Climate Change and European Agriculture

Modelling Impacts of Cereal and Oilseed Markets by 2050

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In loving memory of my mother

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Abstract

This study aims to assess potential economic effects of climate change on European agricultural markets at member state level by 2050, focusing on cereal and oilseed markets. The future scenarios include social as well as economic developments derived from two potential emission scenarios. In this modelling framework, crop simulation results of crop productivity changes from the dynamic vegetation model LPJmL, which are based on five individual climate projections, serve as inputs which are administered as a supply shock to the European Simulation Model (ESIM). ESIM is a partial equilibrium model depicting the agricultural sector of the EU in substantial detail. Changes in yields, production quantity and crop prices by the year 2050 are simulated.

In order to account for the uncertainty inherent in climate impact assessments, two approaches are considered in this thesis. First, in order to account for climate change increased yield variability, stochasticity is implemented in ESIM, using the method of Gaussian Quadratures. Despite the necessity of sensitivity analysis in climate impact assessments, stochastic analysis has so far been neglected in literature. The second method uses the five individual LPJmL outputs to generate a distribution of results. That way, uncertainty stemming from different climate projections is accounted for. Further, a closely connected purpose of this study is to consider climate change induced adaptation of farmers to changes in the relative profitability of crops. Thereby, it is shown that climate change assessments are likely to overestimate impacts, when not accounting for adaptation.

Simulation results indicate, that agricultural productivity in most European countries is positively affected by climate change, at least until the year 2050. However, the degree of impacts vary among crop categories and countries and are also dependent on scenario assumptions. Accounting for the so called CO2 fertilization effect yields higher gains in all countries and regions depicted in ESIM as compared to the scenarios without fertilization effect, underlining the necessity of including both assumptions in impact assessments. Particularly the grain sector of countries in higher latitudes show relatively high yield increases, which is confirmed by other studies. By contrast, in regions outside Europe, simulations deliver productivity declines, particularly when the fertilization effect is not taken into account.

This thesis contributes to the current discussion about climate change impacts by quantifying the potential damages and benefits that may arise from climate change on EU member state level, as well as globally. Further, the stochastic and multiple simulation results based on different future climate and emission projections deliver a more realistic spectrum of potential impacts. The more accurate estimates of future climate change impacts on European agriculture are, the better the chance to mitigate and adapt to future threats, or take advantage of possible benefits.

Keywords:

Climate Change, European Agriculture, Uncertainty, Partial Equilibrium Models

Zusammenfassung

Die Dissertation beschäftigt sich mit den Auswirkungen des Klimawandels auf europäische Agrarmärkte im Jahre 2050, unter besonderer Berücksichtigung der Getreide- und Ölsaatenmärkte. Dazu werden die klimabedingten Änderungen der Pflanzenproduktivität des Vegetationsmodells LPJmL, welche auf fünf unterschiedlichen Klimamodellprojektionen basieren, in das Marktmodell ESIM implementiert. ESIM ist ein partielles Gleichgewichtsmodell, welches explizit Agrarmärkte der einzelnen EU-Mitgliedsstaaten simuliert, und den Rest der Welt in hochaggregierter Form.

Um den Unsicherheiten die der Klima-Einfluss-Modellierung obliegt Rechnung zu tragen, werden in dieser Arbeit zwei Ansätze berücksichtigt. Zunächst wird, basierend auf der Methode der Gauss-Quadraturen, Stochastizitätin das Marktmodell implementiert, um die Unsicherheit bezüglich klimawandelbedingter steigender Ertragsvariabilität, zu berücksichtigen. Dies ist, trotz der Notwendigkeit von Sensitivitätsanalysen, in vergangenen Klimastudien vernachlässigt worden. Die zweite Methode verwendet die fünf individuellen Produktivitätsänderungen aus dem Vegetationsmodell, woraufhin eine Verteilung der Ergebnisse generiert wird. Damit wird die Unsicherheit bezüglich unterschiedlicher Klimaprojektionen dargestellt. Darüberhinaus wird das Anpassungsverhalten der Landwirte, mittels Berücksichtigung der durch den Klimawandel veänderter Profitabilität der Ackerpflanzen, in das Marktmodell integriert.

Die Ergebnisse weisen darauf hin, dass der Agrarsektor der EU, zumindest bis zum Jahre 2050, positiv vom Klimawandel beeinflusst wird. Die Stärke der Auswirkungen variiert jedoch stark zwischen den einzelnen Ackerpflanzen und Ländern, welche stark von den zugrundeliegenden Annahmen und Emissionszenarien abhängen. Es wird gezeigt, dass die Ertragsänderungen positiv vom so genannten CO2 Düngeeffekt beeinflusst werden, womit die Notwendigkeit hervorgehoben wird Alternativszenrien, ohne Düngeffekt, zu simulieren. Vor allem in Ländern höherer Latituden zeigt sich eine besonders hohe Ertragssteigerung des Getreidesektors. Dies wird auch von anderen Studien bestätigt.

Simulationsergebnisse für Regionen ausserhalb der EU fallen jedoch weniger positiv aus, und zeigen vor allem ohne CO2 Düngeeffekt negative Produktivitätsänderungen.

Die vorliegende Arbeit trägt zur aktuellen Klimawandeldebatte bei, in dem potentielle Schäden, sowie positive Entwicklungen, aufgrund von Klimaänderungen in europäischen Mitgliedsstaaten, und der aggregierten Welt, quantifiziert werden. Darüber hinaus liefert die stochastische Analyse, sowie die Verwendung mehrerer

Klimaszenarien, eine realistischere Abbildung des potentiellen Spektrums von Klimawandeleinflüssen auf den Agrarsektor. Eine akkurate Schätzung der potentiellen Veränderung des europäischen Agrarsektors auf Mitgliedsstaatenebene, bietet die Grundlage adequate Anpassungen zu Implementieren um mögliche künftige Schäden zu minimieren, oder auch größtmöglichen Nutzen aus den sich zum positiven veränderten Bedingungen zu ziehen.

Schlagwörter:

Klimawandel, Europäische Landwirtschaft, Unsicherheit, Partielles Gleichgewichtsmodell

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1 Introduction

> Isn't it interesting that the same people who laugh at science fiction listen to weather forecasts and economists?
> *Kelvin Throop III*

Climate change is one of the greatest threats the global society is facing today. Profound alterations of life supporting systems are already happening and will have dramatic impacts in the future. Increased emissions from the energy sector and deforestation are major sources of global warming, a development which has been observed over the past 150 years. Since the middle of the 19th century, the average surface temperature has risen by 0.76°C, with most of the warming occurring over the last half-century (EU, 2010a). The Intergovernmental Panel on Climate Change (IPCC) predicts a future average global temperature increase for the next two decades by 0.2°C per decade for a range of emission scenarios. Even if concentrations of all green house gases (GHGs) are kept constant at year 2000 levels, a warming of 0.1°C per decade would be expected. However, not only temperature increase gives cause for concern. Other possible events due to climate change are an increased frequency of extreme weather events, sea level rise, and changed precipitation patterns (IPCC, 2007a).

For Europe, an annual temperature increase between 0.1°C and 0.4°C per decade is currently estimated, with a projected warming being highest in Northern Europe during winter and Southern Europe during summer. Widespread increases in annual precipitation in northern Europe, between 1% and 2% per decade, are projected, whereas estimates over southern Europe project comparatively small decreases with a maximum of 1% per decade (Olesen and Bindi, 2004).

Given the vulnerability of the agricultural sector to variations in weather conditions, it will be one of the sectors most affected by climate change. For most parts of the world, agricultural production will face substantial productivity changes, although impacts will vary by regions and crops (Rosenzweig and Parry, 1994). The agricultural sector itself is threatened and decision makers and agricultural policy are going to face profound challenges. Climate change effects are already impacting policy making and will certainly further affect them substantially in the long run.

In the light of the additional challenges European and global agricultural markets are to face in the coming decades, such as competition for water and soil resources, growing population and urbanity, it is essential to improve the understanding of climate change and its potential effects. It is also crucial to quantify the potential damages and benefits that may arise from climate change regionally, as well as globally, since the assessments will affect domestic and international policies, trading patterns, resource use, regional planning, and the welfare of people (Tubiello, 2007).

Against this background, the main objective of this study is to assess potential economic effects of climate change on European cereal and oilseed markets at member state level. The future scenarios include social as well as economic developments derived from the emission scenarios A1B and B1 (Nakicenovic et al., 2000). In this modelling framework, crop simulation results of crop productivity changes from the dynamic vegetation model LPJmL (Bondeau et al. 2007; Müller et al. 2009; Waha et al., 2011) serve as inputs which are administered as a supply shock to the European Simulation Model (ESIM) (Banse et al., 2005). ESIM is a partial equilibrium model depicting the agricultural sector of the EU in substantial detail, and the rest of the world in a highly aggregated form. Changes in yields, production quantity, crop prices and farm production value of crops by the year 2050 are simulated for the two emission scenarios.

An important issue concerning the magnitude of economic effects in the agricultural sector from climate change are adaptation measures at the farm as well as national level. Farm level adaptations, for instance, can be made in planting and harvest dates, crop rotations, selection of crops and varieties or production inputs. These production decisions are the natural response of a producers' goal of maximizing returns (Adams et al., 1998). Since any adaptation measure can lessen potential yield losses from climate change and improve yields where climate change is beneficial, the extent to which adaptation is taken into consideration in climate impact studies is crucial to evaluate potential changes. Therefore, a closely connected purpose of this study is to consider climate change induced adaptation of farmers to changes in the relative profitability of crops. In this study, this is done by relating changes of climate change induced production costs to the area allocation function in ESIM.

According to the IPCC, one of its major functions is to assess the state of our understanding and to judge the confidence with which projections of climate change and its impacts are made. However, past and future climate change estimates, projections of future greenhouse gas (GHG) emissions and their effects are subject to various uncertainties (Wanner et al., 2006). This uncertainty is increasing from emission paths to climate change, from climate change to possible impacts and finally to formulating adequate adaptation and mitigation measures and policies (Iglesias et al., 2009). Furthermore it is important to understand the origin and evaluate the range of uncertainty for an adequate interpretation of climate impact studies. Therefore, another major contribution of this work is to present two approaches to account for the uncertainty inherent in climate impact assessments. This is done by the following methods: First, the method of Gaussian Quadratures is introduced. This is a convenient and computational time-saving way to approximate the distribution of historical error terms when stochasticity is implemented into the market model ESIM. Second, the mean value and standard deviation of five different ESIM outcomes, which are based on five individual climate- and crop model results, is analysed in order to account for uncertainty by considering a variety of potential future climate scenarios. Future developments of crop yields, supply quantities, prices and farm values of crop production are simulated for the year 2050 for two emission scenarios (A1B and B1), and the relative changes, compared to the reference scenario where no climate change is assumed, are derived. Two methods of implementing the crop productivity changes into the market model are being used. One is by using the mean of all five individual climate- crop model results and the other by implementing each of the five individual outcomes in the market model. Finally, the results of both methods are compared and it is examined to which extent the exogenous variables, which serve as climate change inputs in the market model, are being translated into market effects.

The present study on the impacts of climate change on European agricultural markets is subdivided into ten chapters. Following this introduction, *Chapter 2* is dedicated to describing the role of agriculture in the context of climate change. Therefore a short introduction into effects on crop productivity as a result of biophysical interactions with changing agroclimatic conditions is given. Firstly, the influence of atmospheric carbon dioxide (CO2) on plant growth is described. Regarding this thesis, CO2 plays a central role for the simulation results. This is because atmospheric CO2 concentrations are on the one hand one of the driving forces of global warming, and on the other hand, a 'natural' fertilizer for plant growth. Hence, an important issue of climate impact assessments is the degree to which the potential positive effect is taken into consideration. Further, the role of changing temperature and precipitation is briefly described, as well as the impact of climate change on the developments of pests, plant diseases and shifts in vegetational zones. Since agriculture is not only a potential victim of future climatic changes, but is contributing to a great extent to global warming by substantial greenhouse gas emissions, the chapter also specifies the agricultural sector as a culprit of climate change.

Following, *Chapter 3* gives an overview of all relevant levels in the chain of climate impact assessments such as underlying emission scenarios, climate forecasts and crop growth simulation and market models. Further, the major methods currently used to measure economic impacts of climate change on the agricultural sector are introduced and their specific characteristics described. The chapter concludes with a literature review of European and global impact studies which are based on a similar modelling approach used in this work. *Chapter 4* explicitly describes the method used in this thesis to measure climate impacts on agricultural markets, and introduces the structure of the joint application of the vegetation model LPJmL and the market model ESIM. ESIM is described in more detail and all structural adjustments in the model are presented. The focus lies, however, on the methodological approach of how climate impacts are introduced in ESIM and how adaptation is accounted for.

Chapter 5 starts with a specification of the sources of uncertainty inherent to climate impact assessments, followed by a description of the difficulties of projecting future climate variability. Climate variability is a major concern for impact assessments of the agricultural sector since it is primarily expressed by extreme climatic events which can not be projected precisely (Solomon et al., 2007). The chapter ends with a description of how uncertainty is dealt with in simulation models and how it was methodologically accounted for in this thesis.

One of the methods for accounting for uncertainty in this study is implementing stochasticity in ESIM. This is done via the method of Gaussian Quadratures, which are introduced in *Chapter 6*. The chapter starts with an overview of existing studies of stochastic market models, followed by a detailed description of Gaussian Quadratures, their mathematical background, and how they are administered in ESIM. A full description of modelled scenarios and how their underlying assumption are implemented in ESIM is given in *Chapter 7*, followed by a detailed presentation of results for all scenario runs in *Chapter 8*. *Chapter 9* summarises the work by reviewing the simulation results. The thesis ends with *Chapter 10* where conclusions are drawn and an assessment of the quality of the work as well as of the limitations of the approach are provided, and finally directions for future research efforts are identified.

2 Climate Change and Agriculture: Cause and Casualty

2.1 General facts

> Climate change in IPCC usage refers to a change in the state of the climate that can be identified (e.g. using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer. It refers to any change in climate over time, whether due to natural variability or as a result of human activity.
>
> *IPCC (2007a)*

The agricultural sector can be considered as one of the most vulnerable to global warming (Cline, 2007). However, impacts of climate change on agriculture depend on very complex and divers relationships based on agrological aspects as well as social and economic responses (Bosello and Zhang, 2005). The agricultural sector being one of the most affected sectors, is at the same time a major contributor to global warming since it produces and releases a significant amount of greenhouse gases such as carbon dioxide, methane, and nitrous oxide. Globally, without considering land use change, agriculture causes around 14% of anthropogenic climate change. When including land use change and deforestation, even as much as a third of man made climate change can be attributed to agricultural activities (von Witzke and Noleppa, 2007). This ambivalent role, however, inheres not only a huge potential in mitigating future climate change impacts on the one hand, but also the capability to adapt to current and future climate change in order to lessen negative impacts.

Regarding crop yields, several uncertainties are attached to future developments. Not only how exactly climate is likely to change, but also changes in CO2 concentration and its impacts on water use efficiency of crops and the effect of CO2 fertilization will play a major role in future crop productivities (Solomon et al. 2007; Tubiello et al. 2007). Moreover, potential changes in management and breeding efforts, as well as changes in cropping area will also affect the agricultural sector (Möller et al., 2009). The following section briefly introduces the complex subject of how climate change can affect agricultural productivity.

2.2 Crop productivity

A change in climatic conditions will alter the environment in which crops grow. Main factors which are subject to change are CO2 concentration in the atmosphere, temperature, precipitation and evapotranspiration (Rosenzweig and Hillel, 1998). Such changes will have profound effects on agricultural sectors worldwide with varying degrees of consequences in different regions. This chapter briefly introduces the major physiological effects of CO2 increase and the primary effects of climate change induced changes in temperature and precipitation patterns on crop yields.

2.2.1 CO2 fertilization effect

One of the most important parameters of climate change impact assessments on crop productivity is the atmospheric concentration of CO2 (Lobell and Field, 2008). Plants take up CO2 via photosynthesis and use it to produce sugars and plant matter (Zavala et al., 2008). When atmospheric CO2 increases, plants produce more vegetative matter. This effect is generally referred to as the "CO2 fertilization effect" (CFE). The magnitude of the CFE depends on whether the plant is a so-called C3 or C4 plant. Since C3 plants use CO2 less efficiently than C4 plants, they are more sensitive to higher concentrations of CO2 and are hence more likely to benefit from a higher atmospheric CO2 concentration (Nelson et al., 2009b). Considering world food production under climate change, this has significant implications since some of the current major staple foods, such as wheat, rice and soy bean are C3 plants. So called C4 plants, such as maize, sorghum and sugar cane, are comparatively less responsive to increased CO2.

The CFE hence could not only increase the capacity of plant ecosystems to absorb and temporarily store excess carbon, it could also potentially lead to significant increases in crop productivity and offset potential productivity declines resulting from climate change such as higher temperature and altered precipitation patterns (Wolfe, 2010). The CFE prescribed in crop models commonly used dictates a yield increase of roughly 0.1% for each 1 ppm CO2 increase for C3 crops (Figure 2.1). Thus, one would expect the average yield change due to CO2 increase in one year to be on the order of 0.14% (Lobell and Field, 2008).

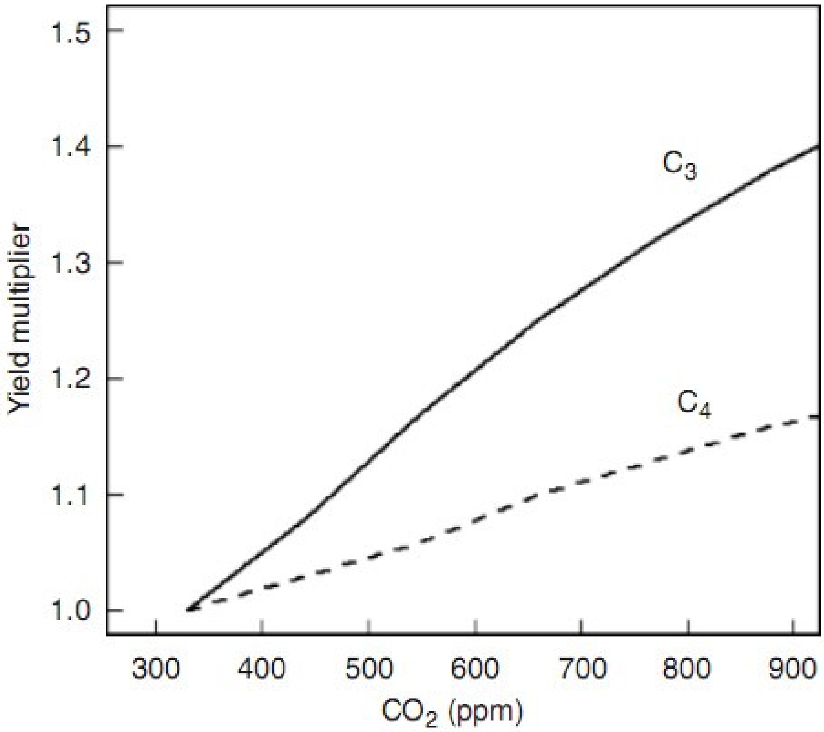

Figure 2.1: Response of yield to CO2 for C3 and C4 crops in the CERES crop model.

