequently, a comprehensive portfolio of adaptation and trade policies can mitigate a long-term rise of commodity prices.

Land Prices

Principally, land prices contain information about the value of various characteristics of land (e.g. Maddison, 2000), and therefore, reflect the productivity of agricultural areas. In contrast to Ricardian analyses which use observed land values across large regions in order to examine the impacts of climate change on agriculture, partial equilibrium

[32] EUFASOM only accounts for gradual changes in the climate. Extreme weather events are expected to increase price volatility and price peaks for food (e.g. Rosenzweig et al., 2001)

models endogenously determine land prices which do not only contain information on the productivity of land, but also include political feedback and behavioural influences, such as scarcity of resources (e.g. land).[33] Accordingly, a variation of regional land prices in the EUFASOM model reflect both, productivity differences and changes in the demand, and thus, land prices can be used as a measure of productivity as well as land scarcity.

Fig. 5.9 illustrates possible land price variations in five major European regions. Land prices increase in all regions, except for Southern Europe, and are influenced by (i) climate change, (ii) bioenergy production, (iii) trade regimes and (iv) adaptation mechanisms.

The impacts of climate change (i) on land price differ considerably between regions (NoBioEng). Southern Europe is the region with the largest land price increase in a low emission based scenario (up to 1750%) if crop portfolios are limited to historically observed crop mixes and trade is unrestricted, because Southern Europe is best adapted to the climatic conditions of the B1 scenario under crop mix restrictions. In Northern Europe, land prices increase significantly more in the A2 scenario (up to 250%) than in the B1 scenario (200%), because of an increase in productivity, whereas in Southern Europe agricultural productivity decreases in the A2 scenario (20%), especially if farmers specialise less and more crops are cultivated that are not suitable for the climatic conditions (CMAdapt). Hence, land prices decrease in Southern Europe. The land price variations between the climate change scenarios, however, are highly dependent on the productivity of agricultural land and the scarcity of cropland areas and the degree of land price changes is considerably influenced by the policy settings.

(ii) Bioenergy production increases land use competition and subsequently the scarcity of resources. Therefore, land prices increase with higher bioenergy production targets. Depending on the comparative advantages of the regions, land prices are more or less affected by bioenergy production. The largest increase in land price (8000%) can be observed in Baltic Europe because of a comparative advantage for bioenergy production. Northern and Central East Europe, on the other hand, have a comparative advantage for food production. Therefore, bioenergy production is only moderately increased, causing less land use competition and resource scarcity. The comparative advantages are also highly influenced by the trade regime and the scale of adaptation.

(iii) Trade barriers can increase land scarcity by restricting trade adjustments.

[33]The land prices are represented by shadow prices. The shadow price is the value of the Lagrange multiplier at the optimal solution.

For example, a net import quota limits the amount of import quantities and thereby preventing import adjustments which increase land scarcity and lead to increasing land prices. Accordingly, more domestic food production is required and total demand for land increases. Hence, in most regions and especially in Southern Europe, Baltic Europe and Mid West Europe land prices increase significantly in a scenario with trade barriers compared to a scenario without trade barriers. The large increases in land prices in Southern and Baltic Europe are also a result of sever climate change in Southern Europe and large-scale bioenergy production in Baltic Europe. Unrestricted trade, on the other hand, allows for an increase in commodity trade and reduces domestic resource scarcity through a virtual import of land and other resources. Therefore, land scarcity is reduced and land prices are significantly lower than if a net import quota is imposed. However, increasing demand for imports also raises the demand for foreign land. This often involves land use change and negative externalities for the environment (e.g. GHG emissions), which can be limited by trade barriers trade barriers (e.g. border tax adjustments). It should be noted that such negative externalities are not internalised in the markets of EUFASOM.

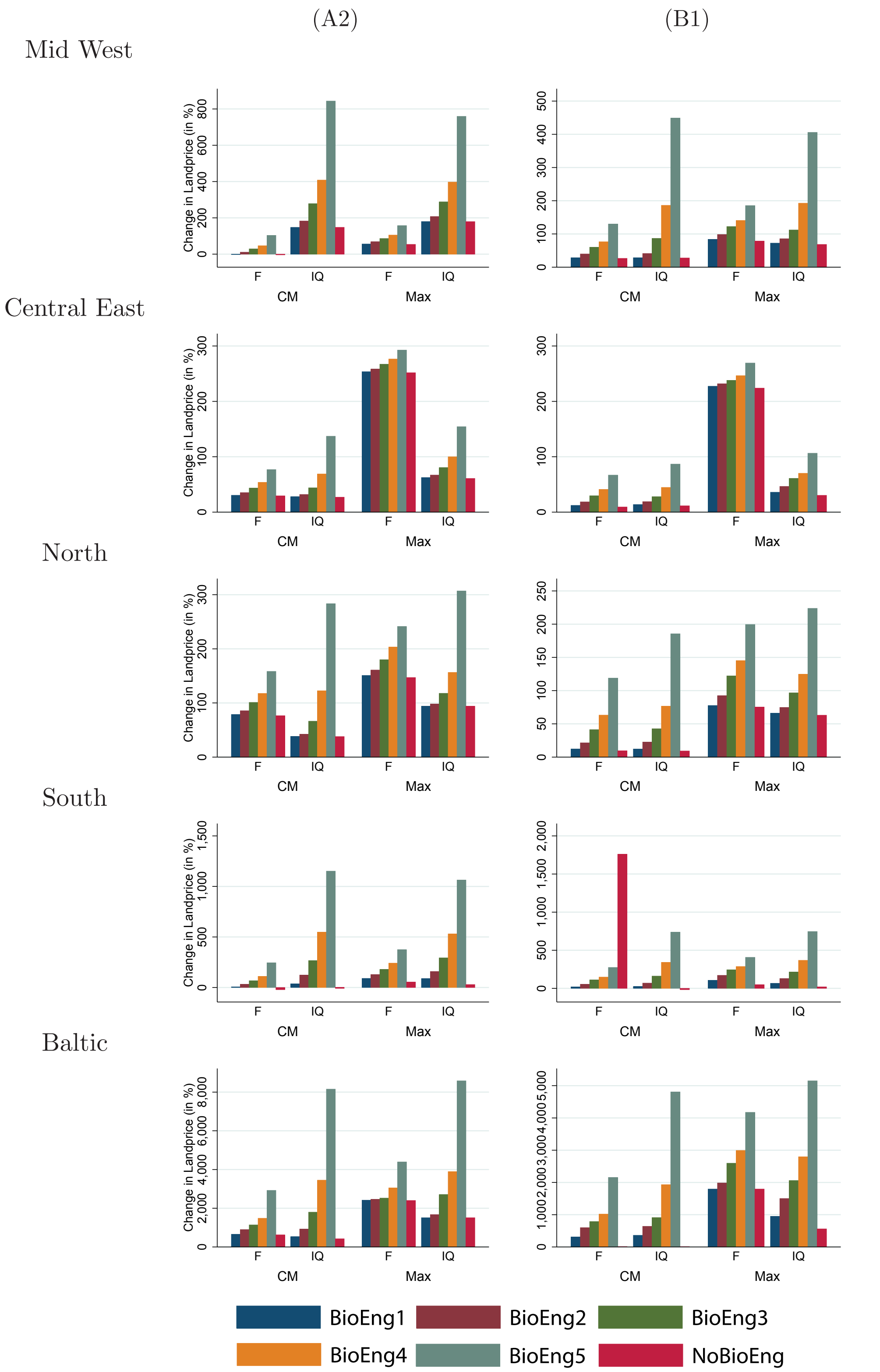
Adaptation (iv) increases the average productivity/value of land (e.g. irrigation, crop portfolio adjustments) and reduces scarcity of land (e.g. cropland expansion). In the MaxAdapt scenario, land prices increase as a result of more specialisation (e.g. reduced resource scarcity), especially in free trade scenario, and reflect the associated higher productivity of land. In the CMAdapt scenario, crop mixes are limited to historically observed crop mixes, and therefore, crop production is more diversified and productivity generally lower. Consequently, productivity and land prices rise more in the MaxAdapt scenario than in the CMAdapt scenario. Moreover, comparative advantages can shift between regions as a result of extensive adaptation. For example, land prices in Central Eastern Europe increase significantly more in a MaxAdapt scenario than in Baltic Europe.