Source: CERES v3.5 source code, as cited in Lobell and Field (2008),p.41.

The extent to which CO2 enrichment leads to positive growth effects, however, also depends on the plants availability of other important growth parameters such as light, water, and soil nutrients (Rosenzweig and Hillel, 1998). Moreover, the degree to which extend farmers will be able to attain increased crop yields under higher atmospheric CO2 concentration will depend on the availability of additional production inputs, especially nitrogen (Tubiello and Ewert, 2002) [1]. Since the magnitude of the CFE[2] is very much debated (Long et al., 2006; Tubiello et al., 2007) and one of the major sources of uncertainty when assessing the potential impacts of climate change on the agricultural sector, most climate impact studies account for the potential yield enhancing effect of increased CO2 by comparing a "with CO2"

[1] Another important effect of CO2 on crop growth is the improved water use efficiency (the ratio of crop-biomass accumulation to the water used in evatranspiration). This could be a beneficial effect for plants grown in environments where moisture is a limiting factor such as in semi-arid regions, or reduce water stress during dry spells (Parry, 1990; Rosenzweig and Hillel, 1998).

[2] Techniques to measure effects of CO2 enrichment include experiments in green houses and chambers (Drake et al., 1985), as well as free-air CO2 enrichment systems (FACE), which are to date the most realistic set of experiments (Hendrey and Kimball, 1994).

effect versus a "without CO2" effect scenario. Results of agricultural sector impact studies vary greatly. Parry et al.(2004), for example, have estimated a global cereal production decline up to about 400 million tons by 2080 under a "without CO2" fertilization effect scenario. However, when the CO2 effect is taken into account, the decrease is reduced by up to 90 million tons. Similarly, according to Moeller and Grethe (2010), a 2% percent decline in global crop production capacity can be expected if carbon fertilization is not considered by 2050, compared to an increase by 1%, if the fertilization effect is accounted for.

2.2.2 Temperature and precipitation

Most plant processes related to growth and yield are highly temperature dependent (Wolfe, 2010). Yet, temperature stress is among the least well understood of all plant processes and less research has been investigated in crop responses to high temperature per se, as compared to CO2 effects on crop growth (Rosenzweig and Hillel, 1998). Whereas an increase in temperature generally accelerates metabolic activity, excessively high temperatures may cause enzymatic damage (Fitter and Hay, 1987). For any crop there is an optimum temperature range for maximum yield which frequently corresponds to the optimum temperature for photosynthesis. Furthermore, higher temperatures accelerate annual crops through their developmental phases which lead to shortened life cycles of certain crops (Wolfe, 2010). Up to a certain level of temperature, faster reaction rates are beneficial, but some plant processes tend to be perturbed beyond that point. The balance of the two effects determines the plant's overall response to higher temperatures and varies among different crops (Rosenzweig and Hillel, 1998). Hence, a temperature increase of several degrees could reduce photosynthesis and shorten the growing period for crops which are currently grown in a climate near its optimum, and lead to reduced yields. As in major production areas the best adapted varieties are being cultivated, an increase of growing season temperature could necessitate shifts to new varieties (Wolfe, 2010). Precipitation, being the major determinant for soil moisture, is probably the most important determining factor of crop productivity. Water stress during sensitive development stages will have severe impacts on crop yields (Rosenzweig and Hillel, 1998). Global Climate Models (GCM) predict an overall increase in mean precipitation as well as changes in total seasonal precipitation, within-season pattern and between-season variability of future precipitation (IPCC, 2007a). This may be even more important than an equal change in the annual total (Iglesias et al., 2009). Increases in the amount of precipitation are very likely in high latitudes, while decreases are likely in most subtropical land regions (IPCC, 2007a). The balance between the potential positive and negative effects of increasing CO_2, changing temperature and precipitation will determine the net change of crop productivity (Adams et al., 1998). However, there are also indirect effects which contribute to crop growth and development which will likely to be altered by climate change. Such indirect effects may arise from changes in the incidence and distribution of pests and pathogens (Sutherst et al. 1995, Patterson et al., 1999), augmented of soil erosion and degradation, and increased tropospheric ozone levels due to rising temperatures (Adams, 1986). They have been addressed to a much lesser extend in the assessment of climate change effects (Adams et al., 1998). The next section describes the potential impacts of climate change on pests and plant diseases.

2.2.3 Pests and diseases

Many assessments of climate change effects on crops have focused on potential yields, but factors such as pests and pathogens which have major effects in determining actual yields have mostly been neglected (Gregory et al., 1999). Elevated levels of atmospheric CO_2 can profoundly affect the interactions between crop plants and insect pests and may even promote the rapid establishment of invasive species[3]. Although it is acknowledged that invasive species can negatively impact on agricultural productivity, most climate impact assessments on the agricultural sector do not consider them (Ziska et al., 2009). Zavala et al. (2008), for example, found that elevated CO_2 increased the susceptibility of soybean plants to the invasive Japanese beetle and to a variant of western corn rootworm. According to Wolfe (2010), the geographic range of insect and disease pests will most likely change. Warmer temperatures in high latitude areas might provide more favourable conditions during winter for more insects and thus increase their ability to survive (Wolfe, 2010). Zhou et al. (1995) showed reduced overwintering mortality of some aphids due to increased temperatures. These studies suggest that climate change is also likely to increase the spread of plant pathogens spread by aphid vectors in several crops which could lead to reduced yields (Harrington et al., 2007). Also fungal and bacterial diseases might have greater potential to spread in temperate regions under warmer and wetter climatic conditions (Wolfe, 2010). Altered precipitation patterns can also have

[3]Invasive species is defined as an "alien species whose introduction does or is likely to cause economic or environmental harm or harm to human or animal health" (National Invasive Species Council, 2006).

significant effects on insect populations. Staley et al. (2007) found that enhanced summer rainfall lead to a rapid increase in wireworm population, which is a damaging pest for crops such as potatoes. The impacts of pests and diseases on crop yields under nowadays conditions are well known, but the consequences of climate change on pests and disease are complex and only imperfectly understood (Gregory et al., 2009). Including realistic impacts of pests and disease into climate impact studies would certainly lead to a more realistic prediction of future crop production under climate change (Ingram et al., 2008).

2.3 Shifts in vegetational zones, planting patterns and area allocation

Climate change is likely to have positive as well as negative effects on the extent and productivity of arable land resources (Fischer et al., 2001). In some areas, prevailing constraints may be somewhat relieved by climate change and hence increase the arable area. Whereas global warming is projected to substantially increase temperature in Northern Europe during winter and in Southern Europe during summer, it is also expected to cause increasing water shortages in Southern Europe. This warming is likely to lead to a northward expansion of suitable cropping areas. Olesen and Bindi (2004) attribute the increase in corn area in Denmark by the warming that occurred over the past two decades. In other areas, however, currently cultivated land may become unsuitable for agricultural production (Fischer et al., 2001). The disadvantages from increases in water shortage and extreme weather events are likely to dominate in Southern Europe. These effects could reinforce the current trends of intensification of agriculture in Northern and Western Europe and extensification in the Mediterranean and southeastern parts of Europe (Olesen and Bindi 2004). Changes in European agricultural land use seem to represent one of the major long-term adaptation strategies available (Olesen and Bindi, 2002). Rounsevell et al. (2005) estimate a decline of up to 50% in cropland and grassland of current areas in Europe by 2080[4]. Changes in farming systems may also play a fundamental role in the adaptation of European agriculture to climate change. The interpretation of various IPCC emission scenarios by Berry et al. (2006) suggests that different types of adaptation of farming systems (intensification, extensification and abandonment) may be appropriate for particular scenarios and areas.

[4]For the A1F and A2 emission scenarios.

3 Measuring Economic Impacts of Climate Change on Agriculture

Economic impacts of climate change have proved more difficult to project than the future climate itself.
Quiroga and Iglesias (2008)

3.1 General overview

Over the past two decades, a variety of methods and modelling techniques have been developed to measure the impact of climate change on agriculture. One can, however, classify most studies according to whether they are "agriculturally oriented" or "economically oriented" (Bosello and Zhang, 2005). Agriculturally oriented studies focus on the explicit productivity impacts of changing climatic conditions on crops and their growing conditions, while economically oriented studies instead analyse agricultural market reactions to climate change based on simple crop response mechanisms only. Past literature distinguishes primarily three prominent methods which have been developed to analyse the impact of climate change on agricultural production and its economic impacts: the Ricardian approach (Mendelsohn et al., 1994), the Agro-Ecological Zones approach (AEZ)(Fischer et al., 2005), and crop growth simulation models (Rosenzweig and Parry, 1994; Adams et al., 1990). The Ricardian method directly links climate change to farm income, whereas the crop model and AEZ approach link productivity outcomes to economic models and can thus also be called indirect methods. The method used for this paper is also based on that indirect approach since crop model results are linked to an agricultural market model. According to Rowhani and Ramankutty (2009), each method has different strengths and weaknesses which can be measured by certain criteria such as the extent of data requirement, regional transferability (spatial extent), structure of the method (process based), or the ability to capture adaptational responses to climate change. The next sections briefly describe the methodology and structure of climate impact modelling.

3.1.1 Emission scenarios

The global climate of the 21st century will depend on natural changes and the response of the climate system to human activities (IPCC, 2001). Climate model predictions about future responses of climate variables are based on assumptions about future greenhouse gas (GHG) and other human-related emissions. Therefore the IPCC established six scenario groups that span a wide range of uncertainty, as defined in the IPCC's so called Special Report on Emissions Scenario (SRES) (Nakicenovic et al., 2000). The scenarios (A1, A2, B1, B2), also called the four SRES scenario families (Figure 3.1), represent four combinations about possible world developments in economic growth, population increase, global approaches to sustainability and other sociological, technological and economic factors that could influence GHG emission trends.

Emission Scenario Families

Figure 3.1 describes the four emission scenario families that share common storylines illustrated as branches of a two-dimensional tree. The two dimensions indicate the relative orientation of the different scenario storylines toward economic or environmental concerns and global and regional scenario development patterns, respectively. There is no implication that these two are mutually exclusive or incompatible. In reality, the four scenarios share a space of a much higher dimensionality given the numerous driving forces and other assumptions needed to define any given scenario in a particular modelling approach. The A1 storyline branches out into different groups of scenarios to illustrate that alternative development paths are possible within one scenario family (Nakicenovic et al., 2000, Chapter 1.7). Figure 3.2 illustrates total annual CO2 emission for the SRES families[1].

In order to account for the uncertainty attached to the scenarios, it is important to incorporate more than one socio-economic scenario in impact and adaptation assessments (a more detailed description on the issue of uncertainty attached to emission scenarios is provided in Chapter 6). In this thesis the SRES A1B and B1 are considered. Figure 3.3 illustrates ranges for surface warming under the different SRES

[1] The 40 SRES scenarios are presented by the four families (A1, A2, B1, and B2) and six scenario groups: the fossil-intensive A1FI (comprising the high-coal and high-oil-and-gas scenarios), the predominantly non-fossil fuel A1T, the balanced A1B in Figure 3.2a; A2 in Figure 3.2b, B1 in Figure 3.2c, and B2 in Figure 3.2d. Each coloured emission band shows the range of harmonized and non-harmonized scenarios within each group. For each of the six scenario groups an illustrative scenario is provided, including the four illustrative marker scenarios (A1, A2, B1, B2, solid lines) and two illustrative scenarios for A1FI and A1T (dashed lines)(Nakicenovic et al., 2000).

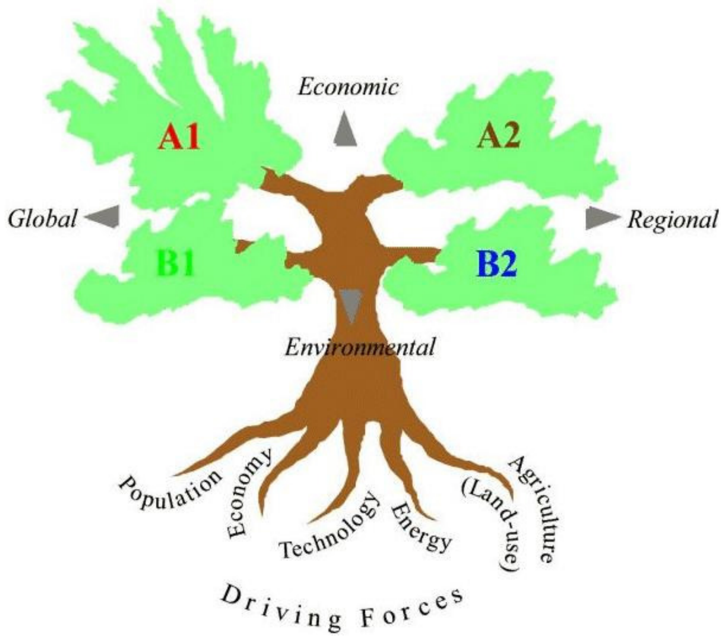

Figure 3.1: The four SRES scenario families

Source: Nakicenovic et al.(2000), A Special Report of IPCC Working Group III, Chapter 1.7, Figure 1-4

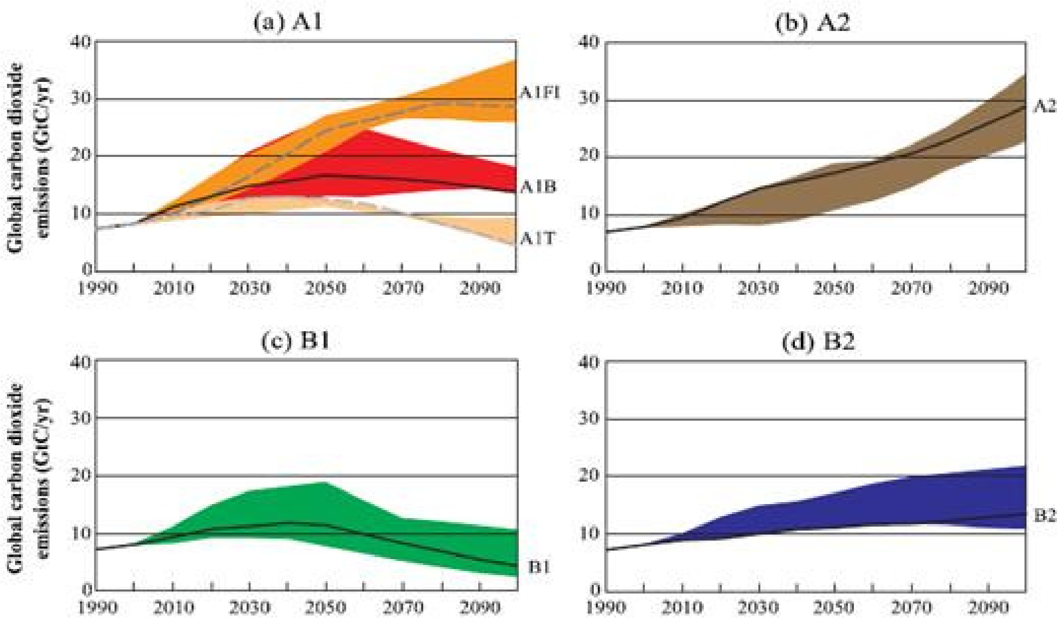

Figure 3.2: Total global annual CO2 emissions from all sources (energy, industry, and land-use change) from 1990 to 2100 (in gigatonnes of carbon (GtC/yr) for the families and six scenario groups.

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Source: Nakicenovic et al.(2000), A Special Report of IPCC Working Group III, Summary for Policy Makers, Figure SPM-3, p.8

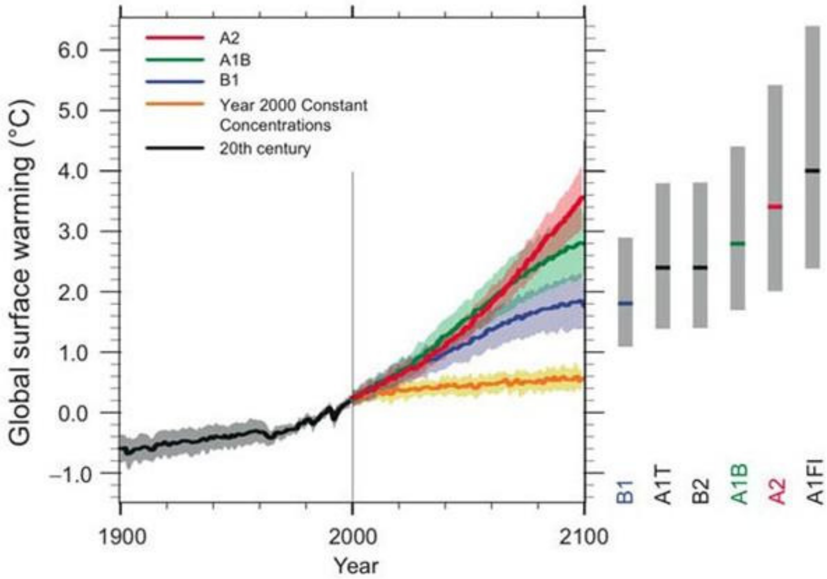


Figure 3.3: Multi-model averages and assessed ranges for surface warming.

Source: IPCC (2007b), Climate Change 2007: The Physical Science Basis, Summary for Policymakers (2007), Figure SPM-5, p.14

scenarios assessed by the IPCC. The solid lines are multi-model global averages of surface warming (relative to 1980-99) for the scenarios A2, A1B and B1, shown as continuations of the 20th century simulations. Shading denotes the plus/minus one standard deviation range of individual model annual averages (IPCC, 2007b). The orange line describes a scenario with constant year 2000 concentration values. The gray bars at right indicate the best estimate (solid line within each bar) and the likely range assessed for the six SRES scenarios. The assessment of the best estimate and likely ranges in the gray bars includes the atmosphere-ocean coupled general circulation models (AOGCMs) in the left part of the figure, as well as results from a hierarchy of independent models and observational constraints (IPCC, 2007b).

3.1.2 Modelling the climate system - Global Climate Models

The earth's overall climate system is composed by a very complex set of dynamic factors and processes. Global Climate Models (also referred to as General Circulation Models (GCMs)) are today's tools for modelling climate response to increased CO2 concentration. They are mathematical models which aspire to determine the dynamic temporal and spatial transport and exchange of heat, moisture, and momentum throughout the earth's atmosphere and its surface, including the continents and oceans (Rosenzweig and Hillel, 1998). GCMs simulate climate by solving se-

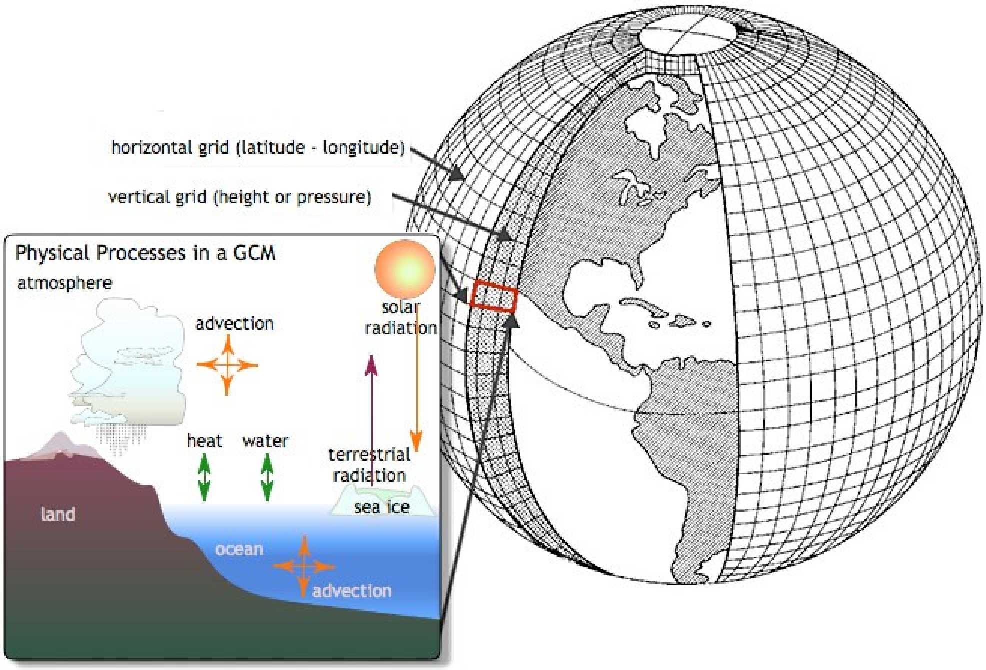


Figure 3.4: Horizontal and vertical grid cells and physical processes in a GCM.

Source: CMMAP(2010)

quentially or simultaneously the fundamental equations for conservation of mass, momentum, energy and water. GCMs depict the climate using a three dimensional grid over the globe (see Figure 3.4), typically having a horizontal resolution of between 250 and 600 km, 10 to 20 vertical layers in the atmosphere and up to 30 layers in the oceans. Their resolution is thus quite coarse relative to the scale of units in most impact assessment studies, which operate usually on much finer grid resolutions. Further, many physical processes occur at smaller scales (such as clouds) and cannot be properly modelled. Instead, their known properties must be averaged over the larger scale in a technique known as parameterization. According to IPCC (2007a) this is one source of uncertainty in GCM-based simulations of future climate. Some GCMs simulations are based on feedback mechanisms such as water vapour and warming, clouds and radiation, ocean circulation and ice and snow albedo. These different GCMs simulate varying responses to the same underlying forcing, because the way certain processes and feedbacks are modelled differs (IPCC, 2007a).

3.1.3 Crop growth simulation models

Crop growth models are computer programs that simulate the growth and development of crops. Data on weather, soil, and crop management are processed to predict crop yield, maturity date, and efficiency of fertilizers and other elements of crop production. The calculations in the crop models are based on the existing knowledge of the physics, physiology and ecology of crop responses to the environment (USDA, 2010). Dynamic crop models are now available for most of the major crops. In each case, the aim is to predict the response of a given crop to specific climate, soil, and management factors governing production. Many of them have been used in climate impact assessments on agricultural productivity e.g. globally (Reilly et al., 2003), the USA (Parry et al., 2004; Beach et al., 2010) and Europe (Quiroga and Iglesias, 2007; Moeller and Grethe, 2010). While the use of crop simulation models makes the assessment of climate effects across a range of crops controllable, such models also have limitations, including isolation from the variety and variability of factors and conditions that affect production in the field (Adams et al., 1998). Generally, two different kinds of crop models can be distinguished: statistical models and process-oriented models. Statistical models predict agricultural yields for large regions based on regression analysis on monthly or annual variables. The process models, in turn, compute crop dynamics at small scales such as leaf to canopy or field levels (Tubiello and Ewert, 2002). The vegetation model LPJmL used for this thesis, belongs to the family of process-oriented models. A more detailed description is given in Chapter 4.1.

3.1.4 Market models

In economics, a market model represents economic processes on one or more markets by a set of variables and their relationships, based on microeconomic theory. It is a simplified framework to illustrate complex processes using mathematical techniques based on economic theory. Market or equilibrium models are a common tool in economic research to investigate market impacts of policy instruments such as trade policies. They can be classified according to their level of coverage and are either called partial or general equilibrium (GE) models. The latter cover the economy as a whole, and explicitly account for all the links between sectors of an economy - households, firms, governments and countries. Partial equilibrium (PE) models, in contrast, solely cover selected sectors of an economy or region, assuming that the impacts of that sector on the rest of the economy, and vice versa, is either non-existent or small. A number of partial equilibrium models have been developed to simulate international trade policy changes (Piermartini and The, 2005). PE models are also commonly used to examine agricultural market policies such as impact assessments of Doha negotiations or the European Common Agricultural Policy (CAP). Examples for partial equilibrium (PE) models which have been applied for the analysis of agricultural markets are CAPRI (Common Agricultural Policy Regionalized Impact (Britz, 2004)), IMPACT (International Model for Policy Analysis of Agricultural Commodities and Trade (Rosegrant et al., (2008)), and the FAPRI Model (FAPRI, 2007). Further, PE models can be distinguished whether they use programming approaches or are based on behavioural equations. General equilibrium models recently applied for the analysis of agricultural markets are for example the GTAP (Global Trade Analysis Project) Model (Hertel, 1997) or the BLS (Basic linked System) (Fischer et al., 2001). Section 6.2 provides an overview of climate impact assessments on agricultural markets based on GE and PE models. Naturally, GE models are more complex in structure and data requirements since they cover all sectors and their interrelation in an economy. However, the high level of aggregation required to be able to use comparable and consistent data, as well as difficulties in parameter specification and functional forms, can be detrimental for some applications. In contrast, PE models can be of an advantage as they solely focus on selected sectors of an economy and hence allows for a more detailed depiction. This characteristic makes them more convenient to interpret impacts of e.g. a certain market instrument in question. Another characteristic of classification of market models is whether current results are impacted by results of the former period, such as lagged price responses. They are called recursive dynamic models. The other group, which do not cover adjustments in time explicitly, is called comparative static. The market model applied for this study, the European Simulation Model (ESIM), is a partial equilibrium, comparative static model, which solely covers the agricultural sector of the EU and an aggregated rest of the world (Banse et al., 2005). It is explained in more detail in Chapter 4.2.

3.2 Ricardian method

Also referred to as the cross-section model, or hedonic approach, the Ricardian method relates agricultural capacity statistically to temperature and precipitation based on farm survey or county data of a certain region (Cline, 2007). This approach is based on the classical economist David Ricardo's theory that the net value of land reflects its net productivity (Ricardo, 1817). Constituted on Ricardo's theory, Mendelsohn, Nordhaus and Shaw (1994) developed an impact model that uses statistical regressions of land values, or net revenue, per hectare on climatic data and other factors such as a variety of fundamental geographic, geophysical, agricultural, economic, and demographic factors to determine the intrinsic value of climate on farmland (Mendelsohn et al., 1994). Their basic hypothesis is that climate change shifts the production function for crops and that farmers take environmental variables as given, adjusting their inputs and outputs accordingly (Mendelsohn et al., 1994). This approach automatically incorporates efficient adaptations to climate change by farmers. Since it relies upon comparisons over vast landscapes, it is thus able to represent actual farm conditions. However, since the Ricardian model links climate directly to net income it is not able to account for any crop specific changes, nor is it able to consider potential CO2-fertilization effects (Adams, 1998). Studies using the Ricardian approach to measure climate impacts on agriculture have, for example, been done for Latin America (Mendelsohn et al., 2007) the US (Mendelsohn et al., 1994) and Egypt (Eid et al., 2007).

3.3 AEZ approach

The Agro-Ecological Zones (AEZ) approach is a GIS-based modelling framework that combines land evaluation methods with socioeconomic and multiple-criteria analysis to evaluate spatial and dynamic aspects of agriculture (Fischer et al., 2005). Developed by the Food and Agriculture Organization of the United Nations (FAO) in collaboration with the International Institute for Applied Systems Analysis (IIASA), it enables rational land use planning on the basis of an inventory of land resources and evaluation of biophysical limitations and potentials. The land resources inventory is used to assess specified management conditions and levels of inputs, all feasible agricultural land-use options and to quantify expected production of cropping activities relevant in the specific agro-ecological context that characterize the study area. The characterization of land resources includes components of climate, soils and landform, which are basic for the supply of water, energy, nutrients and physical support to plants. It simulates the availability and use of land resources, options for farm-level management, and potentials of crop production as a function of climate (IIASA, 2010; Riahi et al., 2006; Tubiello and Fischer, 2007).

Outcomes are then linked to the world agro-economic model BLS. The BLS is a general equilibrium model system which represents all economic sectors and links countries through trade, world market prices, and financial flows (Fischer et al., 2001). A disadvantage of this approach is that predicted potential yields from AEZ models are often much larger than current actual yields. Hence, critics argue that the model may overestimate the effects of autonomous adaptation and claim that AEZ studies also tend to overestimate benefits of warming in cold high-latitude regions, thereby overstating global gains from climate change (Cline, 2007). The AEZ approach is primarily used to study climate change impacts on a global scale (Fischer et al., 2007; Parry et al., 1999).

3.4 Estimating production functions

Yield response functions are developed by estimating statistical relationships between crop yields on the one hand and temperature and precipitation on the other (Hertel and Rosch, 2010). Multivariate models are either estimated on empirical data, or mixes of empirical and simulated data from process based models, and are also often used to predict climate change impacts on crop yields considering changes in temperature, rainfall, sowing date and fertilizer application (Antle and Capalbo, 2001). Yield functions, derived from regional crop models, have for example been used to evaluate climate impacts in Europe (Quiroga and Iglesias, 2007; Iglesias et al., 2009 [2]) and China (Rosenzweig et al., 1999). Using simple yield response functions for climate impact studies might never provide detailed outlooks such as complex process models, but are also useful tools for supporting decision making processes of farmers and policy-makers since their results allow a more direct interpretation (Quiroga and Iglesias, 2009). Lobell et al. (2008) for example developed statistical crop models based on past harvest data and monthly temperature and precipitation in order to prioritize investment needs regarding adaptation for the most affected crops in 12 food insecure regions. Quiroga and Iglesias (2009) estimated multiple linear regression models of Spanish farming systems, using climatic data as explanatory variables, in order to address policy and risk management decisions. A major advantage of this approach is that it requires less data as compared to the other approaches. Further it can be implemented for large geographic areas. On the other hand, the future predictions rely on past observations and thus do not take into account potential adjustments such as the changes in varieties grown or changing planting and harvesting dates (Hertel and Rosch, 2010).

[2] They quantify crop responses to climate by deriving crop production functions from process-based calibrated models. Firstly crop responses at the site level are determined, and then production functions at the regional level, which take the level of farm management, water supply and adaptive capacity into account, are estimated.

3.5 Crop growth simulation models linked with market models

Another seminal method broadly used for measuring climate change impacts on agriculture is the application of crop model analysis (Rosenzweig and Parry, 1994). Crop models simulate the bio-physical reactions of different crops to changing agro-climatic conditions (Bosello and Zhang, 2005). They are based on experiments where crops are grown in field or laboratory settings under different simulated climates and CO2 levels. Farmer's potential adaptation measures can also be included in the crop models, such as changes in planting dates, choice of variety and crop, and applications of irrigation and fertilizer. Nevertheless, it has to be taken into account that the level of adaptation is subject to uncertainty since the scope of adaptation is limited to assumptions made by the modeller. The field or laboratory experiments are then extrapolated over regions. This is a disadvantage of crop models compared to the Ricardian method which compares actual farm conditions over many regions (Mendelsohn et al., 2007).

Many climate impact studies use crop models to predict future crop productivity changes. In particular, such crop models are useful regarding climate change impact assessments since they are able to simulate the effects of elevated CO2 concentrations

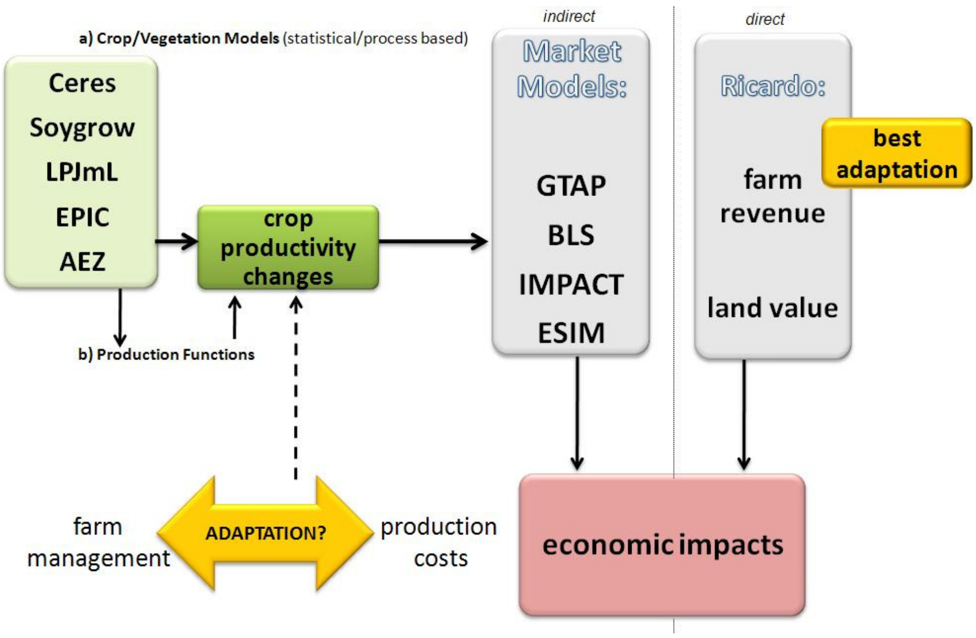


Figure 3.5: Methodologies of measuring economic impacts of climate change on agricultural markets.

Source: Own compilation.

on agricultural production (Tubiello and Ewert, 2002). A large body of work has been devoted to analysing such potential impacts on future local, regional and global crop production (e.g., Rosenzweig and Parry, 1994; Rosenzweig et al., 1995; Reilly et al., 2001; 2003;). In the majority of these studies, crop models were employed to assess the simultaneous effects on crop growth and yield of future elevated CO2 concentrations, regional climate change, and adaptation measures.

Important strengths of crop simulation modelling include the growth simulation of crops on a daily basis so they can be utilized to assess the impact of extreme events. Further, depending on the model, crop varieties can be specified and production inputs such as fertilizer and water availability can be included (Hertel and Rosch, 2010). These factors play not only an important role for climate impact assessments, but also for developing adaptation strategies.

To translate crop model results into economic effects, they are linked with general or partial equilibrium models such as GTAP, BLS or IMPACT (Rosenzweig and Parry, 1994; Parry et al., 2004; Fischer et al., 2005; Nelson et al., 2009a). There is a huge variety of crop models and incorporated approaches to modelling the effects of elevated CO2 concentration and its interaction with other important factors on plant physiology such as temperature and precipitation. This heterogeneity makes it difficult to compare results (Tubiello and Ewert, 2002). Figure 3.5 displays the different structure of all approaches described in the previous sections.

3.6 Review of studies on the impact on climate change on agricultural markets

Over the past two decades a broad spectrum of literature of the economics of climate change on agricultural markets evolved. This section briefly reviews some of the main studies based on the joint crop and market model approach. Results are difficult to compare regarding the underlying assumptions such as the different implemented emission and climate scenarios. Nonetheless, the objective of this section is to provide a short review of major studies of climate impacts for Europe and the world and aims at a comparison of the results to the extend possible.

3.6.1 Impacts in Europe

Only a small number of studies who follow the approach of linking productivity outcomes of crop models to market models exist for evaluating impacts on the European agricultural sector solely.

Iglesias et al. (2009) for example, assess the potential effects of climate change on agriculture in Europe in the context of a broad project by the European Commission on climate change effects in Europe (PESETA[3]). Apart from the agricultural sector, the study covers also other sectors of the economy such as tourism and health (Ciscar et al., 2009). The agricultural sector assessment by Iglesias et al. (2009) used the validated site crop model DSSAT[4] (Iglesias, 2005) and estimated production functions derived from the crop models where the functional forms for each region represent the realistic water availability and potential conditions for the mix of crops, management alternatives and potential endogenous adaptation. Crop productivity changes account for changes in crop distribution in the scenario due to modified crop suitability under warmer climate and farmers' non-policy driven adaptation.

Scenarios: The crops simulated are winter wheat, spring wheat, rice, grassland, maize and soybeans. The uncertainty of the climate scenario is characterised by selecting two emission scenarios (A2 and B2), two global climate models (HadCM3 and ECHAM) downscaled across Europe, and two time frames (2020 and 2080). The HadCM3 under the A2 and B2 scenarios and the ECHAM4 under the A2 scenario for 2080 serve as the three climate change scenarios. The time period 1961-1990 serves as the comparative baseline. **Adaptation** is considered by assessing country or regional potential for reaching optimal crop yield. Optimal yield is the potential yield given no limits on water application, fertilizer and management constraints, and adapted yields are calculated by the ratio of current yields to current yield potential. The CO2 effect is included in the yield changes, as well as rainfed and irrigated simulations. The results are aggregated in nine agro-climatic European zones.

Results: For a comprehensive depiction, results are aggregated over 9 agro-climatic zones over Europe. The average regional changes in crop yields under the HadCM3 A2 and B2 scenario for 2080, compared to the period 1961 - 1990, range between + 39% for Northern Europe and -12 % for Southern Europe. For the ECHAM4 A2 and B2 scenario for the same period, average crop yield changes vary between + 52% for Northern Europe and -27% for Southern Europe. The aggregated effect for Europe ranges between -10% and +3% under ECHAM4 and between -2% and +3% under HadCM3.

[3]Projection of Economic impacts of climate change in Sectors of the European Union based on boTtom-up

[4]DSSAT is a software package integrating the effects of soil, crop phenotype, weather and management (ICASA, 2010).

As mentioned before, the underlying study of the work by Igelasias et al. (2009) was an assessment of the whole European economy not solely focusing on the agricultural sector. Hence, the yield changes presented are used as an input to a market model. In order to evaluate the economic impacts of climate change on the agricultural markets, the global GTAP general equilibrium model (Hertel, 1997) has been employed. Climate change has been introduced in the model as land-productivity-augmenting technical change over crop sectors in each region resulting in changes of the GDP[5]. Agriculture-related productive impacts are negative in most scenarios for Europe as a whole, with particularly negative effects in Southern Europe with decreases between 0.3% and 1.26% of GDP. Increases for Northern Europe in turn are in a range of 0.8% to 1.1% of GDP. The EU-aggregated effect are ranging between 0% and -0.3% for the scenarios considered (Ciscar et al., 2009). The study is different to the present work in the following points:
Firstly, it uses a consistent crop simulation methodology on a regional scale and also employs regional climate models. This provides for a more explicit estimation of crop yield changes on a regional level. However, one disadvantage in terms of the agronomic evaluation is the broad aggregation in nine agro-climatic zones in DSSAT and eight agricultural regions in GTAP. In the present study, the market model ESIM allows for an explicit description of the European agricultural sector for each member state for 15 crops. Whereas only 6 crops have been modelled with DSSAT. Further, productivity changes induced in the region outside the EU in this study stem only from the crop model LPJml which makes results better comparable. The GTAP model in turn uses productivity change data for regions outside the EU from a different study (Parry et al., 2004).