Overall, the experiments suggest that the impact of adaptation and policy change on land prices is greater than that of climate change.

5.4.3 Adaptation Strategies at Farm-Level

Changes in the climatic conditions increase the uncertainty, vulnerability and complexity of agricultural management and production. Production technologies and management practices need to be adjusted in order to reduce the vulnerability of agricultural pro-

Figure 5.9: Land price variations by 2100



F: Free trade, IQ: Net Import Quota, CM: CMAdapt, Max: MaxAdapt, BioEng1-BioEng5: Bioenergy production targets (80Mt, 160Mt, 240Mt, 320Mt, 400Mt) duction. The adaptive capacities, however, are not only dependent on the biophysical aspects of climate change, but also on policy regulations and policy response strategies to climate change. Therefore, adaptation strategies are determined by the access to adaptation options (e.g. regulations), the policy framework (e.g. land use competition) as well as some other factors (e.g. individual adaptive capacity). This study examines three adaptation mechanisms at a farm-level: (i) adjustment of crop portfolios, (ii) expansion of agricultural areas dedicated to food crops and (iii) adjustment of management practices (i.e. irrigation) and the influence of policy changes on them. The alternative adaptation options for each mechanism are summarised in Table 5.3.

Crop Portfolio Adjustments

Farmers can adjust their crop portfolios by choosing crop types that are more resilient to climatic stress (e.g. heat, drought, pests, salt) in order to mitigate declining productivity or production risk. Crop portfolio adjustments are depicted by the change in the crop composition (i.e share of crop area) and are mainly influenced by environmental and political change. Fig. 5.10 depicts the results for four scenarios that show the combined effects of climate change, policy regulations and adaptation strategies on major crops.[34]

In a CMAdapt scenario (a), the crop portfolios mainly consist of wheat, followed by corn, barley, potatoes, oats and rye in both trade regimes. Cropland for most crop species decrease in the A2 and B1 scenario for both trade regimes. In particular, the agricultural areas dedicated to potatoes, barley, rye and oats are reduced in both climate change scenarios (up to 10%). The areas of wheat and corn production, however, are increased by up to 10%. In the A2 scenario, cropland decreases for most crops due to the preference of crop species that are less vulnerable to the climatic conditions in a high emission based climate scenario. Corn, for example, particularly benefits from the climatic conditions in a high emission based climate scenario and therefore is more increased in the A2 scenario than in the B1 scenario.

The adjustment of crop shares in the crop portfolio is partly market-driven but also climate-driven, because corn has a higher heat resistance (Roberts & Schlenker, 2011), and therefore, is more profitable in a high emission based climate scenario (A2). The choice of crops for crop portfolios, thus, depends on cost and productivity advantages. Moreover, a free trade scenario allows for a higher degree of specialisation of agricultural activities because changes in crop production can be balanced by trade adjustments.