Another prominent study covering the impacts of climate change on the agricultural sector, was published by *Parry et al. (2004)*. They estimate global food production changes, and the risk of hunger for the four SRES emission scenarios A1F1, A2, B1 and B2 developed from the global climate model HadCM3. Yield changes were calculated by using functions derived from crop model simulations. The economic model BLS, described in Chapter 3.3, was applied to evaluate changes in global cereal production, prices and the number of people at risk of hunger. Im-

[5]Moreover, in the last stage of the PESETA project the four impact categories that were considered as 'market' impacts (agriculture, river floods, coastal systems and tourism) have been integrated into the computable general equilibrium GEM-E3 Europe model, in order to have a comparable vision of impacts across sectors. The ultimate purpose of this preliminary analysis has been to get insights on which aspects of the European economy and which geographical areas are more vulnerable to climate change, without considering public adaptation (Ciscar et al., 2009, Chapter 8).

pacts were estimated for the time slices 2020, 2050 and 2080. Crop yield changes were estimated for the crops wheat, rice, maize and soybean. To provide estimates of yield changes for other crops and commodity groups included in the BLS, the site specific crop yield changes were extrapolated (Parry et al., 1999). Regarding

adaptation, the functions incorporate farm-level adjustments, such as changes in planting dates, application of additional fertilization and irrigation. On the regional scale, yield changes represent potential changes that require investments such as the development of new cultivars and irrigation infrastructure. Economic adjustments within the food trade model BLS is incorporated by accounting for agricultural investment, re-allocation of agricultural resources (such as crop switching) according to economic returns, as well as the use of additional arable land as a response to higher cereal prices. These economic adjustments, however, do not feed back in the yield levels predicted by the crop modelling study (Parry et al., 1999).

Effects of climate change were introduced to the BLS as changes in the average national or regional yield per commodity including i.a. wheat, rice and coarse grains. Yield change estimates for coarse grains were based on the percentage of maize grown in the country or region, and the estimates for the non-grain crops were based on the modelled grain crops and previous estimates of climate change impacts. Within each regional unit, the supply modules allocate land, labour, and capital as a function of the relative profitability of the different economic sectors in each regional unit. In particular, actual cultivated acreage is computed from agroclimatic land parameters (derived from AEZ) and profitability estimates. Once acreage, labour, and capital are assigned to cropping and livestock activities, actual yields and livestock production is computed as a function of fertilizer applications, feed rates, and available technology (Fischer, 2009).

The annual yield trends used in the BLS for the period 1980-2000 are 1.2, 1.0, and 1.7% for global, developed country, and developing countries, respectively (Parry et al., 1999). In BLS, agriculture produces nine aggregated commodities and national level estimates were aggregated into 11 broad regions (Parry et al., 2004). **Results:** Here, for simplification, only results for the B1 emission scenario driven by HadCM3 by the year 2050 compared to the reference scenario without climate change, are presented. Further, yield changes in this section of the literature review present impacts for the region of Western Europe only. The global results are shown in the next section for the same study. Estimated aggregated crop yield changes for wheat, rice and soybean range between - 2.5 % when CO2 fertilisation effect is not considered ("without CO2"), and 5% when fertilization effect is taken into account ("with CO2") as compared to the reference scenario without climate change.

The study is different to the present work in the following points:

Farm level adaptation considered in the crop models in this study, as well as crop switching according to economic returns in the BLS are the same approach as in the present study. However, the aggregation over regions and major crops is, compared to the present study, less detailed and estimated results more vaguely. Comparing yield changes of the present study by 2050 under the B1 HadCM scenario, shows, that simulation results for the aggregated crops wheat, rice and soybean in Western Europe[6] are much more positive as compared to study results in Parry et al. (2004). When CO2 fertilization is considered, an increase of 15 % as compared to the scenario without climate change is predicted. Also when CO2 fertilization is not accounted for, yield changes for Western Europe are still positive with 7%. By contrast, for the same emission and climate scenario (B1 and HadCM), Parry et al. (2004) project an increase by only 5% for the CO2 scenario, and a decline by 2.5% when CO2 is not accounted for. Again, comparing the results is not straight forward, since simulation results for yields of the present study incorporate economic adjustments, whereas yield change results of Parry et al. (2004) are estimated with yield transfer functions derived from crop simulation models.

Moeller and Grethe (2010) estimate changes in crop yields by 2050, as compared to the reference scenario without climate change, between 5% and 8% under the A1B ECHAM5 scenario and aggregated yield changes range between 9% and 14% (for the "without CO2" effect scenario and "with CO2" effect scenario, respectively) under the ECHAM5 B1 scenario. Crop productivity changes and their implementation in the market model, as well as adaptation, is based on the same method as described in this thesis in Chapter 4.

As mentioned above, according to the different emission scenarios, time frames and aggregation of crop categories, it is difficult to directly compare the results of the reviewed studies. However, projected impacts indicate more losses for southern, as compared to northern regions, which is in line with results of the present study. A more detailed comparison of results is provided in Chapter 10. Table 3.1 provides a summary of the studies described above according to their major characteristics and results.

[6] Excluding results of the new member states in ESIM.

Crop Model	Market Model	Region	GCMs	SRES	Horizon	%Δ yield w/o CO2	%Δ yield w CO2	Source
DSSAT	GTAP	Europe	ECHAM4 HadCM3	A2 B2	2080	n.a	-10 % to 3 %[1] -2 % to 3 %[2]	Iglesias et al. (2009)
Production functions			ECHAM4	A2 B2	2020	n.a	~ 17 %	
Various, location specific	BLS	Western Europe	HadCm2 **HadCm3**	A1F1 A2 **B1** B2	2020 **2050** 2080	- 2.5 %[3]	5 %[3]	Parry et al. (2004)
LPJmL	ESIM	Europe	ECHAM4	A1B	2050	5 %	8 %	Moeller and Grethe (2010)
				B1		9%	14%	

[1]Aggregated European effect under ECHAM4, ranging from regional effects of +54% for Northern Europe to -27% for Southern Europe; [2]Aggregated European effect under HadCM3, ranging from regional effects of +41% for Northern Europe to -12% in Southern Europe; [3]Averaged national changes for wheat, rice, maize and soybean (bold letters indicate scenarios considered);

Table 3.1: Overview impact studies for Europe.

Source: Own compilation.

3.6.2 Global impacts

Fischer (2009) examined a spatial global assessment of the interlinkages of emerging biofuels developments, food security and climate change. The modelling framework includes the AEZ model which is described in Chapter 3.3, and the BLS [7], the same as described in the section above. Results derived from the AEZ are based on different assumptions concerning autonomous **adaptation** such as change of cropping dates and types (but limited to local crop types as compared to best suitable types), and CO2 fertilization effect on crop yields. Data on crop yield changes were estimated with AEZ for different scenarios of climate change and were compiled to provide yield-impact parameterizations for the regions covered in the BLS model. Yield changes were introduced into the yield response functions as multiplicative factors. Results were derived for climate change **scenarios** under the HadCM3 model and the SRES A2 emissions pathway. Exogenous variables, population growth and technical progress, were left at the levels specified in the respective reference projections. The adjustment processes are triggered by the imposed yield changes which in turn lead to changes in national production levels and costs, and finally changes of agricultural prices in the international and national markets. Following these changes, investment allocation and labour migration between sectors as well as reallocation of resources within agriculture are affected (Fischer 2009). **Results** for crop yield changes under the Hadley model and A2 emissions scenario range between

[7]In that paper the BLS is referred to as the world food system (WFS) (Fischer, 2009).

-10.5% ("without CO2") and 7.5% ("with CO2"), whereas under the climate model CSIRO[8] model the range is between -3% and 10% ("with CO2"). Table 3.2 provides more details on results.

Results for *Parry et al. (2004)* are based on the same study as described in the European impact section above, but show net global effects. Predicted global yield changes between -30% and 2.5% if CO2 fertilization is not taken into account and between -10% and 10% if fertilization effect is considered under the HadCM3 B1 scenario by 2050 as compared to the reference scenario without climate change.

The study conducted by *Nelson et al. (2009a)*, which examined climate change, the risk of hunger and the cost of adaptation focusing on developing countries, is the study which is most suitable for a direct comparison to the present thesis regarding the methodological framework, as market effects are also modelled with a partial equilibrium model covering the agricultural sector. It uses a global agricultural supply-and-demand projection model (IMPACT) which is linked with a biophysical crop model (DSSAT) to estimate the impact of climate change on the five crops rice, wheat, maize, soybeans, and groundnuts. The model was originally developed for projecting global food supply, food demand, and food security to 2020 and beyond. It includes 32 crop and livestock commodities in 281 regions of the world that together cover the earth's land surface, which are called food production units. Production and demand relationships in countries are linked through international trade flows. The crop production is determined by crop and input prices, externally determined rates of productivity growth and area expansion, investment in irrigation, and water availability. Demand is determined by prices, income, and population growth. The 2009 version of IMPACT includes a hydrology model and is linked to the DSSAT crop-simulation model, which is used to assess climate-change effects and CO2 fertilization. In the DSSAT-IMPACT modelling framework, it is also distinguished between rainfed and irrigated crops.

Regarding **adaptation**, the study provides an assessment of the costs of productivity-enhancing investments in agricultural research, rural roads, and irrigation infrastructure and efficiency that can help farmers adapt to climate change. Moreover, autonomous adaptation is considered as farmers response to changing prices with changes in crop mix and input use.

Climate change is introduced into IMPACT by altered crop area and yield. Yield is a function of crop, labour and capital prices as well as an intrinsic yield growth

[8] A climate model developed by the Australian Commonwealth Scientific and Industrial Research Organisation (CSIRO)(Hirst et al., 1996).

coefficient. This coefficient, which depends on the crop, management system and location, is changed based on the ratio of yields in 2000 and yields in 2050 which are affected by climate change. The A2 emission **scenario** using the climate models CSIRO and NCAR[9] is used. Climate change impacts are projected for the year 2050. **Results** indicate yield reductions for wheat, rice and corn between 30% and 23% under CSIRO "without CO2" and "with CO2", respectively. Under the NCAR the decline range is even bigger between 35% and 30%. These results are direct results from the DSSAT model and do not include any economic adjustments. Nelson et al. (2009a) present in their study only those yield results. Results from the IMPACT model, based on DSSAT outcomes, are given for changes in crop production quantities only. Climate change results in additional price increases of 32% to 37% for rice, 52% to 55% for maize, 94% to 111 % for wheat, and 11% to 14% for soybeans. If CO2 fertilization is effective, these 2050 prices are about 10 percent smaller.

Table 3.2 reports the effects of climate change on crop yields in 2050 as compared to yield developments without climate change, based on the NCAR and CSIRO scenarios, accounting for both, the direct changes in yield and area caused by climate change, and autonomous adaptation as farmers respond to changing prices with changes in crop mix and input use. The table also provides a summary of the studies described above according to their major characteristics and results. Comparing global production potential changes for rainfed wheat and maize under the A2 CSIRO scenario between Fischer et al. (2009) and Nelson et al. (2009a), results are more positive for the former study. Whereas Fischer et al. (2009) predict production potential changes under the "with CO2" scenario of -3% and +10% for wheat and maize, Nelson et al. (2009a) projects declines for both crops of 16% and 12%, respectively. Also under the "without CO2" scenario, production potential changes by Fischer et al. (2009) indicate a decline of 8% for wheat and an increase of 6% for maize. Nelson et al. (2009a), by contrast, estimate declines of 23% (wheat) and 8% (maize). The more positive results of Fischer et al. (2009) may result from the overestimation of the effects of autonomous adaptation of the AEZ approach. Further, as argued by Cline (2007), the benefits of warming in cold high-latitude regions tend to be overestimated, thereby overstating global gains from climate change. Even though both studies use the CSIRO climate model projections under the same emission scenario A2, results vary greatly. Again, this underlines

[9] A climate model developed by the American National Centre for Atmospheric Research (NCAR) (Meehl, 2997).

the fact that one has to take a closer look regarding underlying assumptions and modelling frameworks when comparing study results of climate impact assessments.

Crop Model	Market Model	Region	GCMs	SRES	Horizon	%Δ yield w/o CO2	%Δ yield w CO2	Source
AEZ	BLS	World	Hadley	A2	2050	- 10.5 %[1] 3.5 % [2] 3.5 %[3]	- 5 %[1] 7.5 %[2] 1.5 %[3]	Fischer (2009)
			CSIRO			n.a	- 3 %[1] 10 %[2]	
Various, location specific	BLS	World	HadCM2 **HadCM3**	A1F1 A2 **B1** B2	2020 **2050** 2080	- 30 % 2.5 %[4]	- 10 % 10 %[4]	Parry et al. (2004)
DSSAT	IMPACT	World	CSIRO	A2	2050	- 10.7 %[5] - 17.7 % [6] - 30 %[7]	- 8.8 % [5] - 7.3 % [6] - 23.7 %[7]	Nelson et al. (2009)
			NCAR			- 14.6 %[5] - 19. 8 %[6] - 35.1 %[7]	- 12.8 %[5] - 8.9 %[6] - 29.3 %[7]	

Averaged changes of production potential of current and adapted crop types rainfed wheat[1], maize[2]and cereals[3]. [4]Averaged national yield changes for wheat, rice, maize and soybean (bold letters indicate scenarios considered); Averaged yield changes for irrigated and rainfed maize[5], rice[6] and wheat[7] (DSSAT results, no economic adjustments included).

Table 3.2: Overview global impact studies.

Source: Own compilation.

4 Joint Model Application of LPJmL and ESIM for Assessing Climate Change Impacts on Agriculture

4.1 Description of LPJmL

The LPJmL is a so-called dynamic global vegetation model which has been developed as an intermediate complex model that can potentially be used for a broad range of applications. It represents land-atmosphere coupling and explicitly includes major processes of vegetation dynamics. Vegetation is described in grid cells in terms of ten different plant functional types (PFTs). PFTs are differentiated by physiological, morphological, phonological, bioclimatic and fire-response attributes. It also includes explicit representation of vegetation structure, dynamics, competition among PFT populations, and soil biogeochemistry (Sitch et al., 2003; Smith et al., 1997)[1]. Production area is static at the year-2000 pattern (Fader et al., under review). The productivity changes due to climate change of major crops implemented in the market model ESIM for this study, were computed by Bondeau et al. (2007). They include effects of climate change and CO2 fertilization on yields of major crops globally at a spatial resolution of $0.5°x0.5°$. Yield simulations are based on process-based implementations of gross primary production, growth- and maintenance respiration, water-stress, and biomass allocation, dynamically computing the most suitable crop variety and growing period in each grid cell as described in more detail by Bondeau et al. (2007) and Waha et al. (2011).

[1]For a detailed description of the model see Sitch et al. (2003), Prentice et al. (1992) and Bondeau et al. (2007).

4.2 Description of ESIM

ESIM is a comparative static, net trade, partial equilibrium model of the European agricultural sector (Banse et al., 2005), including the extensions described in Banse et al. (2007). The version of the model used for this study has the base period 2005 and includes 27 EU Members, Turkey and the US. All other countries are aggregated in one region, the so-called rest of the world (ROW). ESIM covers 15 major crops, 6 animal products, 14 processed products and a range of other products such as pasture and voluntary set aside. ESIM is mainly designed to simulate the development of agricultural markets in the EU and accession candidate countries. Hence, policies are modelled in great detail for these countries. All behavioural functions in ESIM excluding area allocation for sugar are isoelastic. Supply at the farm level is defined for 15 crops, 6 animal products, pasture and voluntary set-aside. Human demand is defined for processed products and for most farm products. Some of these products enter only the processing industry, e.g. rapeseed, and others are used only in feed consumption, e.g. fodder or grass from permanent pasture. The price formation mechanism in ESIM assumes an EU point market for all products except for non-tradables (potatoes, milk, grass, fodder). Domestic price formation in the EU depends on endogenous world market prices, EU market and price policies, and the EU net trade position.

4.3 Adjustments of ESIM

Estimating future climate impacts on agricultural or any markets is a difficult task for the following reasons: Climate change projections go far beyond the standard projection horizon of market models. Usually their time frame covers ten to 20 years in the future. By contrast, climate projections are as long as 100 years and beyond. Here lies one of the major challenges when adapting existing market models to extend their standard projection period in order to cope with long term climate changes. ESIM depicts agricultural markets of EU member states, and hence a high variety of policy instruments, such as tariffs, intervention prices or export subsidies are implemented in the standard version. Extending the standard projection horizon from 2020 to the year 2050, therefore requires fundamental assumptions about future economic, social end political developments. This justifies the application of sensitivity analysis for different development paths, but also makes an isolated climate impact assessment more difficult due to interaction effects of politics and climate change. Hence, for this thesis, all implemented agricultural policies in ESIM were abolished and therefore fully liberalized agricultural markets are assumed.

Further, the macro shifters population and income growth until 2050 are adjusted in line with the IPCC's emission scenario assumptions used for this study (A1B and B1, further described in Chapter 7.1). Based on these assumptions, annual population growth rates for the aggregate ROW (rest of world, all regions outside excluding the EU, US and Turkey) are about 0.78. Annual income growth rates for ROW are between 5.49 and 4.98, depending on the scenario. Growth rates for all other regions and countries in ESIM can be found in Annex A.

4.3.1 Adjusting demand elasticities in ESIM

The income growth rates implemented in ESIM as described above, are optimistic assumptions, indicating a rather rapid global economic growth. This certainly has implications for future demand patterns. Demand for food will increase from rising per capita incomes, which is particularly valid for developing countries and countries in transition. According to Engel's law,

> "the poorer a family, the greater the proportion of its total expenditure that must be devoted to the provision of food". *Engel (1857)*

Engel's law, which is supported by numerous empirical studies, requires a demand system to generate declining budget shares for food as income rises which implies an income elasticity of demand less than one. Econometric studies of income elasticities for countries at different stages of development often show that demand for food in low-income countries is relatively more elastic than in wealthy countries. This suggests that when economic growth in poor countries raises consumer expenditure, the demand for food should become less elastic (Yu et al., 2004).

Figure 4.1 shows the inverse relationship between per capita income and income elasticity of food[1]. This development agrees with a study from Abler (2010), who reviews and evaluates a number of studies made on the effects of economic growth in large developing and emerging economies on agricultural product demand and the structure of demand. The report evaluates the effects of economic growth and rising incomes on the composition of agricultural product demand across product categories, and on the evolution of price and income elasticities of demand for agricultural products. The studies reviewed in his report indicate, that income elasticities

[1]Income elasticity of demand for food, beverages, and tobacco (calculated by ERS 2006, as cited by Cline (2007 p.88), and purchasing power parity (PPP) GDP per capita for 64 countries (World Bank 2006, as cited by Cline 2007, p.88).