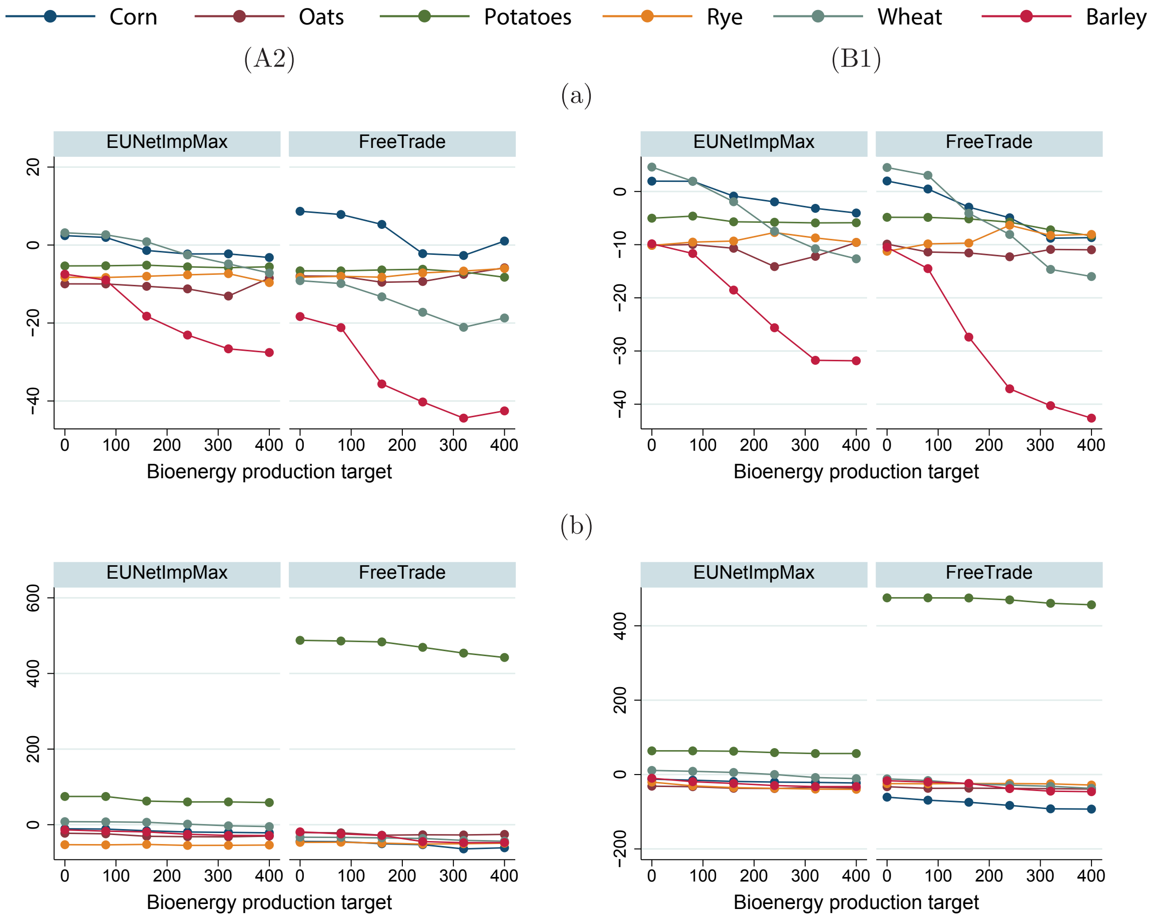
[34] Fig. 5.10 only depicts the results for barley, corn, oats, potatoes, rye and wheat.

If trade is restricted by a net import quota, more domestic production is required in order to meet demand in the EU. Therefore, the degree of crop area adjustments are larger in a free trade scenario than in a regime with a net import quota. Land use competition between food and bioenergy crops induces additional land use change and correspondingly adjustments to the crop portfolio. Due to the reduction in food crop areas, a higher percentage of heat resistant and less vulnerable crop types (e.g. corn) is preferred and the percentage of more vulnerable crop types (e.g. barley) is reduced. Accordingly, bioenergy policies promote a higher degree of specialisation.

In a scenario (b) with maximised adaptation (MaxAdapt), most agricultural areas are dedicated to wheat, followed by barley, corn, potatoes, oats and rye in both trade regimes. The maximum adaptation scenario allows for a higher degree of specialisation in the production. Crop choices in the MaxAdapt scenario, therefore, are better adapted to climatic and political changes. In the A2 scenario, the share of potatoes in crop portfolios increases significantly in both trade regimes (100% to 500%), due to better growing conditions in Northern Europe, whereas the share of rye decreases significantly (>100%) and also of other more vulnerable crop species (e.g. barley). Unrestricted trade, in the A2 scenario, leads to especially high specialisation in the crop portfolio (e.g. increase in share of potatoes) as a result of adaptation to climate change and comparative advantages. In the B1 scenario, potato production is also substantially increased (> 400%), but less than in the A2 scenario. Moreover, corn production is further decreased if trade is not restricted by quotas due to less favourable climatic conditions and less comparative advantages for corn production. Furthermore, bioenergy policies have a significantly smaller impact on crop portfolios in a MaxAdapt scenario because of a higher degree of specialisation in combination with cropland expansion which reduce land use competition between bioenergy and food commodities.

The various crop portfolios suggest that climate change and comparative advantages affect the adaptation strategy of farmers. Farmers choose crop portfolios that are more heat and drought resistant or prefer crop mixes which allow to exploit comparative advantages depending on the given climatic conditions and policy settings. It should be noted, however, that the crop portfolios can vary greatly between European regions. Crops, for example, can show a tendency towards higher shares in northern Europe and lower shares in southern Europe or vice versa.

Figure 5.10: Crop portfolio adjustments in % by 2100 with (a) adaptation within historically observed crop mixes (CMAdapt) and (b) maximised adaptation (MaxAdapt)



Crop portfolio adjustments are depicted by the change in crop area in %. It should be noted that the figure only depicts major crops. EUFASOM also considers rice, soya, sugar beet and sugarcane.

Change in cropland

Climate change can reduce agricultural productivity whereas bioenergy policies can reduce agricultural areas for food commodities. In order to maintain food production, cropland areas dedicated to food commodities can be increased.[35] The net change in food crop areas for the EU are depicted in Fig. 5.11.

If adaptation strategies are limited (CMAdapt), total crop areas decline by 3% to 11% because of higher production costs for crops that are observed within historical crop mixes. Total cropland area gradually decreases by up to 30% for large-scale bioenergy production targets because more agricultural area is dedicated to bioenergy production. Moreover, food crop areas decrease further in a free trade scenario because of a shift in the comparative advantages and an increase in imports of agricultural commodities. If agricultural imports are limited (i.e. IQ), more domestic production is required so that crop areas decrease less than in a free trade scenario. Lastly, crop areas decrease especially in a high emission based climate scenario (A2) in combination with unrestricted trade because comparative advantages for food production shift to non-EU countries, which are not affected by climate change in EUFASOM.

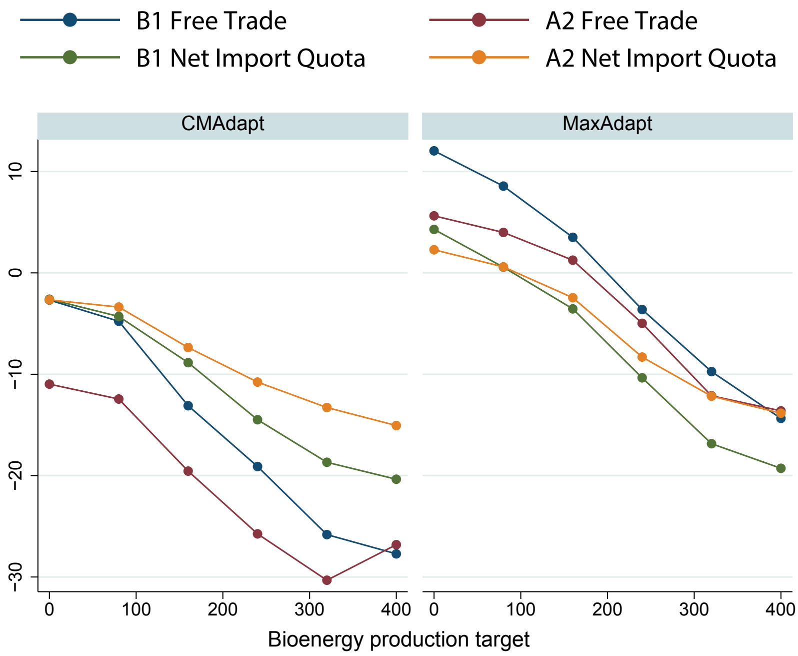
If farmers use all available adaptation options (MaxAdapt), crop areas increase by 3% to 11% and decrease gradually with increasing bioenergy production. The EU has an additional comparative advantage for crop production in the MaxAdapt scenario due to a higher degree of specialisation, and therefore, crop areas increase more in a free trade scenario, which allows for the full exploitation of comparative advantages, than in a trade regime with net import quotas, which require more diversified domestic production. Consequently, domestic food production can be increased despite the climatic conditions and policy settings.

It should be noted that massive land use change would have serious implications for the carbon cycle and the surface-energy budget (Pielke et al., 2002) because an increase in agricultural areas is often at the expense of carbon sinks (e.g. forests, wetlands). As a result, greenhouse gas (GHG) emissions increase with large-scale land use change. Such disruptions in the climate balance contribute to global climate change and can exacerbate negative impacts of climate change on agriculture and reduce the efficacy of some adaptation strategies. Negative environmental externalities resulting from land use change are not internalised in the markets of EUFASOM, thus, carbon emissions

[35] Agricultural areas can be dedicated to food crops and bioenergy crops. In this section, cropland only refers to agricultural areas dedicated to food crops.

and feedback effects are ignored.

Figure 5.11: Cropland use for food commodities by adaptation, climate change and trade scenario by 2100 (in%)



Note that agricultural areas dedicated to bioenergy crops are excluded.

Irrigation

Farmers can reduce the vulnerability of crops to droughts or heat waves and reduce water-stress of plants by adopting irrigation technologies. The adoption of irrigation is dependent on a number of characteristics, including the geographic location of the farm which determines the suitability for irrigation (e.g. elevation), the cost of irrigation water, the efficacy of alternative adaptation options, the crop portfolio, policy regulations and climate change. Fig. 5.12 illustrates the combined effects of climate change, trade policies and adaptation strategies for different regions according to their percentage of irrigated land. In all scenarios (a-d) most of northern and central Europe do not irrigate, whereas irrigation increases in most regions in southern and eastern Europe. Surprisingly, the difference in the share of irrigated area between the A2 and B1 scenario is relatively small.

In scenario (a) farmers use the full range of adaptation options (MaxAdapt) and trade is not restricted by quotas. The share of irrigated area increases (40.6%) if climate change is severe (A2). Most regions in Baltic Europe and Southern Europe increase the percentage of irrigated areas, largely due to an expansion of total agricultural areas but also due to a higher degree of specialisation. In other regions, the amount of irrigated areas can be reduced by the choice of crop mixes with different irrigation requirements or reduced agricultural activities. Some regions increase the amount of irrigated areas in the B1 scenario even more than in the A2 scenario with a different crop mix, but the net irrigated area is lower (41.4%). Crop portfolios in the A2 scenario are better adapted to the climatic conditions in a high emission based climate scenario and require less irrigation. Furthermore, agricultural activities are reduced in regions with higher production costs, whereas crop production increases in regions with a comparative advantage for food production.

Scenario (b) describes a scenario with unrestricted trade (Free Trade) but limited adaptation (CMAdapt). In this scenario, irrigated areas are significantly less increased than in a MaxAdapt scenario with A2 climate conditions (28.6%) due to restrictions in the crop portfolios and the free trade scenario. Unrestricted trade reduces water use in water scarce regions (Calzadilla et al., 2011) by an increase in trade of water intensive products. Hence, it is more beneficial to increase trade of water intensive crops than to increase irrigated areas because of the limitation in crop mix adjustments. In addition, the percentage of irrigated areas is also marginally higher than in the B1 scenario (30.8%). If climate change is less severe (B1), cultivating crops, which were historically observed, can be more productive than in a high emission based climate scenario (A2) which is accompanied by significantly higher temperatures and a decline in precipitation. Accordingly, comparative advantages shift between regions due to changing climatic conditions such that irrigation is more beneficial in the B1 scenario if adaptation options are limited.

In scenario (c), farmers use the full range of adaptation options (MaxAdapt) but trade is restricted by a net import quota. The share of irrigated areas increases significantly more in the A2 scenario (45.8%) because more domestic food production is required and the trade of water intensive commodities is restricted. The percentage of irrigated areas rises significantly, partly due to cropland expansion and partly due to adjustments in the crop portfolios - especially in Southern Europe (i.e. Spain, Italy, Greece) but also in Baltic Europe. In the B1 scenario, on the other hand, irrigated areas are lower (41.3%), as a result of more favourable climatic conditions.