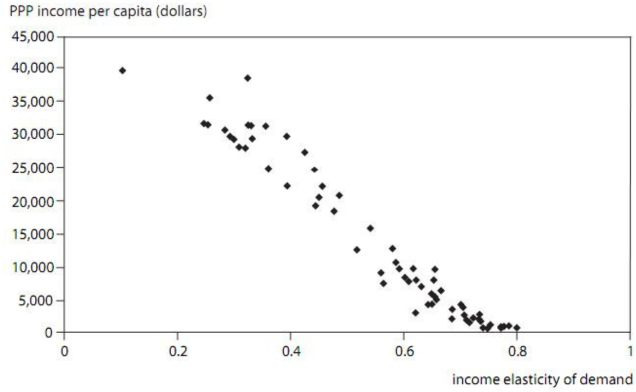


Figure 4.1: Income elasticity of demand for food, tobacco, and beverages and purchasing power parity (PPP) income per capita.

Source: Cline (2007), p.88.

of demand for agricultural commodities are likely to decline for most commodities as economic growth continues in developing and emerging economies. Further, Abler (2010) points out, that the reviewed studies, which estimate both, the income and own-price elasticities, indicate that there is some tendency for the absolute value of the own-price elasticity to decline as the income elasticity declines. Also Seale and Regmi (2006) find that both, the estimated income elasticity and the absolute value of the estimated own-price elasticity, decline as per capita income increases. Using the demand elasticities of ESIM (for the standard projection horizon of 15 years), would hence overstate the demand for agricultural products by 2050 (von Lampe, 1998). Therefore, assuming a high increasing income over 45 years, requires an adjustment of the demand elasticities in ESIM. On account of this, the original income and price elasticities of demand are multiplied by 0.5.

Table 4.1 presents the globally weighted[2] price elasticities of demand for crops implemented in ESIM. A decline in the absolute value of the own-price elasticity means a more-price inelastic demand, causing any given shock to supply to lead to a larger change in the price (Abler, 2010). This is confirmed by the simulation results described in Chapter 9, where small supply changes lead to relatively large alterations in world market prices.

[2]Price elasticities of demand are weighted with demand quantity.

Barley	-0.013	**Manioc**	-0.076	**Rye**	-0.022
Biodiesel	-1.500	**OthGrain**	-0.016	**Soybean**	-0.001
Corn	-0.027	**Palmoil**	-0.026	**Soyoil**	-0.019
Wheat	-0.075	**Potato**	-0.056	**Sugar**	-0.147
Durum	-0.072	**Rapoil**	-0.026	**Sunoil**	-0.027
Ethanol	-1.500	**Rice**	-0.078	**Sunseed**	-0.002

Table 4.1: Global weighted price elasticities of demand.

Source: Own compilation.

4.3.2 The depiction of climate change effects in ESIM

Climate change induced impacts on crop productivity are shocks on the supply-side. In ESIM, such effects are introduced as changes in average national yields. Supply of crops in the EU is defined as area multiplied by yield, whereby yield and area functions are specified separately. Yield is dependent on own price, the price index of non-agricultural inputs and a productivity shifter. The latter reflects rates of technical progress as well as climate change induced productivity changes. The degree to which productivity will potentially decline or increase is provided by the Potsdam Institute for Climate Impact Research derived from the vegetation model LPJmL (Bondeau et al., 2009; Waha et al., 2009). To account for farmer's adaptation to changes in relative productivity of crops, area allocation functions are shifted based on yield trends and elasticities with respect to yield trends. These elasticities were derived based on yield driven cost changes generated by the farm level model FARMIS (Offermann et al., 2005).

4.3.3 Supply in ESIM

In European countries, supply of crops is modelled as a two-stage function, consisting of an area function which is multiplied by a yield function (4.1). In other countries, supply is a direct function of own and cross producer prices as well as technical progress. Thereby, yield is a function of the own price (PP), the costs for labor (labor) and intermediate inputs (intermed), and a productivity shifter (trend) (4.2).

$$\text{Supply}_{c,cr} = \text{Area}_{c,cr} * \text{Yield}_{c,cr} \tag{4.1}$$

$$\text{Yield}_{c,cr} = \text{yield int}_{c,cr} * \text{PP}_{c,cr}^{\epsilon_{c,cr}} * \text{intermed}^{\delta} * \text{labour}^{\mu} * \text{trend}_{c,cr} \tag{4.2}$$

where

$$\begin{aligned}
\text{yield int}_{c,cr} &= \text{Yield intercept of country c of commodity cr} \\
\text{PP}_{c,cr} &= \text{Producer price in country c of commodity cr} \\
\epsilon_{c,cr} &= \text{Elasticity of yield with respect to own price in country c of commodity cr} \\
\delta &= \text{Elasticity of yield with respect to costs of intermediates} \\
\mu &= \text{Elasticity of yield with respect to labour costs} \\
\text{trend} &= \text{Trend parameter in country c of commodity cr}
\end{aligned}$$

In the version of ESIM whch is used as the basis for this thesis, the area allocation process takes place in two simultaneous steps. First, area is allocated as a function of own and cross incentive prices (PI)[3] as well as a labor, capital and intermediate cost indexes (4.3).

$$\text{Area}_{c,cr} = \text{area int}_{c,cr} * (\prod_{cr} \text{PI}_{c,cr}^{\epsilon_{c,cr,cr}}) * \text{capital}^{\lambda} * \text{intermed}^{\delta} * \text{labour}^{\mu} \tag{4.3}$$

where

$$\begin{aligned}
\text{area int}_{c,cr} &= \text{Area intercept of country c of commodity cr} \\
\text{PI}_{c,cr} &= \text{Incentive prices in country c of commodities cr} \\
\epsilon_{c,cr,cr} &= \text{Elasticities of area allocation with respect to own and cross incentive prices} \\
&\quad \text{in country c of commodities cr} \\
\lambda &= \text{Elasticity of area allocation with respect to capital costs} \\
\mu &= \text{Elasticity of area allocation with respect to labour costs} \\
\delta &= \text{Elasticity of area allocation with respect to costs of intermediates}
\end{aligned}$$

In a second step, the area allocated to all crops covered by the model is summed and the resulting total area is scaled down (except obligatory set-aside area) in case the total base area is exceeded. Own price, cross price, and input price elasticities of supply are calibrated to fulfil the conditions derived from economic theory, which are homogeneity of degree zero in input and output prices, symmetry of cross price effects, and non-negativity of the own price effect.

[3] Incentive prices are the sum of farm gate prices and area based direct payments multiplied by a decoupling factor.

4.3.4 Adjusting yield trends

	BASE		
	EU	NEU	WORLD
WHEAT	0.71	0.87	0.72
DURUM	0.36	0.43	0.36
BARLEY	0.87	0.70	0.85
RYE	1.11	0.89	1.08
OTHGRA	0.96	0.53	0.92
CORN	1.79	2.07	1.82
SMAIZE	1.77	1.34	1.73
RICE	1.11	1.67	1.17
SUGAR	1.78	1.70	1.77
POTATO	1.15	1.30	1.17
SOYBEAN	1.79	1.70	1.78
RAPSEED	1.63	1.63	1.63
SUNSEED	1.19	0.77	1.14

Table 4.2: Baseline growth rates of selected crops for the EU, non European countries, and the world.

Source: Own compilation.

Technological progress shifters applied in the crop supply of ESIM are based on a yield trend analysis from FAOSTAT data of the period 1992 to 2007. For any climate change scenarios, an additional component was added to these shifters to incorporate productivity changes from climate change. The vegetation model LPJmL delivered mean yield changes for the period 1996-2005 to 2046-2055 based on climate data from the five global circulation models CCSM3 (Collins et al., 2006), ECHAM5 (Jungclaus et al., 2006), ECHO-G (Min et al., 2005), GFDL (Delworth et al., 2006), and HadCM3 (Cox et al., 1999). Based on the percentage yield changes from the vegetation model, an annual growth rate was derived and added to the technical progress shifter "trend" in the log linear yield function (4.2). Tables 4.2 and 4.3 show technical progress shifters for the baseline scenario and the additional growth rate for all climate change scenarios, expressed as annual percentage changes for the "with" and "without" a CO2-fertilization effect scenarios for the aggregated EU, non European countries and regions (NEU) and the aggregated world (WO). Rates for all countries and crops for each scenario can be found in Annex B.

The colours in Tables 4.2 and 4.3 underline the values of the rates, with green indicating positive values and red negative rates. Therefore it can easily be seen, that under the "without CO2" scenarios, particularly in regions outside the EU, climate change is likely to have negative impacts on crop productivity.

	A1B w			A1B w/o		
	EU	NEU	WORLD	EU	NEU	WORLD
WHEAT	0.33	0.24	0.32	0.07	-0.05	0.06
DURUM	0.33	0.24	0.32	0.07	-0.05	0.06
BARLEY	0.33	0.24	0.32	0.07	-0.05	0.06
RYE	0.33	0.24	0.32	0.07	-0.05	0.06
OTHGRA	0.33	0.24	0.32	0.07	-0.05	0.06
CORN	0.85	0.12	0.78	0.62	-0.16	0.54
SMAIZE	0.85	0.12	0.78	0.62	-0.16	0.54
RICE	0.19	0.65	0.24	0.03	-0.28	0.00
SUGAR	0.41	0.15	0.38	-0.02	-0.30	-0.05
POTATO	0.41	0.15	0.38	-0.02	-0.30	-0.05
SOYBEAN	0.30	0.64	0.33	0.23	-0.11	0.20
RAPSEED	0.23	0.52	0.26	0.03	0.33	0.06
SUNSEED	0.43	0.51	0.44	-0.07	-0.30	-0.10

	B1 w			B1 w/o		
	EU	NEU	WORLD	EU	NEU	WORLD
WHEAT	0.32	0.21	0.31	0.11	-0.02	0.10
DURUM	0.32	0.21	0.31	0.11	-0.02	0.10
BARLEY	0.32	0.21	0.31	0.11	-0.02	0.10
RYE	0.32	0.21	0.31	0.11	-0.02	0.10
OTHGRA	0.32	0.21	0.31	0.11	-0.02	0.10
CORN	0.77	0.17	0.71	0.62	-0.04	0.56
SMAIZE	0.77	0.17	0.71	0.62	-0.04	0.56
RICE	0.16	0.56	0.20	0.04	-0.13	0.02
SUGAR	0.41	0.21	0.39	0.10	-0.12	0.07
POTATO	0.41	0.21	0.39	0.10	-0.12	0.07
SOYBEAN	0.32	0.65	0.35	0.13	0.12	0.13
RAPSEED	0.24	0.44	0.26	0.08	0.29	0.10
SUNSEED	0.41	0.56	0.43	0.06	-0.06	0.05

Table 4.3: Additional annual growth rates of selected crops for the EU, non European countries (NEU), and the world (WO) for the A1B and B1 scenario with (w) and without (w/o) CO2-effect.

Source: Own compilation.

4.4 Adaptation

An important issue concerning the magnitude of economic effects in the agricultural sector from climate change are adaptation measures at the farm as well as national level. Farm level adaptations for instance, can be made in planting and harvest dates, crop rotations, selection of crops and varieties, input quantity of water or fertilizers, as well as tillage practices. These production decisions are the natural response of a producers' goal of maximizing returns (Adams et al., 1998). Each adaptation can lessen potential yield losses from climate change and improve yields where climate change is beneficial. Therefore the extend to which adaptation is taken into consideration in climate impact studies is crucial to evaluate potential changes.

4.4.1 General facts

As described in Chapter 3.2, the Ricardian approach assumes perfect adaptation to changing agro-climatic conditions whereas in most crop model studies farmers' response to climate change is strictly hypothesized (Reidsma et al., 2009; Nhemachena and Hassan, 2008). However, past climate change impact studies such as Rosenzweig and Parry (1994) showed how potential negative climate change effects on the agricultural sector can be substantially impaired when adaptation measures are considered, and results demonstrate that adaptation will affect production outcomes to a high degree (Mendelsohn and Dinar, 1999). The IPCC defines adaptations as adjustments or interventions in order to manage the losses, or take advantage, of the opportunities presented by a changing climate (IPCC, 2007c). Adaptation can be classified in short term (e.g. seasonal to annual) or long term (e.g. decades to centuries) processes. Long term adaptations include e.g. breeding of crop varieties, new land management techniques to conserve water or increase irrigation use efficiencies (Olesen and Bindi, 2004). Short-term adjustments include efforts to optimize production without major system changes and can be classified as being autonomous since no other sectors, such as policy and research, influence their development and implementation. Examples of short-term adjustments include changes in varieties, water supply and irrigation system, sowing dates, fertilizer use and the introduction of new varieties (Olesen and Bindi, 2004; Reilly and Schimmelpfennig, 1999, p.768ff.). Further, Bradshaw et al. (2004) and Kandlinkar and Risbey (2000), define two scales of adaptation: (a) the farm- or micro-level, that focus on farmer decision making and (b) the national- or macro-level, that is about agricultural production at the national or regional scales and its relationships with policies. Micro-level analysis focuses on tactical adaptation decisions farmers make in response to seasonal variations in climatic, economic, and other factors (Nhemachena and Hassan, 2008).

This thesis concentrates on short term adjustments on farm-level only. This is due to the fact that adaptation within the crop model approach can be either implemented in the crop model via farm practices, such as changing optimal planting dates, or by changing production costs or farm income in the economic model (as described in Chapter 3, Figure 3.5). Certainly the degree of adaptation that can be accounted for in this approach depends on the structure of the crop and market model used. The next section briefly describes the degree of adaptation in the vegetation model LPJmL, followed by a section how adaptation is implemented in the market model ESIM.

4.4.2 Adaptation in LPJmL

The model LPJmL considers adaptation processes in management only to a limited extend (Möller et al., 2009). Sowing dates are based on the last 20 years farming practices, and therefore take changing climate conditions into account. This means that it is assumed that farmers react to changing climatic conditions over time. Adaptation regarding the selection of most suitable varieties are only considered for wheat, maize, sunflower and rapeseed (Bondeau et al., 2007). Planting area is kept at current levels over the whole prediction horizon.

4.4.3 Adaptation in ESIM – area allocation

Farmers have always carried out adaptive changes to their businesses based on the weather and respond in the short-term by altering cropping patterns and management practices (Iglesias et al., 2007). In this thesis, adaptation within the market model is regarded as adaptive behaviour regarding changed profitability of crops based on the assumption that farmers allocate their acreage to crops according to their relative profitability based on input and output prices and yields. The area allocation decision can also be classified as short-term adjustment. However, most partial equilibrium models, such as IMPACT (Nelson et al., 2009a) and the standard version of ESIM, define area allocation as purely price driven and hence do not account for farmers' yield level related decisions. As a result, these models would underestimate the supply effect of an increase in the relative yield for any crop. Other approaches, such as CAPRI, take changes in yield levels automatically into account by modelling area allocation as a function of gross margins (Britz, 2004). Nonetheless, such approaches require substantial data on country level production costs and do not fit the aspired simple structure of ESIM. Against this background, farmers' reaction to changes in climate induced yield levels are considered by shifting area allocation functions by adding yield shifters to the power of the elasticities of area allocation with respect to own and cross yield trends.

$$\text{Area}_{c,cr} = \text{area int}_{c,cr} * \left(\prod_{cr} \text{PI}_{c,cr}^{\epsilon_{c,cr,cr}}\right) * \text{capital}^{\lambda} * \text{intermed}^{\delta} * \text{labour}^{\mu} * \text{trend}_{c,cr}^{\beta_{c,cr,cr}} \quad (4.4)$$

with

$\beta_{c,cr,cr}$ =Elasticity of area allocation with respect to yield shifter of country c of crops cr

4.4.4 Calibration of elasticities of area allocation with respect to yield trends

Elasticities are derived based on own and cross price elasticities of area allocation corrected for yield driven cost changes generated by the farm level model FARMIS[5] (Offermann et al., 2005).

It is assumed that without any cost changes in case of higher yield trends, an increase in yield would have the same effect on area allocation as an increase in price, i.e. elasticities of area allocation with regard to own and cross yield trends would equal own and cross price elasticities of area allocation. Yet, knowing that higher yields go together with higher costs, especially input costs for fertilizer, elasticities of area allocation with respect to yield trends are expected to be lower. The increase in costs in case of higher yield trends is approximated based on FARMIS by running the model with the same climate change induced yield changes as in ESIM for the year 2050 compared to a situation without climate change. The increased/decreased input costs from this with climate change scenario in FARMIS is than compared with input costs results from a no climate change scenario. With a relative yield increase of about 37% (A1B with CO2-effect) from effects of climate change, input costs for wheat, for example, would increase by an amount equal to 14.1% of revenue. This implies that per percent of yield increase, input costs will increase by an amount equalling about 0.38% of revenue. One minus this figure delivers the factor by which the original price elasticities of area allocation are multiplied and implemented in the area allocation function. Table 4.4 shows changes of input costs and revenue compared to the baseline scenario in 2050 for selected crops.

Through this method factors were derived for wheat, barley, corn, rye, and rapeseed. The mean value of those grains was also used for the categories of other grains and rice. For oilseeds, soybean and sunflower seeds, the same factor that was used for rapeseed was applied. Silage maize elasticities were multiplied with the same factor that was derived for corn (see Table 4.5). Due to lack of data, it is assumed, that change in costs in all other regions and countries depicted in ESIM react similar as in Germany.

[5] EU-FARMIS is a comparative-static process-analytical programming model based on Farm Accountancy Data Network (FADN) data, which aggregates individual farm data into farm groups. Production is differentiated for 27 crop activities and 15 livestock activities. The model specification is based on information from the German farm accountancy data network covering about 11,000 farms, supplemented by data from farm management manuals. Key characteristics of FARMIS are the use of improved aggregation factors that allow for a representation of the sector's production and income indicators, input-output coefficients which are consistent with information from farm accounts, and the use of a positive mathematical programming procedure to calibrate the model to observed base year levels. Fertilizer and pesticide input costs are generated endogenously and serve as a basis for the estimation of elasticities.

	△% costs	△% yield	costs % of revenue	factor
WHEAT	14.1	37	0.3811	0.6189
BARLEY	6.5	18	0.3611	0.6389
CORN	19.9	64	0.3109	0.6891
RYE	1.8	5	0.3600	0.6400
RAPESEED	12	27	0.4444	0.5556

Table 4.4: Input costs in % of revenue compared to baseline scenario "no CC" and changes in crop yields in % vs. baseline scenario by 2050 (A1B "with CO2" efffect).

WHEAT	0.6189	**OTH GRAINS**	0.6412
BARLEY	0.6389	**RICE**	0.6412
CORN	0.6891	**SMAIZE**	0.6891
RYE	0.6400	**RAPSEED**	0.5556
SOYBEAN	0.5556	**SUNSEED**	0.5556

Table 4.5: Factor for multiplying price elasticities for calculating trend elasticities wrt. area allocation.