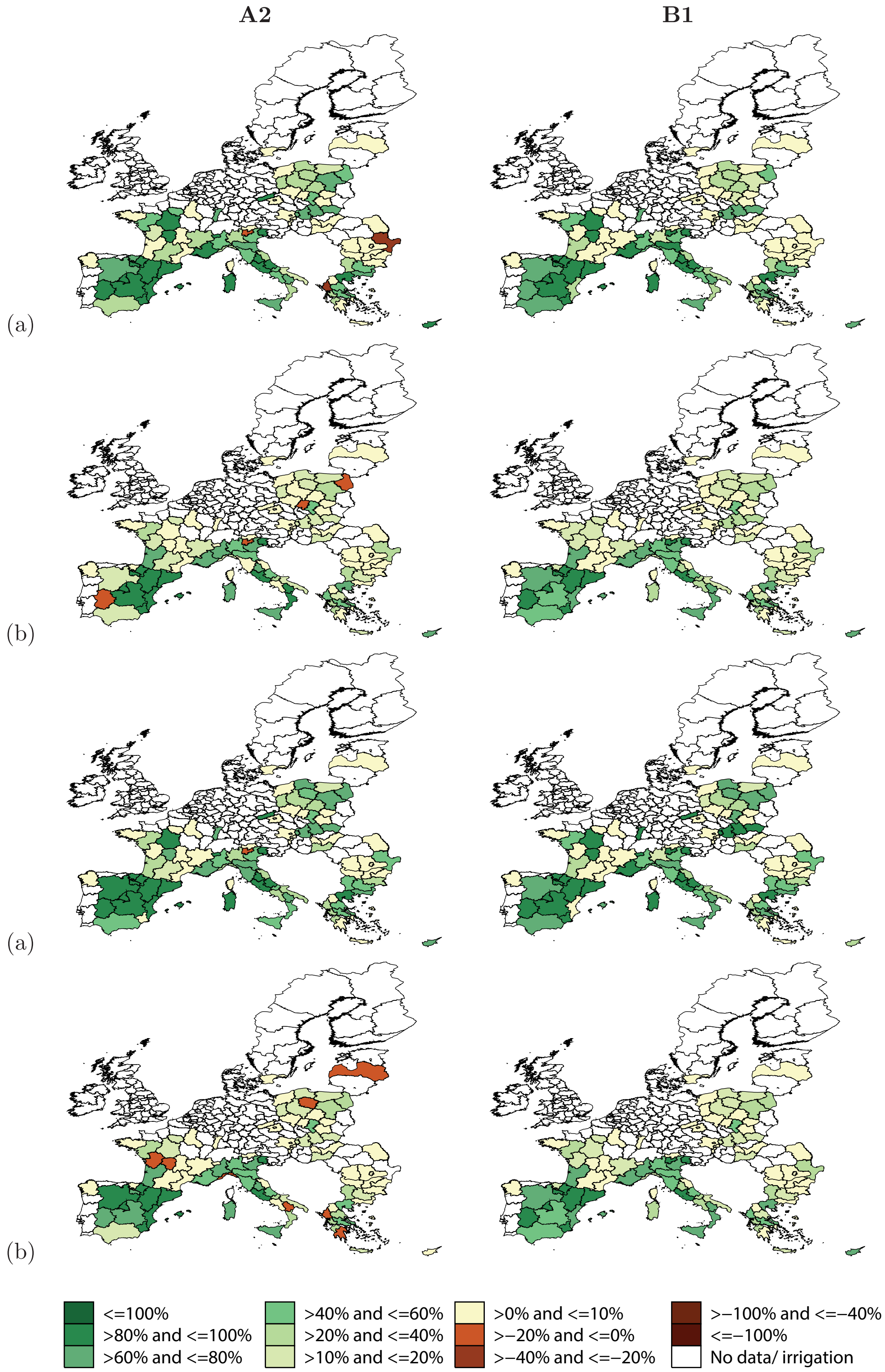
Scenario (d) describes a scenario in which trade (EUNetImpMax) and adaptation options (CMAdapt) are limited. The restriction in adaptation options has a stronger effect on the share of irrigated areas than the trade restrictions, and therefore, the results for the A2 (30.6%) and B1 (27.7%) scenario resemble scenario (a). It should be noted, however, that EUFASOM does not take a possible increase of the irrigation costs into account due to climate change induced scarcity of irrigation water.

5.4.4 Adaptation Strategies at Policy-Level

Global trade is guided by the General Agreement on Trade and Tariffs (GATT), which is a multilateral trade agreement, developed by the World Trade Organization (WTO), aimed at reducing trade tariffs and other barriers to international trade. The environmental principles embodied by the WTO are grounded on the belief that the environment benefits from open trade regimes because resources are used more efficiently (WTO, 2004). Calzadilla et al. (2011) demonstrate that water usage in agricultural production can also be reduced with unrestricted trade. Furthermore, an undistorted trading system facilitates trade of food and agricultural products which assists in offsetting climate-induced changes in the agricultural production and in improving access to inputs. A reduction of trade barriers could also lead to a more economical and environmentally "prudent" demand. On the other hand, climate change can alter the comparative advantage of countries, for example, through climate-induced biophysical changes. A comparison of the impact of different trade regimes on consumer surplus, as discussed in section 5.4.2, exemplifies the theoretical benefits of unrestricted trade. Fig. 5.13 depicts the consumer surplus for each major European region and allows for an examination of the comparative advantages for different regions, trade regimes and adaptation strategies.

Consumer surplus is overall larger in the low emission based climate scenario (B1) because of a higher agricultural productivity and a lower cost per unit output. As a result commodity prices in the B1 scenario are lower and consumer surplus is larger. These welfare gains, however, vary between different regions, trade regimes, adaptation strategies and bioenergy policies. For example, consumer surplus is substantially higher in a free trade scenario compared to a regime with a net import quota. A net import quota drives a wedge between the import demand and export supply curve and raises commodity prices in the EU, hence, a quota reduces consumer surplus (compare Fig. 5.4). Unrestricted trade, on the other hand, reduces trade distortions and lowers domestic prices in the EU and so increases consumer surplus. Depending on the region,

Figure 5.12: Percentage change of irrigated area by 2100 with (a) free trade and MaxAdapt, (b) free trade and CMAdapt, (c) net import quota and MaxAdapt and (d) net import quota and CMAdapt



climatic conditions and the adaptation strategies, the difference in consumer surplus between the two trade regimes ranges from 4% to -18%.