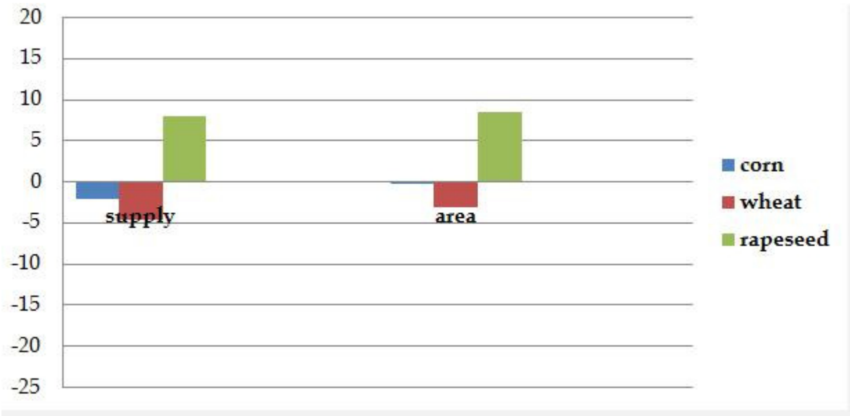
Source: Own compilation.

Results of adding the trend parameter to the area allocation function

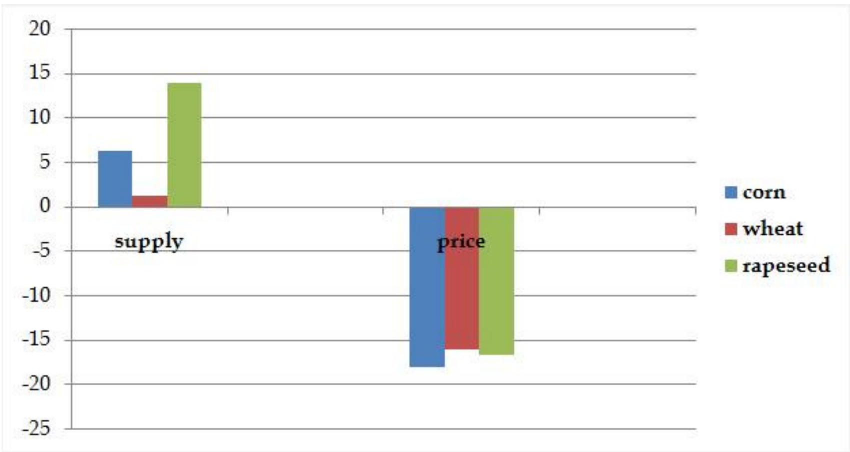
The supply effects of the additional trend parameter and the cost adjusted elasticity is shown in Figure 4.2. Substitution effects among crops within the EU are shown in Figure 4.2 a) for corn, rapeseed and wheat. Results indicate the relative change of area, supply and price resulting from adding the trend parameter to the area allocation function. Strong area effects can be observed for rapeseed with an increase of 8.5%, whereas area effects for corn and wheat are negative with decreases of 0.1% and 3%, respectively. The overall supply effect of rapeseed in the EU hence increases by 8% and declines for corn by 2% and 5% for wheat. The strong area increase for rapeseed results from the relatively high price elasticity of the area allocation function for most European countries of about 0.8. The elasticities for corn and wheat, by contrast, are lower with about 0.3 and 0.5, respectively. Moreover, the trend shifter in the EU for rapeseed is bigger than the trend shifter for wheat (1.6 and 0.7, respectively). Hence, area increase is much more pronounced for rapeseed as compared to most other crops. Outside the EU, however, trend shifter of corn, wheat and rapeseed are higher as compared to the EU, and hence supply outside the EU is increasing by 7%, 3% and 16% respectively. This leads to aggregated global supply increases of 6% for corn, 1% for wheat and 14% for rapeseed. World market prices decrease according to the aggregated supply increase for all crops (Figure 4.2 b).

The aggregated crop supply and price indices results for the European Union (EU), aggregated non European regions (NEU) and the aggregated world (WO) with and without the added trend to the area allocation function is shown in Figure 4.2 c).

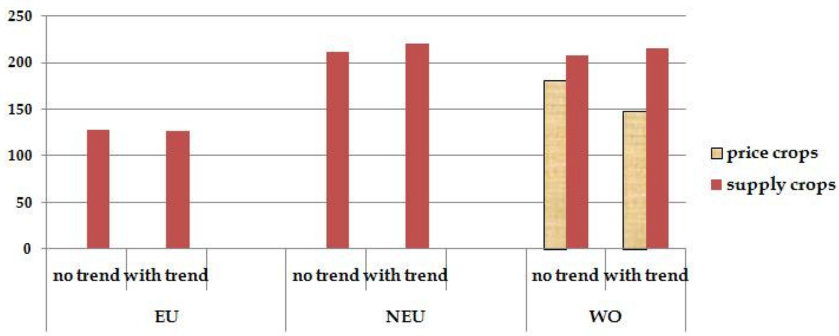
The added trend parameter leads to an overall increase in crop supply in the world by 3% as compared to results from supply without the trend parameter in the area allocation function. Likewise, the crop price index is reduced by 19% as compared to the initial scenario result without the added trend (Figure 4.1.c).



a) Area, supply and price effects of adding the trend parameter to the area allocation function in % in the EU , A1B baseline scenario.



b) Supply and price effects of adding the trend parameter to the area allocation function in % in the WORLD , A1B baseline scenario.



c) Crop supply and price indices by 2050, A1B baseline scenario (2005=100).

Source: Own compilation.

Figure 4.2: Effects of adding the trend parameter to the area allocation function in ESIM.

5 Accounting for Uncertainty

5.1 Sources of uncertainty in climate impact studies

Due to the IPCC, one of its major functions is to assess the state of our understanding and to judge the confidence with which we can make projections of climate change and its impacts. However, past and future climate change estimates, projections of future greenhouse gas (GHG) emissions and their effects are subject to various uncertainties (Wanner et al., 2006). This uncertainty is increasing from emission paths to climate change, from climate change to possible impacts and finally to formulating adequate adaptation and mitigation measures and policies (Iglesias et al., 2009). The following section briefly describes the major sources of uncertainty.

5.1.1 Emission scenarios

The SRES emission scenarios are not only driving forces for climate models, but their underlying assumptions about socio-economic developments also serve as inputs for crop and market models (e.g. CO2 concentration or economic development, respectively). There is huge uncertainty adjacent to future emissions as well as to the potential development of their underlying driving forces (Iglesias et al., 2009). The socio economic development under different SRES emission scenarios plays a major role in future CO2 concentrations, but also in the capabilities of a society to be able to adapt to changing climatic conditions which in turn influence the overall climate change impacts. On the other hand, future CO2 concentration, which extend is also much debated (as described in Chapter 2.2.1), also influences plant photosynthesis and water use (Olesen et al., 2007). Major determinants for the emission scenarios are drivers such as population, economic development and technological change. On the other hand, for mitigative and adaptive capacity other important factors such as governance, education and accessibility of information matter. These additional factors increase uncertainty in projections of vulnerability and mitigation and adaptation options. The IPCCs Third Assessment Report (TAR) even states that the uncertainty in projected climatic changes is about equally attributable to uncertainties in emission scenarios and uncertainty in climate models (Manning et al., 2004). The socio-economic scenarios are also key for understanding the potential adaptation capacity of agriculture to climate change (Iglesias et al., 2009). The recognized cascade of uncertainty when proceeding through projected climate change, its effects and adaptational or mitigative responses is shown in Figure 5.1.

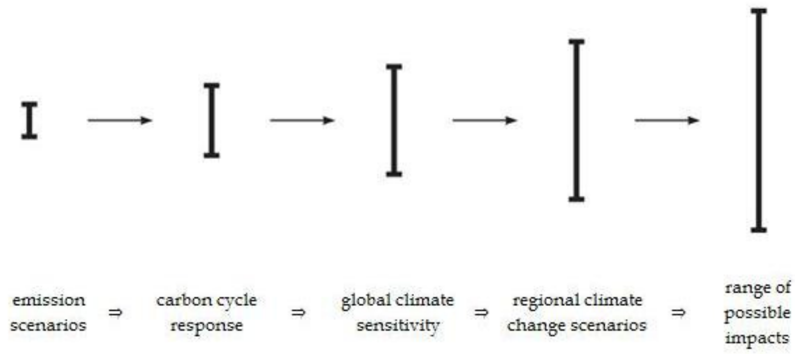


Figure 5.1: Cascade of uncertainties in the relationship between emissions and impacts.

Source: Manning et al. (2004, p.16)

5.1.2 Climate models

Climate models are based on well-established physical principles. Their reproduction of observed features of recent and past climate changes has been proved with confidence. Global circulation models (GCMs) provide credible quantitative estimates of future climate change, particularly at continental scales and above, whereupon reliance in these estimates is higher for some climate variables such as temperature, than for others (e.g., precipitation). However, problems remain in the simulation of some modes of variability (Solomon et al., 2007).

The IPCC Workshop on Communicating Uncertainty and Ris suggested a classification of uncertainty in climate forecasting as follows:

1. Uncertainty in anthropogenic forcing due to different emission paths (scenario uncertainty)

2. Uncertainty due to natural variability, encompassing internal chaotic climate variability and externally driven (e.g. solar, volcanic) natural climate change (natural variability)

3. Uncertainty in the climate system's response to external forcing due to incomplete knowledge of feedbacks and time scales in the system (response uncertainty) (Allen et al., 2004).

The outputs generated by the GCMs such as temperature, precipitation and radiation, are the most crucial climate variables in modelling impacts on crops and other natural vegetation. However, the horizontal spatial scale of GCMs of hundreds of kilometres is considerably bigger than scales of crop- or vegetation models (Easterling et al. 2001; Olesen et al., 2007). Therefore, most impact studies downscale with high resolution regional climate models (RCMs), driven by the same boundary conditions as the GCMs. Yet, there is also uncertainty associated with the RCMs and the downscaling mechanism, and it is not reliable to consider their outcomes, though more precise, better than those based on direct GCM outputs (Mearns et al. 2001; Tsvetsinskaya et al., 2003). The IPCC even suggest that across all areas of climate change uncertainty tends to increase going from global to regional scales (Manning et al., 2004).

One common approach to represent uncertainty stemming from climate models is to implement output from different climate models as input for e.g crop models (Müller et al., 2009; Rosenzweig and Parry 1994; Reilly et al., 2003; Fischer et al., 2001; Rosenzweig and Iglesias, 2006). However, regarding climate impact studies on agriculture, Lobell and Burke (2008) suggest that this approach risks an overestimation of the current ability to predict responses of the agricultural sector to climate change. Most climate models are not very reliable of reproducing current climate variability for summer temperatures, and therefore are not very secure for examining changes in variability. Moreover, there is little agreement among models as to whether variability will increase or decrease, indicating the need for further research in this area. Since separating the impact of extreme temperatures relative to average is difficult, due to high correlations between the two in most regions, a major question which needs to be clarified is whether yield losses are primarily due to the average increase in temperature, or if the extreme days are disproportionately damaging (Lobell et al., 2009).

5.1.3 Crop models

Not only does the level of future CO2 concentration determine future outcomes of crop models regarding plant productivity, but also local soil conditions, water availability or whether adaptation is taken into account, influence productivity outcomes

(Wassenaar et al., 1999). One major source of uncertainty in local and national yield projections are differences in climate patterns, especially precipitation, between different GCMs which serve as inputs for crop models (Müller et al., 2009). Further, there are a large number of structurally different crop models. Aggarwal and Mall (2002) for example, examined differences in rice productivity using two structurally different crop growth models (ORYZA1N and Ceres-rice[1]). They report great yield differences between the two models, given similar inputs of climate models, nitrogen and management levels (Aggarwal and Mall, 2002). Other studies reported differences between crop models as big, or even greater, than those resulting from different climate models (Mearns et al., 1999). They compared the responses of the crop models Ceres and Epic for wheat and corn, and identified the crop model type as an important uncertainty in impacts assessments. Their projected effects of climate change differed significantly, indicating huge structural uncertainties in modelling biological responses (Mearns et al., 1999). Manning et al. (2004) identify such differences in biological modelling outcomes due to different assumptions about physiological parameter-processes relationships and poorly known parameters.

5.1.4 Market models

Many factors also contribute to the uncertainty of market model results. Critics argue, that the degree of precision in simulations of the future cannot be warranted by the quality of information that goes into the model nor the degree of sensitivity of the results to assumptions (Piermartini and The, 2005). Equilibrium models are generally aggregated to such a degree, that some important relationships might be neglected. Further data inputs sometimes lack quality, are missing, or parameters such as supply and demand elasticities are poorly estimated. Results depend highly on data inputs and can vary greatly among chosen scenarios and model specification. Further, static simulations are likely to miss crucial parts of the story and dynamic simulations are more complex and assumption-driven than static ones (Piermartini and The, 2005). These issues can be addressed by using sensitivity analysis which compares results of different alternative assumptions underlying the model. Simulation results are necessarily subject to error and the quality of the results will vary with the appropriateness of the model to the problem at hand, the quality and timeliness of the data and parameters chosen (Piermartini and The, 2005).

Especially impact analysis under climate change scenarios is a challenge for market modellers. Time horizons of 50 years might be a comparatively small time scale

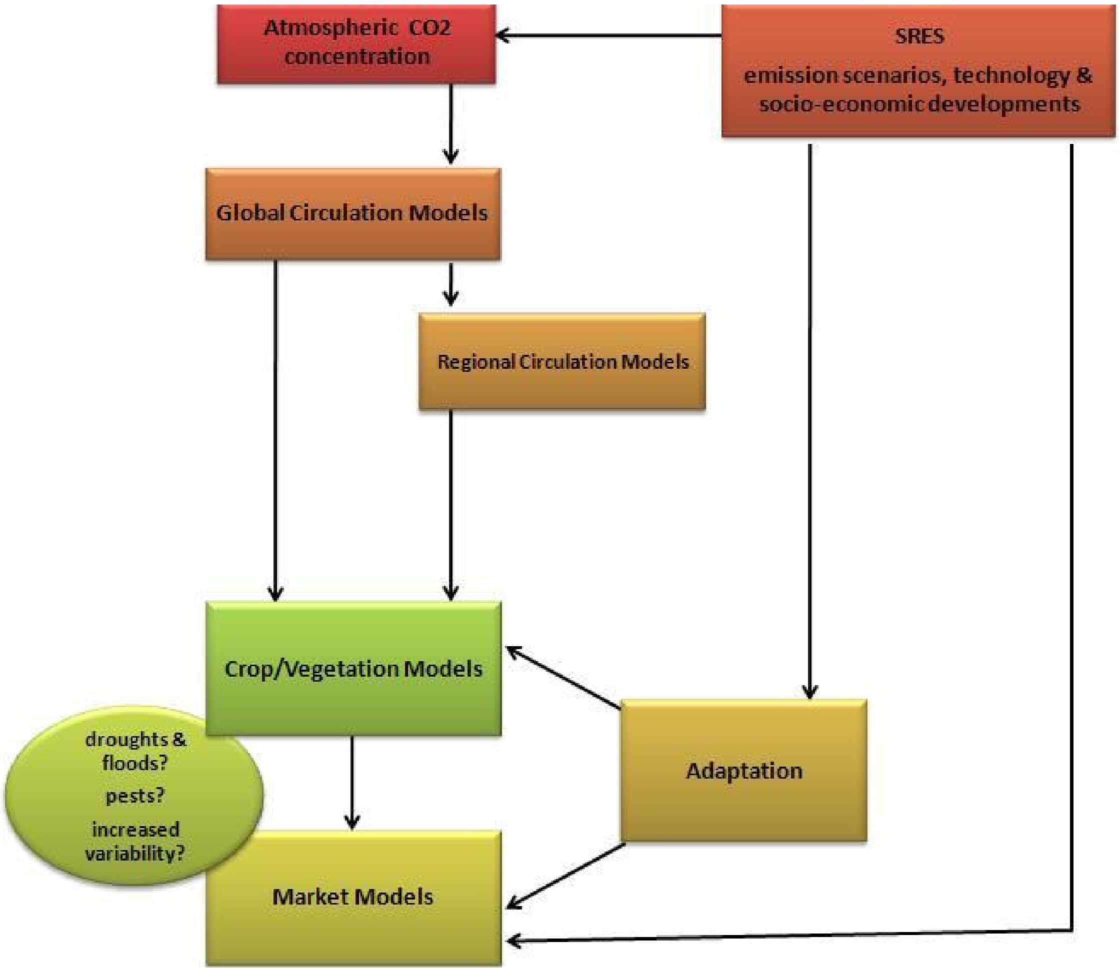
[1]For further details of the models see Aggarwal et al.(1997) and Singh et al.(1993), respectively.

for climate models, for economists, however, to model such long time scales is an ambitious task since it is not possible to make unambiguous assumptions about social and economic parameter developments which are the major drivers of market models. Besides, making plausible assumptions about technological developments in certain sectors is a difficult task. An example in this study is the future global demand for biofuels in the year 2050 and its underlying processing technology. Which technology will be used for converting biomass and particularly which crops will be processed will also have major implications for agricultural markets. Hence, sensitivity analysis is crucial regarding long time projections when applying market models for impact assessments.

5.1.5 Implication

The described problems regarding uncertainty in climate impact modelling show the importance of implementing sensitivity analysis to climate impact studies were appropriate. Olesen et al. (2007) for example, addressed a wide range of climate impact assessment uncertainties by applying different crop and ecosystem models at different spatial scales, using outputs from several GCMs and RGMs. However, uncertainty from the different socio-economic drivers was not considered in the analysis (Olesen et al., 2007). Figure 5.2 shows the different sources of uncertainties of climate impact modelling.

Since there are an infinite number of possible climate change outcomes, detailed estimates of the effects or responses to one scenario do not provide sufficient information. As a consequence putting uncertainty into a deterministic model of climate change assessment is not a straight forward task (Schimmelpfennig, 1990). In this study, one approach of dealing with uncertainty is by using productivity change outputs from the vegetation model LPJmL which are based on five different GCMs and the two emission scenario families A1B and B1. For the second approach, a stochastic version of the agricultural market model is used to derive economically adjusted yields and production quantities. A detailed description of the stochastic approach applied in this study is provided in Chapter 6.



Source: Adapted and modified from Olesen et al. (2007, p.3).

Figure 5.2: Sources of uncertainty.

5.2 Weather variability

The potential for an increasing probability of extreme weather events[2] is an additional major concern in climate impact assessments on the agricultural sector. It is important to point out, that climate variability is primarily expressed by extreme climatic events (Solomon et al., 2007). Extreme climate events can be defined as extreme daily temperatures, extreme daily rainfall amounts, large areas experiencing unusually warm monthly temperatures, or storm events such as hurricanes (Easterling et al., 1999). However, due to the IPCC (2007b) it is more difficult to analyse and monitor changes in extreme events, such as droughts, cyclones, extreme temperatures and the frequency and intensity of precipitation, than for climatic averages. This is because longer data time-series of higher spatial and temporal resolutions are required. However, the availability of observational data restricts the types of extremes that can be analysed (IPCC, 2007b). Increased greenhouse gas concentration can lead to a changed occurrence of both, mean climate parameters and the frequency of extreme meteorological events, whereupon relatively small changes in mean temperature can result in disproportionately large changes in the frequency of extreme events (Rosenzweig et al., 2001). Katz and Brown (1992) demonstrated that changes in variability have a greater effect on changes in the frequency of climatic extremes than do changes in the mean[3].