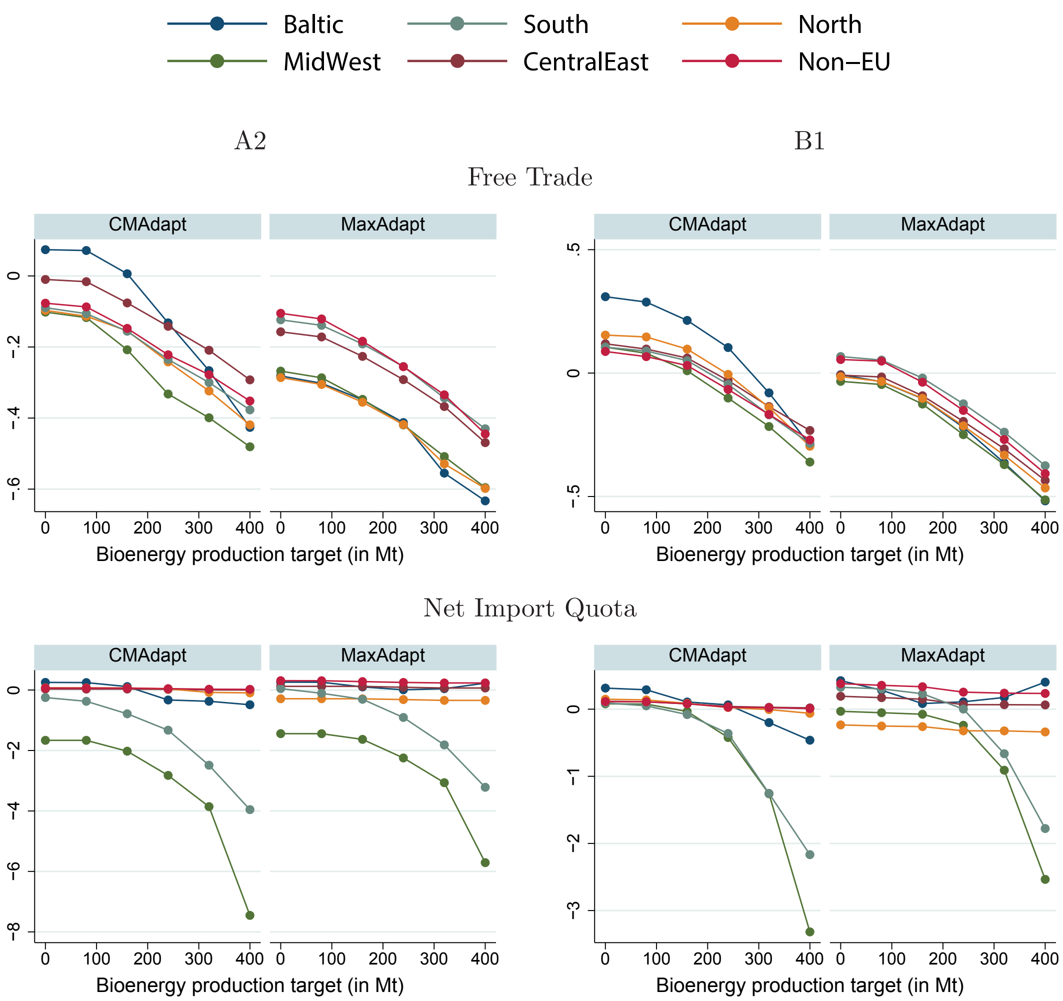
Consumer surplus marginally decreases in most regions in a free trade scenario with severe climatic change (A2). If crop portfolio adjustments are limited (CMAdapt), Mid West, Northern, Southern Europe and non-EU countries are amongst those which have the highest welfare losses (up to 0.1%), whereas consumers in Baltic Europe gain welfare (up to 0.1%). If adaptation options are unlimited (MaxAdapt), regions show a higher degree of specialisation in agricultural production assuming a constant production in the rest of the world. Accordingly, prices increase for some commodities and decrease for others. The results suggest that the effect of price increases for some commodities outweighs the price reduction for others. The net impact on consumer surplus is, therefore, negative for all EU and non-EU regions. The same effects apply to the B1 scenario, but the agricultural productivity is higher due to more favourable climatic conditions. Accordingly, all consumers gain welfare in a scenario (CMAdapt) with limited crop mixes (0.1 to 0.3%), but in a scenario with unlimited adaptation options (MaxAdapt) consumers in Southern Europe and non-EU regions gain welfare (0.1%) and marginally lose (0.05%) in other regions.

If European net imports are restricted (EUNetImpMax), demand for domestic resources (i.e. land) and production increases in order to balance supply and demand. Therefore, consumers gain in some regions and lose welfare in other regions. In the A2 scenario, consumers in Southern Europe and Mid Western Europe lose welfare because climate change induced production declines cannot be balanced by increased imports but are balanced by price increases. Consumers in Baltic Europe, Northern Europe and Central Eastern Europe gain welfare compared to the Base Trade scenario as a result of lower prices. In the B1 scenario, consumers in most regions gain welfare due to more favourable climatic conditions and associated higher production levels. As a result, the demand for trade is lower and consumers are less affected by the net import quota. Accordingly, all regions gain (up to 0.4%), except for Northern Europe. Consumer welfare in Northern Europe decreases due to less favourable climatic conditions and lower production levels. Furthermore, the impacts of the two adaptation strategies (CMAdapt, MaxAdapt) differ in comparison with a free trade scenario. In the CMAdapt scenario, the losses in consumer surplus are larger than in the MaxAdapt scenario. On the one hand, trade barriers prevent the exploitation of efficiency gains (e.g. specialisation), on the other hand, comparative advantages arising from specialisation, are distorted.

Land use competition between food and bioenergy crops increases if additional bioenergy production targets are imposed. The loss in consumer surplus can be substantial, depending on the scale of bioenergy production and the trade regime. If trade is not restricted by quotas, land can be virtually imported by increasing food imports which mitigates land use competition and loss in consumer surplus. In the MaxAdapt scenario, cropland is expanded and crop mixes are fully adjusted such that land use competition is additionally reduced. The loss of consumer surplus for bioenergy targets of up to 400Mt can range between 0.5% in the CMAdapt scenario and 0.3% in the MaxAdapt scenario if climate change is severe (A2) and between 0.04% in the CMAdapt scenario 0.05% in the MaxAdapt scenario if climate change is moderate (B1). Comparative advantages of the EU and non-EU for food or bioenergy production become increasingly closer in a free trade scenario. If imports are limited (EUNetImpMax), comparative advantages for food and bioenergy production are more concentrated in Mid Western and Southern Europe. Food production declines as a result of large-scale bioenergy production and cannot be balanced by increased import adjustments such that domestic prices increase significantly. Consumers lose, especially in Mid Western and Southern Europe, because of comparative advantages for bioenergy production and higher import costs than in a free trade scenario. If climate change is severe (A2), consumers lose between 8% (CMAdapt) and 6% (MaxAdapt) in Mid West Europe, whereas Northern Europe, for example, has a comparative advantage for food production so that consumer surplus is significantly less reduced (0.1% to 0.4%). Losses in consumer surplus are considerably lower if climate change is less severe (B1). For example, consumers lose between 3.4% (CMAdapt) and 2.6% (MaxAdapt) in Mid West Europe, but gain in non-EU countries due to lower world prices.