5.2.1 Forecasting extreme events

In the IPCC's 4th assessment report, no specific documentation about changes in heat waves (very high temperatures over a sustained period of days) exists. However, an increased risk of more intense, longer-lasting and more frequent heat waves in a future climate have been predicted by several studies (Schär et al., 2004; Meehl and Tebaldi, 2004). Meehl and Tebaldi (2004) project a future pattern of changes in heat waves, with the greatest intensity increases over parts of western Europe and the Mediterranean region. They also found similar results for the southeast and western USA. Schär et al. (2004) and Beniston and Diaz (2004) use the Eu-

[2]The IPCC AR4 Synthesis Report defines an extreme weather event as: "An event that is rare at a particular place and time of year". By definition, the characteristics of what is called extreme weather may vary from place to place in an absolute sense. "When a pattern of extreme weather persists for some time, such as a season, it may be classed as an extreme climate event, especially if it yields an average or total that is itself extreme (e.g., drought or heavy rainfall over a season)" (IPCC, 2007b).

[3]A detailed description about statistical methods of analysing extreme events and variability can be found in Katz (2010).

ropean 2003 heat wave as an example of the types of heat waves that are likely to become more frequent in a future warmer climate. Schär et al. (2004) point out that the increase in the frequency of extreme warm conditions is also associated with a change in inter-annual variability, meaning that the statistical distribution of mean summer temperatures is not merely shifted towards warmer conditions, but also becomes wider. However, according to Mearns (2000), it is the combination of the two types of changes that is important, thus underlining the need to understand how climatic variability might change in the future. However, it is a difficult task to attribute any individual event to climate change. Further, records of variability typically extend over about 150 years, which only provide limited information for a characterization of potential future extreme events (Solomon et al., 2007). Additionally, several factors usually need to amalgamate to produce an extreme event. This makes linking a particular extreme event to a single specific cause problematic. Solomon et al. (2007) argue that simple statistical reasoning indicates that substantial changes in the frequency of extreme events can result from a relatively small shift of the distribution of a weather or climate variable. Figure 5.3 shows the scheme of the effect on extreme temperatures when the mean temperature increases, for a normal temperature distribution. in contrast, when the variance of the tem-

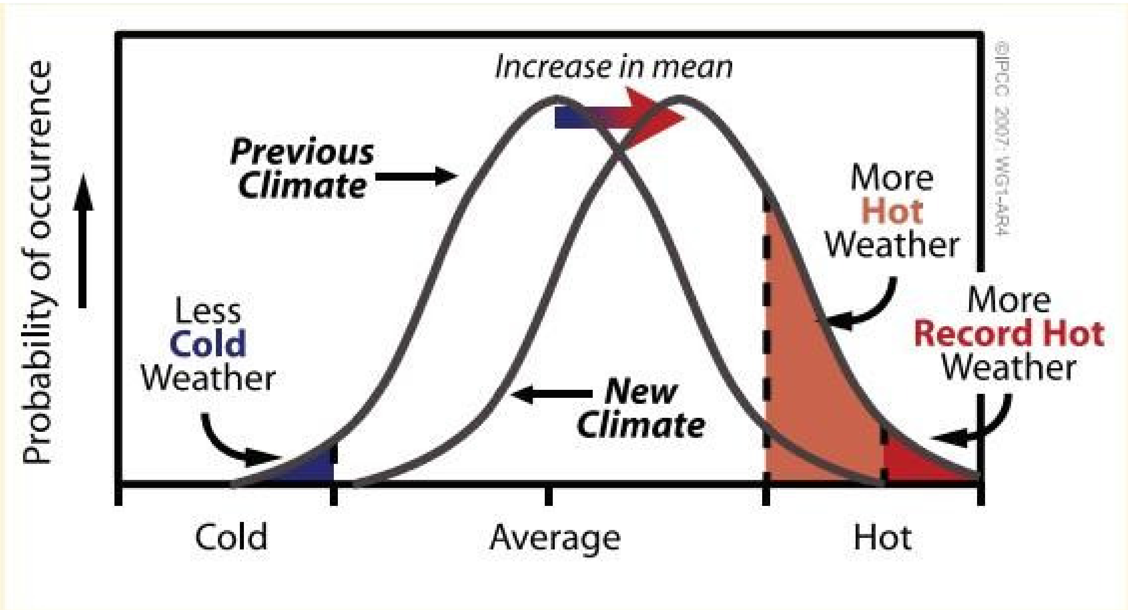


Figure 5.3: Schematic showing the effect on extreme temperatures when the mean temperature increases, for a normal temperature distribution.

Source: Solomon et al. (2007, WG1-AR4, Box TS.5, Figure 1, p.53).

perature distribution increases and the mean is unchanged, agriculture experiences more hot and cold extreme events. Only few studies focus attention on the effect of extreme events on agriculture by examining the effects of historical extremes for heat and drought as described in the next section.

5.2.2 Extreme events and agriculture

The agricultural sector is naturally particularly vulnerable to extreme events. Climatic events and the outbreak of pests introduce variability not only in agricultural production, but also in the income of farmers (EU, 2010b). Nevertheless, most studies of climate change impacts on agriculture have analysed the effects of mean changes of climatic variables on crop production only, whereas the impacts of changes in climate variability have been studied to a much lesser extend (Alexandrov and Hoogenboom, 2000; Mearns et al., 1997). However, it is well known that changes in the variability can be equal to or more important than changes in the mean to many resource systems, including agriculture (Mearns, 2000). Mearns et al. (1997) for instance, showed that crop models are affected by changes in both the mean as well as the variance of climate time series. Also, due to Porter and Semenov (2005), changes in mean and frequency of extreme events, especially temperature and precipitation, can have large effects on crop yields and their variability. Potential impacts of climate change on agricultural productivity should not only consider mean values of expected climatic parameters but also the probability, frequency, and severity of possible extreme events (Rosenzweig et al., 2001).

Past extreme events such as the European heat wave during the summer of 2003 have been examined by several studies (Schär et al., 2004; Ciais et al., 2005). Based on their analysis, Schär et al. (2004) for example predict an increase in future year-to-year variability for European summer climate, which could lead to more frequent occurrence of heat waves and related droughts towards the end of the century (Schär et al., 2004). According to Ciais et al. (2005) the 2003 heat wave was a major contributor to the estimated reduction of 30% of European's gross primary production of terrestrial ecosystems. It is estimated that the heat wave led to financial losses in the agricultural and forestry sector in parts of Europe of 13 billion Euros (Fink et al., 2005), whereof a reduction of about 23 million tons[4] of cereal production can be attributed to the shorter growing season combined with a higher frequency of extreme events, both in terms of maximum temperatures and longer dry spells (Olesen and Bindi, 2004).

[4] With respect to the year 2003.

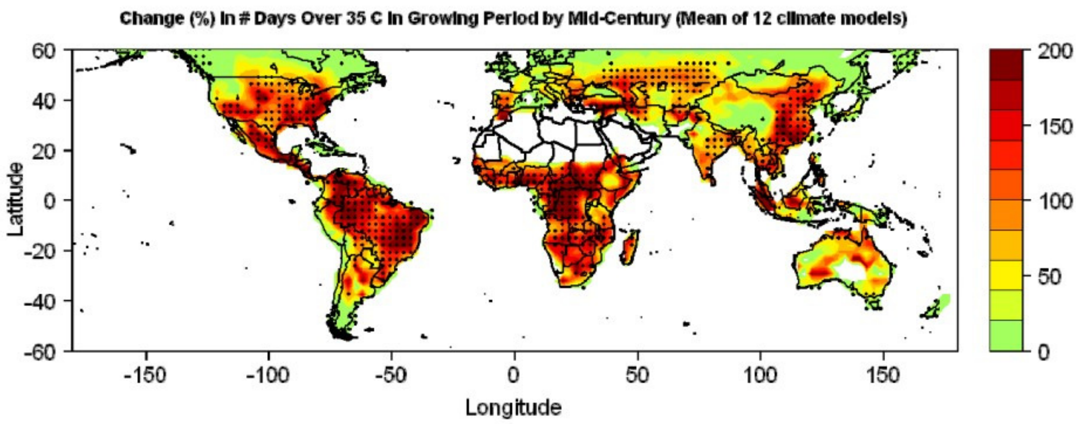


Figure 5.4: Simulated change in days above 35°C during the growing season in 2050 (% increase above 1990 levels), averaged across 12 climate models. Dots indicate where at least 10 of 12 models agree on the direction of change.

Source: Lobell et al. (2009, p.3).

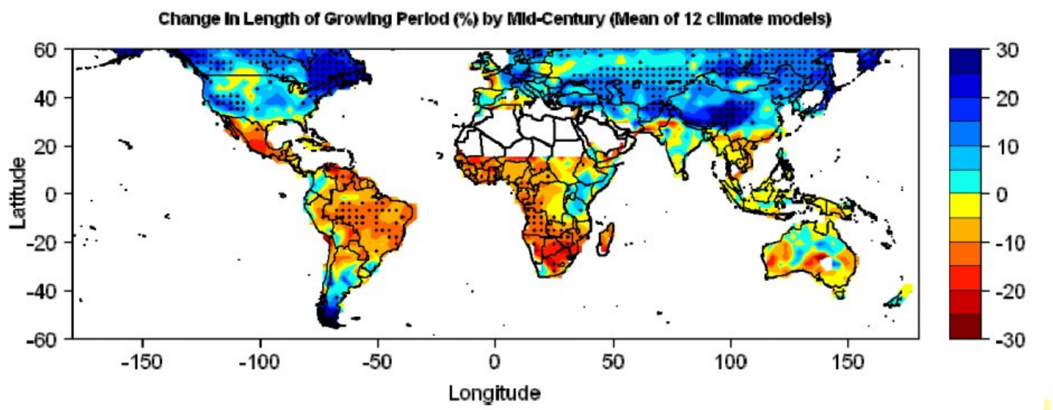


Figure 5.5: Simulated change in growing season length in 2050 relative to 1990.

Source: Lobell et al. (2009, p.4).

An expert meeting on climate extremes and crop adaptation (Lobell et al., 2009), concluded that many major cropping regions will experience a rapid increase in days above 35°C. This is shown in Figure 5.4, where the dots indicate areas where at least 10 out of 12 climate models being presented at the meeting agree on the direction of the change. Higher average temperatures will also lead to higher evapotranspiration rates, which in turn is likely to dry out soil leading to more frequent occurrence of low moisture extremes (Lobell et al., 2009). As a consequence, the length of the growing period is anticipated to shorten in many regions in the world (see Figure 5.5). According to Moriondo et al. (2011), if the role of extreme events is neglected in future impact assessments, the potential impact of a warmer climate on yield losses could be underestimated and hence also lead to inappropriate applied adaptation measures. This emphasizes the necessity to further investigate the potential increase of extreme weather events and implement adequate mitigation measures in order to minimize future damages.

5.3 Accounting for uncertainty in simulation models

Inter-annual variability of crop yield is affected by many factors, including improvements in the production practices, the appearance of new diseases and pests, changes in governmental policies, and differences in the climate settings from year to year. Experiments with climate models suggest that the latter could be enhanced by global warming (Räisänen, 2002). Due to Rosenzweig et al. (2001), precipitation is probably the most important factor determining the productivity of crops and hence identifies inter-annual precipitation variability as a major cause of variation in crop yields and yield quality. Future predictions of changes in crop variability, however, remain a more difficult area of study due to the varied dimensions of variability (daily, seasonal, inter-annual) and the different crop responses to extreme climatic conditions (Reilly et al., 2001). Since a reliable accurate prediction of extreme climatic events, and hence weather variability, is not possible under the current state of science, the question remains how this potential increase in weather variability can be appropriately translated in impact assessments studies of the agricultural sector. As mentioned before, one can account for the uncertainty of climate predictions by using multiple GCM results as inputs for crop models. Yet, the direct application of the same approach is not straight forward for the joint application of economic models. As described in the previous sections, most climate impact studies implement sensitivity analysis using a wide range of point estimates by using inputs of e.g. several climate change scenarios or impact models. However, most studies miss to viewing climate change as causing changes in distribution of random variables (Schimmelpfennig, 1990). Stochastic simulation modelling is an additional method capable of capturing the uncertainty attached to variables, such as yield, which may vary due to climatic conditions. It can also be useful to model parameters which are based on weak empirical data, such as supply and demand elasticities (Artavia et al., 2009). Such simulations can generate model results which give more information than point estimates and capture some of the uncertainty attached to climate change. Chapter 6 describes how stochastic modelling is applied for this thesis and with which method random variables have been generated.

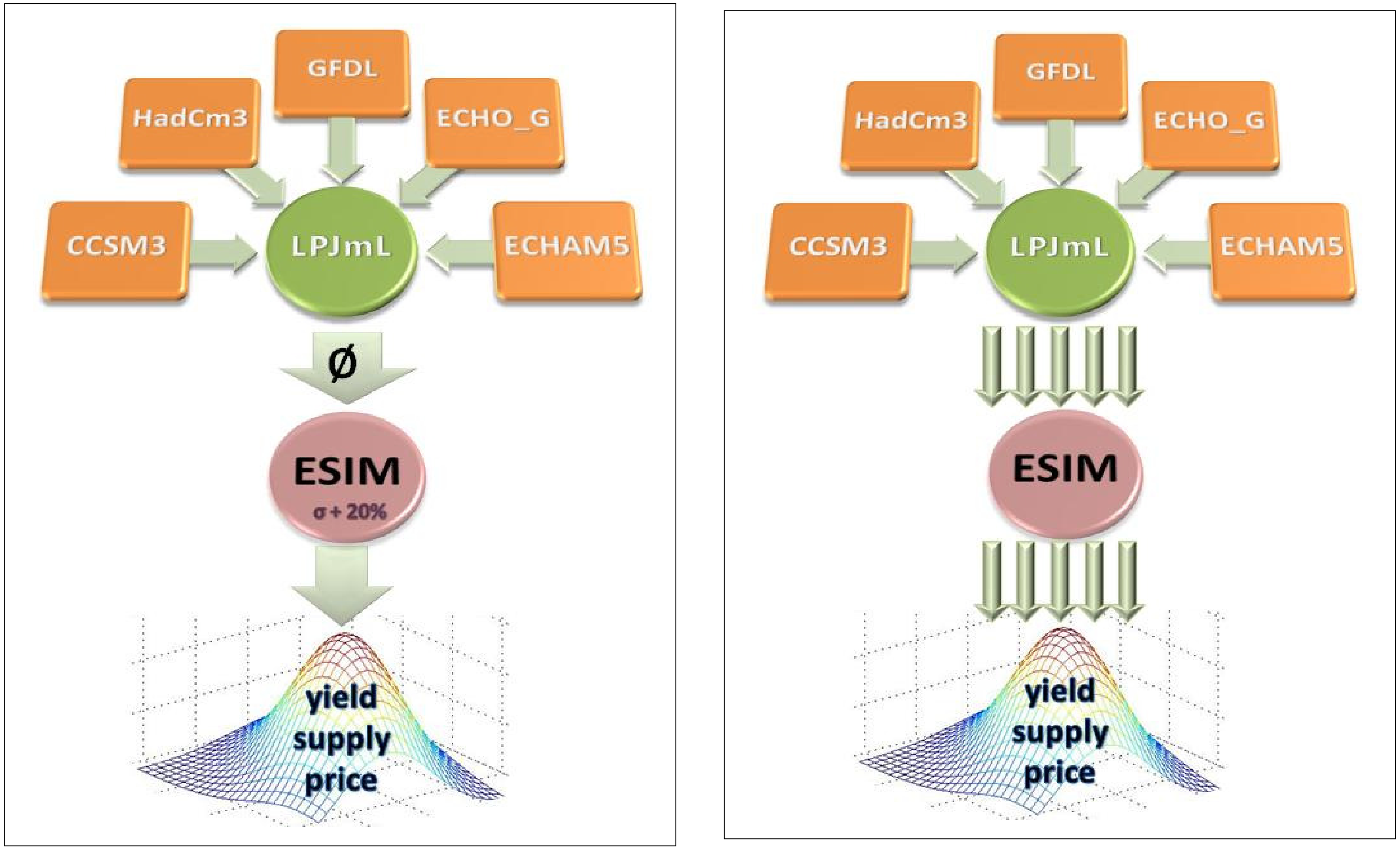
5.3.1 Dealing with uncertainty in ESIM

For this thesis, two methods were applied to account for uncertainty. First, 20 scenarios were run in which productivity changes from the vegetation model LPJmL based on five different GCM climate parameter inputs have been applied[5]. Second, the stochastic version of the market model ESIM is used. Since it is not possible to rely on empirically founded future climate and yield variable distributions, the variance of the historical stochastic term distribution of the market model's yield function is increased by 20% for the A1B "with CO2" scenario[6]. The underlying productivity changes from the LPJmL model being fed into ESIM for this approach is the mean of all five GCMs outcomes of the vegetation model. The two methods are illustrated in Figure 5.6., where a) is the method where a distribution of results is obtained by increasing the historical stochastic term and implementing Gaussian Quadratures, and b) indicates the method of deriving a distribution from five individual climate and crop model outcomes.

The next section provides an overview of stochastic applications in market equilibrium models and briefly describes how random variables have been generated. Further, the approach of generating Gaussian Quadratures is introduced, which is an additional major contribution of the thesis. The Gaussian quadratures (GQ) are a numerical integration approach where points and associated weights are generated with their weighted sum matching the moments of the original distribution function. This procedure, when compared to e.g. Monte Carlo sampling, reduces the number of points needed to approximate a desired distribution and hence requires less computing capacity and time.

[5]Each of the five GCM outcomes served as input for the A1B and B1 "with" and "without CO2", resulting in 20 scenarios.

[6]The A1B scenario is assumed to show greater variability in the future due to a higher CO2 concentration as compared to the B1 scenario (Tebaldi et al., 2006; IPCC, 2007b).



a) Stochastic approach based on Gaussian Quadratures with an increased variability by 20%

b) Obtaining mean results and distribution based on 5 individual GCM-LPJmL outputs per emsission scenario

Figure 5.6: Illustration of the two methods used to account for uncertainty.

Source: Own compilation

6 Implementing Stochasticity in Market Models

6.1 General facts

There are several methods in economics for adding uncertainty to deterministic models. These methods require knowledge on the parameters of the distributions of random variables. Basic descriptors of this distribution, and hence uncertainty, are parameters like mean and variance. However, variance is rarely included with discussion of results. This is certainly a problem in climate impact studies, since reliable information about probability distributions of random variables for the future does not exist (Schimmelpfennig, 1990). Even though stochastic modelling can capture some of the uncertainties described above, this approach has rarely been used in the past. However, it is a useful application for analysing variations in agricultural production due to climate, policies or other causes more realistically. Parts of sections 6.3.1 and 6.3.2 is primarily based on a joint paper with Marco Artavia, Harald Grethe and Georg Zimmermann (Artavia et al., 2009).