There are several important implications that can be understood from the unrestricted trade exercise. Firstly, trade is able to play a moderating role, in which less severely affected regions of climate change may profit by selling commodities to more severely affected regions. Hence, regions can reduce production risk and exploit their comparative advantages for food and bioenergy production. Trade barriers (e.g. net import quota) impede such adjustments to trade flows and reduce consumer surplus. The net import quota, however, can reflect the impact of border tax adjustments and is more suitable for depicting the costs of bioenergy production, because it impedes a shift of food production to non-EU countries. Secondly, changing comparative advantages require strategic trade policies (Reilly et al., 1994). The costs of investing in the ability of farmers to compete in the future need to be weighed up against the cost of supporting an industry that will become less competitive. For example, if projections indicate that the agricultural sector in a country will be negatively affected by climate change,

Figure 5.13: Change in consumer surplus (food commodities only) by 2100 as a result of food production changes by trade scenario (in%)



investments into research, improving management practices or expanding agricultural areas can be increased. These investments, however, will have high opportunity costs if agriculture in the rest of the world is less affected by climate change and the domestic agricultural sector will require constant subsidisation. Thirdly, a free trade scenario allow for adjustments in case of lower regional or national production, whereas in a scenario with trade barriers, production declines can reduce consumer surplus through rising commodity prices. Fourthly, bioenergy could additionally alter the comparative advantages of countries. High bioenergy production targets, for example, increase land use competition, reduce food production and eventually raise commodity prices. Higher world prices can increase the competitiveness of the agricultural sector in countries that are negatively affected by climate change and make adaptation investments more profitable and shift comparative advantages. Finally, restrictive adaptation policies in a free trade scenario can reduce the comparative advantage of countries that are positively affected by climate change in comparison to countries that are negatively affected by climate change. As a consequence regional impacts of climate change on agriculture and comparative advantages may be concealed.

5.4.5 Limitations

Several limitations of the model should be noted. Firstly, we do not have data for climate change impacts on yields, but use a state-of-the-art statistical model that estimates the relationship between yields and weather variability; we assume that observed yield variability will be consistent to historically observed yield variability. Secondly, partial equilibrium models only examine the partial impacts of environmental and policy change. Climate change or bioenergy policies will have impacts on a number of markets and sectors and in turn can affect the agricultural sector. Thirdly, the employed model is comparative static, and therefore, ignores any dynamic process. For example, technological progress or dynamic transition costs are neglected. Fourthly, input requirement parameters are estimated via a behavioural model which does not account for input adjustments to changes in the climatic conditions. Accordingly, the model estimates are highly dependent upon the input data and the estimation of the parameters. Fifthly, irrigation water can become more scarce and expensive in the future. This can affect the farmers' decision to irrigate and subsequently alter the productivity of farmland. The modified version of the EUFASOM only accounts for the amount of irrigation water with current costs but ignores possible cost increases of irrigation water in the future. Finally, we do not account for negative externalities of bioenergy promotion or land use change (e.g. environmental impacts, commodity prices).

5.5 Conclusion

This study is novel in combining farm level econometric models with a partial equilibrium model, to investigate the medium to long-term impacts of climate change on agriculture in more detail. The model quantifies the impacts of climate change on regional food production and welfare taking into account the influence of non-food demand (i.e. bioenergy production) and adaptation at both the farm and policy-levels (i.e. irrigation technologies, crop portfolio adjustments, cropland expansion and trade).

Before discussing the results, two important limitations should be mentioned, because the results of the model crucially depend on the assumptions of the model: (i) the model does not simulate climate change impacts on non-EU production, and (ii) it does not consider market and non-market based welfare gains from bioenergy production.

Despite these assumptions, the analysis gives some important insights into the interactions of climate change, adaptation and mitigation.

Firstly, the model demonstrates that negative impacts of climate change can be largely mitigated by a combination of different adaptation strategies and by shifting food crop production to Northern Europe. The magnitude of climate change impacts thereby varies with the degree of adaptation. Moderate adaptation (CMAdapt), which incorporates a higher percentage of irrigated areas in Southern Europe (up to 80%), a larger share of corn production (up to 5%) and a lower share of barley production (up to 20%), results in higher food production and lower commodity prices (-3%) in a low emission based climate scenario and lower production and higher commodity prices (+10%) in a high emission based climate scenario. Unrestricted adaptation (MaxAdapt) leads to a higher degree of specialisation which improves the productivity of agricultural land and raises total production. Hence, welfare losses can be significantly reduced.

Secondly, climate change impacts on agricultural commodity markets can be further reduced by a better integration into the world market, because trade plays a moderating role. It enables consumers in more severely affected regions to benefit from increased commodity imports from less severely affected regions.

Thirdly, large-scale bioenergy production, as targeted by the EU, can have a greater impact on agriculture than climate change by initiating land use competition and reducing total production of agricultural goods in the EU. The results show that trade substantially reduces the costs of bioenergy production in the EU by shifting food production to the rest of the world. This result, however, does not consider the impact of large-scale bioenergy production on environmental externalities (e.g. carbon emissions from land use change).

Lastly, to approximate the external costs of bioenergy production, a net import quota is implemented, which impedes a shift of food production to non-EU countries. The results from this trade policy experiment show much stronger commodity price impacts. By comparing the results for different bioenergy production levels, it can be seen that the costs of bioenergy increase in a non-linear manner: small-scale bioenergy production can be achieved at relatively low costs, but large-scale bioenergy production will affect agricultural production substantially through changes in land allocation (e.g. up to 30% less of the agricultural area is used for food commodities). This implies that sustainable bioenergy production has a limited potential at low cost.

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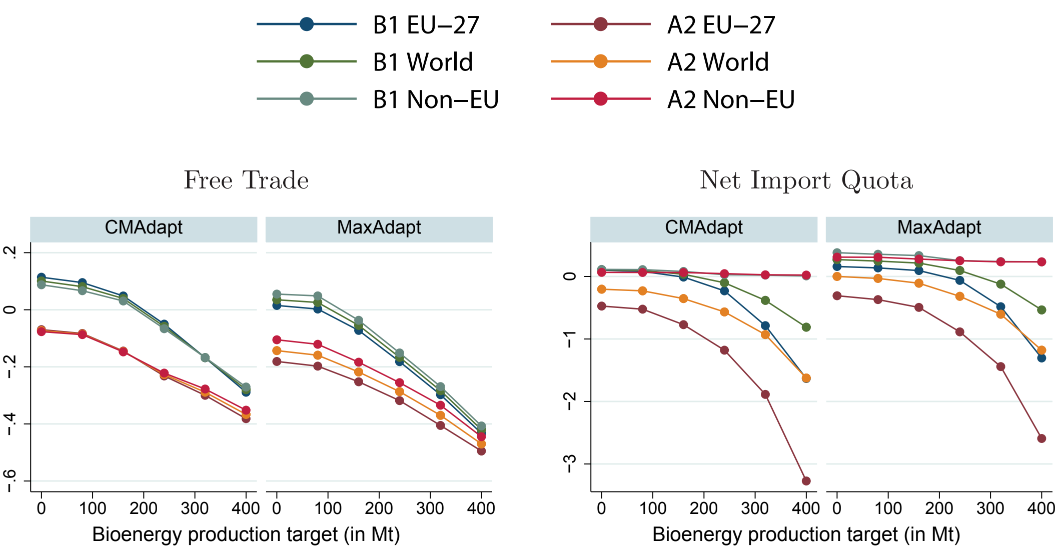
5A Appendix

5A.1 Consumer Surplus

Figure 5A.1: Change in consumer surplus (food commodities only) by adaptation mechanism, trade policies, bioenergy production and region (in%)



5A.2 Price Adjustments

Figure 5A.2: Crop price adjustments by crop type

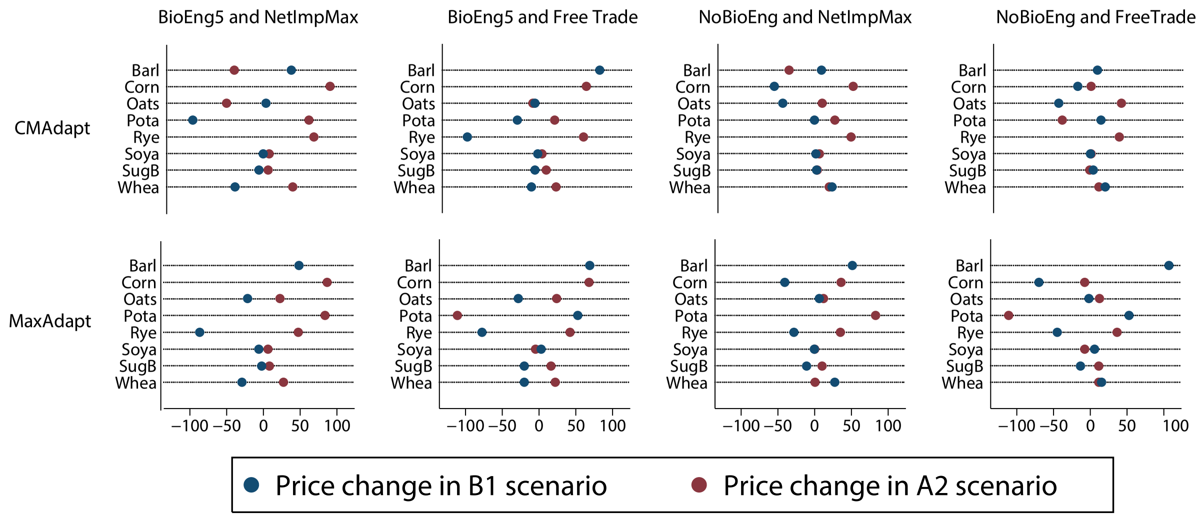
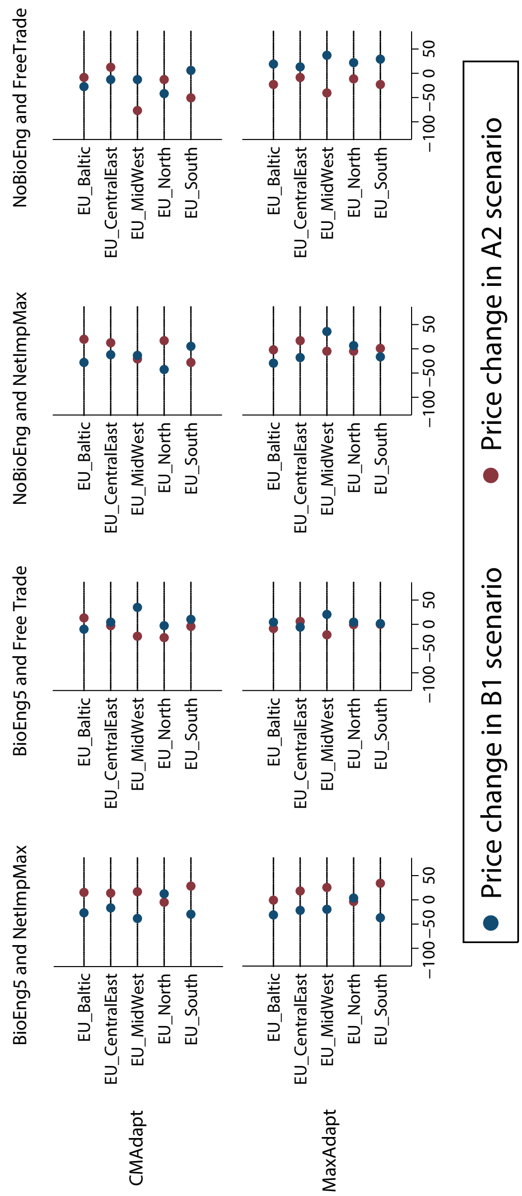


Figure 5A.3: Crop price adjustments by region



Eidesstattliche Versicherung

Hiermit erkläre ich, Natalie Trapp, an Eides statt, dass ich die Dissertation mit dem Titel:

"The Economic Impacts of Climate Change and Options for Adaptation: A Study of the Farming Sector in the European Union"

selbständig und ohne fremde Hilfe verfasst habe.

Andere als die von mir angegebenen Quellen und Hilfsmittel habe ich nicht benutzt. Die den herangezogenen Werken wörtlich oder sinngemäß entnommenen Stellen sind als solche gekennzeichnet.

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