6.2 Overview of existing studies

Tyers and Anderson (1992) examined the role of trade on price fluctuations by including supply functions with error terms to their agricultural trade model. They added 200 sets of normally distributed random numbers to the term. A partially stochastic version of the Food and Agricultural Policy Institute model (FAPRI) has been used for several different policy scenario analyses (FAPRI, 2007). Westhoff et al.(2006), for example, evaluated the probability of failing to cope with World Trade Organization (WTO) commitments, and Kruse et al. (2007) analysed biofuel's tax credits and the import tariff policy impacts on agricultural markets in the US. The stochastic version of the FAPRI model utilizes the historically correlated distributions of crop yields and correlated distributions of the errors in key demand equations including exports, and constructs 500 possible scenarios based on the historical variability in these equations using Monte Carlo sampling (FAPRI, 2007). Adelmann and Berck (1990) exposed a general equilibrium model to a common set of stochastic shocks, constructed by drawing 100 quadruples, arising from fluctuations in domestic food supplies and international prices for analysing welfare and food security effects. OECD (2003) presents a stochastic application of the AGLINK model assessing yield volatility, and Hertel et al. (2005) formulate a stochastic version of the GTAP model to analyse the linkage between supply-side uncertainty and stockholding. In the recent past, market analyses of climate change impacts using stochastic applications have become more common. Beach et al. (2010) for example, used a stochastic version of the Forest and Agricultural Sector Optimization Model (FASOM) to model crop allocation decisions under yield distributions associated with climate scenarios in order to examine impacts of climate change on US agriculture. The US agricultural sector model (ASM), which is a price endogenous, mathematical programming model (McCarl and Spreen, 1980), includes stochastic yield data derived as the residuals from a set of trend model estimates (Lambert et al., 1995), and was used to analyze economic impacts of future El Niño and die Southern Oscillation[1] events (Chen et al., 2001). Furuya and Meyer (2008) use a stochastic supply and demand model for rice in Cambodia in order to analyse impacts of water cycle changes by introducing water variables in the yield and area functions of the model. Furuya and Kobayashi (2009) examined climate change impacts on global agricultural markets by using the International Food and Agricultural Policy Simulation Model (IFPSIM), implementing temperature and rainfall variables into the yield function. For other large scale partial equilibrium models used to analyze agricultural markets such as AGMEMOD (Donnellan and Hanrahan, 2006), CAPSIM (Witzke and Zintl, 2005), CAPRI (Britz, 2005) and IMPACT (Nelson et al., 2009a), no stochastic versions have been published so far.

Except Hertel et al. (2005), all studies mentioned above apply the Monte Carlo (MC) procedure in order to approximate an empirical distribution of stochastic variables. A major disadvantage of the MC approach is the high computational requirement which results from the high number of solves required, and is hence not easily applicable for most complex and large scale general equilibrium market models.

[1] El Niño/La Niña-Southern Oscillation (ENSO) is a climate pattern that occurs across the tropical Pacific Ocean roughly every five years, causing extreme weather events in many regions of the world.

Hertel et al. (2005) apply the Gaussian quadratures (GQ) method which is an alternative numerical integration approach to approximate the original distribution. The main idea behind GQ is to generate points and associated weights to match the moments of the original distribution function. Compared to MC, this procedure reduces considerably the number of points needed to approximate the desired distribution. A detailed description about the method used by Hertel et al. (2005) to characterize the supply side uncertainty based on the Gaussian quadratures can be found in DeVuyst and Preckel (1997) and DeVuyst (1993). Arndt (1996) presents another way to obtain Gaussian quadratures based on formulae given by Stroud (1957). Considering yield stochasticity in market and policy analysis, the correlation of the stochastic terms over products as well as countries is also an important issue. Nonetheless, the topic of Gaussian quadratures with correlated terms has been rarely addressed in literature. To the best of the author's knowledge, correlated GQs in stochastic market models have only been introduced by Preckel and DeVuyst (1992), DeVuyst (1993) and Arndt (1996).

As compared to the above mentioned authors, rather simplified formulas for generating GQs have been used for this thesis, since only Stroud's theoretical scheme on the conditions that must be fulfilled is applied (Artavia et al., 2009). The next section describes the theorem of Stroud (1957) for generating order three GQs to approximate integrals with multivariate, independent normal distributions. Further it is shown that for stochastic modelling purposes Stroud's formulas can be simplified. Furthermore, since the correlation of the stochastic terms in question, such as crop yields of different crops in different countries, is an important issue in market and policy analysis, one method of inducing a desired covariance or correlation matrix to the generated GQs is explained.

6.3 Gaussian Quadratures

6.3.1 Mathematical background

Quadratures are a numerical method for approximating definite integrals of a function usually defined as a weighted sum of function values at specific points within the domain of integration. Gaussian quadratures are constructed to obtain an exact result for polynomials of the degree 2n−1 or less. This is archived by choosing suitable points $x_1, ...x_N$ with associated weights $p_1, ...p_N$. The points and their weights are chosen in such a way as to maximize the degree of polynomials for which the quadrature formula yields the correct value. Given a continuous distribution for several variables, a Gaussian Quadrature for this distribution is a discrete distribution whose first several moments are identical with those of the continuous distribution. The quadrature is said to be of order d if the first d moments agree. For example, considering a (univariate) density function f, the expected value of a function $g(x)$, denoted by $E[g(x)]$, is estimated by (1)

$$E[g(x)] = \int_{\Re} g(x)f(x)dx \approx \sum_{k=1}^{N} p_k g(x_k).$$

where,

$f(x)$ - density function of x

p_k - probabilities (of the discrete points x_k)

Formula (1) has on the left side the expected value of a certain moment of the distribution of $g(x)$, in the middle the continuous distribution of this moment, and on the right hand the discrete approximation of it.

The degree of exactness d , which means the first d moments are preserved, leads to the following equations obtained by letting $g(x) = x^j, j = 1, ..., d$, in the above

$$\begin{aligned}
E[x^0] &= \int_{\Re} 1f(x)dx = 1 = p_1 + p_2 + ... + p_N \\
E[x^1] &= \int_{\Re} xf(x)dx = 1 = p_1x_1 + p_2x_2 + ... + p_Nx_N \\
E[x^2] &= \int_{\Re} x^2f(x)dx = 1 = p_1x_1^2 + p_2x_2^2 + ... + p_Nx_N^2 \\
&\vdots \\
E[x^d] &= \int_{\Re} x^df(x)dx = 1 = p_1x_1^d + p_2x_2^d + ... + p_Nx_N^d
\end{aligned}$$

where,

j - moments of the distribution (order of accuracy of the quadratures)

In the multivariate case, a multiple integral over $\Re^n$ is considered. Hence, the quadrature points will be vectors with n components corresponding to n stochastic variables. Each quadrature point is associated with a weight representing a probability. The number N of required quadrature points is dependent on the dimension n and the desired degree d of exactness.

The integrals with multivariate normal distribution $N\ (0, \Sigma)$ as weights, with a covariance matrix $\Sigma \neq I_n$ need to be approximated.

The first moments which shall be matched have to be defined first, and than the set of points consisting of values and associated probabilities (weights) that solve the system of equations, have to be found, delivering quadratures of order j.

6.3.2 Application of Stroud's theorem

For this thesis, the correlated error terms of yield time series analysis built the multivariate normal symmetric distribution which needs to be approximated with $N\ (0, \Sigma)$ as weights, and with covariance matrix $\Sigma \neq I_n$.

The approach for the multivariate case is the same as above but the expected value of the function of interest will be the result of a multiple integral over each of the variables, n, in order to get the volume of the region expanded in the n - dimensional Euclidean space. Furthermore, instead of a quadrature point defined by 1 coordinate, points defined by n-coordinates or vectors will be generated. Each of these points, as before, associated to a probability.

Stroud's theorem is used for this purpose (Stroud, 1957). He introduced an attractive numerical integration formula of degree 3 for symmetrical regions for solving the equation systems presented above deriving directly the necessary quadrature points.

More explicitly, approximate values for the integral of the form

$$I(f) = \int_{\Re^n} ... \int_{\Re^n} f(x) \frac{1}{\sqrt{(2\pi)^n det(\Sigma)}} e^{-1/2(x-\mu)^T \Sigma^{-1}(x-\mu)} dx_1 ... dx_n$$

need to be found.

For this purpose, a quadrature formula whose degree of exactness is 3 is employed with points

$$x_1, ..., x_N \quad \in \Re^n \quad \text{and with weights} \quad w_1, ..., w_N$$

such that the numerical integration formula

$$I_d(f) = \sum_{k=1}^{N} w_k f(x_k)$$

satisfies $I_d(f) = I(f)$ for all polynomials of total degree at most 3.

Polynomials of degree 0 are simply constants, and letting $f \equiv 1$ yields the condition

$$\sum_{k=1}^{N} w_k = \int_{\Re^n} ... \int_{\Re^n} \frac{1}{\sqrt{(2\pi)^n det(\Sigma)}} e^{-1/2(x-\mu)^T \Sigma^{-1}(x-\mu)} dx_1 ... dx_n = 1$$

Furthermore, the numerical integration formula shall be equally weighted, and therefore, $w_k = 1/N, \quad k = 1, ..., N$.

From the probability point of view, this approach amounts to approximating the continuous normal distribution $N(\mu, \Sigma)$ with density:

$$\frac{1}{\sqrt{(2\pi)^n det(\Sigma)}} e^{-1/2(x-\mu)^T \Sigma^{-1}(x-\mu)}$$

by a discrete equidistribution on N points exhibiting the same moments up to order 3.

Finally, for symmetry reasons, the vertices shall be in pairs of the form $\{x, -x\}$.

Stroud's theorem shows that $N = 2n$ quadrature points are needed to obtain formulas of degree 3 for symmetrical regions in $\Re^n$.

> *"A necessary and sufficient condition that* $2n$ *points* $x_1, ..., x_n, -x_1, ..., -x_n$ *form equally weighted numerical integration formula of degree 3 for a symmetrical region is that these points form the vertices of a* Q_n *whose centroid coincides with the centroid of the region and lie on an n-sphere of radius* $r = \sqrt{nI_2/I_0}$*"*

(Stroud, 1957 p.259).

where:

n - is the dimension of the problem (here, the number of stochastic variables)

Q_n - is the n-dimensional generalized octahedron ("n-octahedron")

I_0 - is the integral of a constant (here, the 0th moment of the distribution)

I_2 - is the integral of the square of any variable (here, the variances) of the distribution)

The fact that I_2 is independent of the variable chosen in the integral stems from the symmetry of the region. Here, an appropriate dilation needs to be applied in order to allow for different 2^{nd} moments.

A standard example for a symmetric region of integration is the $n-$cube with vertices $(\pm a, \pm a, ... \pm a)^T$. The standard $n-$octahedron has the vertices

$$(\pm b, 0, ..., 0)^T, (0, \pm b, ..., 0)^T, ..., (0, ..., 0, \pm b)^T.$$

The condition $r = \sqrt{nI_2/I_0}$ from Stroud's theorem means that $b = \sqrt{\frac{n}{3}}a$ which implies that for $n \geq 4$, the vertices of the standard $n-$octahedron will lie outside the $n-$cube. For this reason, the $n-$octahedron has to be rotated to obtain a quadrature formula for the $n-$cube with vertices inside the region of integration ($cf.$ Stroud, 1957).

However, for the underlying problem, it is not integrated over an $n-$cube, but over the $n-$dimensional Euclidean space $\Re^n$ (with a weight function). Hence, there is no need to apply the rotation suggested in Stroud (1957). Here, the vertices of the standard $n-$octahedron can simply be used. Nonetheless, those vertices have to be transformed in order to introduce the desired covariance terms as described in the next section.

Quadratures for the multivariate standard normal distribution with independent terms ($\Sigma = I_n$)

The density of the multivariate standard normal distribution $N(0, I_n)$ shows spherical symmetry. Therefore, all rotations of the n-octahedron are equally well suited. This means, that a standard $n-$octahedron of the appropriate size, given by $r = \sqrt{n}$, can be used, as the following calculations show.

The vertices are

$$\xi_{1,2} = (\pm\sqrt{n}, 0, ..., 0)^T, \xi_{3,4} = (0, \pm\sqrt{n}, 0, ..., 0)^T, ..., \xi_{2n-1,2n} = (0, 0, ..., \pm\sqrt{n})^T.$$

Using these as quadrature points with equal weights $\frac{1}{2n}$, the following moments up to order 3 are obtained:

1. $$\frac{1}{2n}\sum_{k=1}^{2n} 1 = 1$$

2. $$\frac{1}{2n}\sum_{k=1}^{2n} \xi_{k,l} = 0 \quad \text{for all } l \in \{1, ..., n\} \Leftrightarrow \frac{1}{2n}\sum_{k=1}^{2n} \xi_k = 0$$

3. $$\frac{1}{2n}\sum_{k=1}^{2n} \xi_{k,l_1}\xi_{k,l_2} = \delta_{l_1,l_2} \quad \text{for all } l_1, l_2 \in \{1, ..., n\}$$
$$\Leftrightarrow \frac{1}{2n}\sum_{k=1}^{2n} \xi_k\xi_{k^T} = I_n$$

4. $$\frac{1}{2n}\sum_{k=1}^{2n} \xi_{k,l_1}\xi_{k,l_2}\xi_{k,l_3} = 0 \quad \text{for all} \quad l_1, l_2, l_3 \in \{1, ..., n\}$$

Since these are the moments of the standard normal distribution, the desired degree of exactness is obtained. Applying any rotation of the $\Re^n$ about the origin will not change these moments, since the symmetry is preserved. Therefore, the use of the vertices suggested in Stroud (1957) for this type of problem is not false, but complicates matters unnecessarily.

Inducing a desired covariance matrix ($\Sigma \neq I_n$)

The above obtained quadrature formula now have to be modified in order to introduce arbitrary variances and correlations. First, it is shown how a linear transformation applied to the vertices of the standard $n-$octahedron will influence the covariance matrix.

Considering an equidistribution on N arbitrary points $x_1, ..., x_N \in \Re^n$ with weight $1/N$ and mean

$$E[x] = (1/N)(x_1 + ... + x_n) = 0.$$

In this case, the covariance matrix can be determined by simply gathering these points in a n x N-matrix

$$X = (x_1 \mid \ldots \mid x_N)$$

and computing

$$COV[X] = \frac{1}{N} X X^T.$$

For the vertices $\xi_1, ..., \xi_{2n}$ of the standard $n-$octahedron described above, this yields

$$\Xi = (\xi_1 | ... | \xi_{2n})$$

$$= \begin{pmatrix} \sqrt{n} & -\sqrt{n} & 0 & 0 & \ldots & \ldots & 0 & 0 \\ 0 & 0 & \sqrt{n} & -\sqrt{n} & \ldots & \ldots & 0 & 0 \\ 0 & 0 & 0 & 0 & \ldots & \ldots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & & & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \ldots & \ldots & 0 & 0 \\ 0 & 0 & 0 & 0 & \ldots & \ldots & \sqrt{n} & -\sqrt{n} \end{pmatrix}$$

and

$$COV\,[\xi] = \frac{1}{2n} \Xi \Xi^T = I_n,$$

as claimed before.

Now let **A** be any regular n x n-matrix and consider the points

$$x_x = A\xi_k, \quad k = 1, \ldots, 2n.$$

This yields

$$X = (A\xi_1 \mid \ldots \mid A\xi_{2n}) = A\Xi$$

with

$$E\left[x\right] = \frac{1}{2n}\sum_{k=1}^{2n} x_k = \frac{1}{2n}A\sum_{k=1}^{2n}\xi_k = AE\left[\xi\right] = A0 = 0$$

and

$$COV\left[x\right] = \frac{1}{2n}XX^T = \frac{1}{2n}A\Xi\Xi^T A^T = AA^T.$$

This way, the desired covariance matrix Σ is expressed in the form AA^T for a regular square matrix A. There are several possibilities of doing this. A description of three different methods, can be found in Artavia et al. (2009). Here the straight forward method of a Cholesky decomposition is used to transform the positive definite matrix

$$\Sigma = LL^T$$

where **L** is the lower triangular matrix. Now let **A=L**.

As shown above, the quadratures of a standard n- octahedron Q_n is Ξ_n.

Multiplying the matrices A and Ξ_0 yields X.[2]

In order to analyse the effect of yield variability on the European net trade situation, the model is solved over the generated quadratures

$$X = (x_{n,1} \mid \ldots \mid x_{n,2n}).$$

[2]The variance-covariance matrix of X : $\Sigma(X)$ serves as control parameter to asses whether $\Sigma(X) = \Sigma$.

6.3.3 Stochasticity in ESIM

As described in Chapter 4, the average change in crop productivity based on five different GCMs served as basis for the adjusted trend shifter in the yield function of ESIM. This is one method to account for uncertainty stemming from different climate models. In a second step, in order to consider yield variability, a stochastic term is added to the yield function of ESIM. The distribution of yield results was derived by using the Gaussian Quadratures as explained in the section above. However, for an adequate interpretation of results (provided in Chapter 8.1.6), the following problem hast to be considered. Since in ESIM stock holding is assumed to be constant, the adaptation of historical yield variability might not result in a realistic price volatility. With unchanged supply elasticities in the year of stochastic solves, price volatility is underestimated since this would imply that farmers can react to alterations of climatic change induced price volatility with their area allocation decisions. In turn, fixing area allocation by its deterministic value for the year of stochastic solves, will overestimate price volatility, since the stabilising effect of stock-holding activities is not included (Artavia et al., 2010). One method to solving this problem is presented in Artavia et al. (2010). They calibrate supply elasticities for the year of stochastic simulations in a way, that the projected yield variabilities result in historically observed price volatilities. However, this approach is not adapted for this thesis. Hence, the projected price variability presented in section 8.1.6 tends to be underestimated.

Stochastic yield terms in ESIM

FAOSTAT time series data for the period 1962 to 2006 is used for estimating the distribution of the stochastic terms of the yield equations for all countries and regions depicted in the model for the crops wheat, barley and rapeseed[3]. Also the correlation between error terms in yields of the considered crops and countries is estimated. The de-trended stochastic variables θ are derived by dividing the observed yield y by the estimated yield

$$\hat{y}$$

in the linear trend. In order to obtain the relative deviation (above or below) of the trend line

$$(y/\hat{y}) - 1$$

[3]This section is primarily based on Artavia et al. (2008).

is calculated (Artavia et al, 2008). Some countries are grouped based on their correlations in order to reduce the number of stochastic variables. Countries which produce rather small quantities are either grouped with large producers they have the best correlation with, or are ignored. The yield functions of those countries run deterministic without a stochastic term. Thus, in total 42 stochastic variables are included in ESIM. According to Stroud's theorem that $2n$ quadrature points for each stochastic term are needed (with n beeing the number of stochastic variables), the model solves for the year in question (2050), repeatedly over the 84 generated quadratures $X = (x_{n1}| \dots |x_{n84})$.

Based on these solves, expected value and standard deviation of the endogenous variables in question are generated. For more details on the grouping see the Appendix A.

7 Scenario Description

As described in detail in Chapter 3, the IPCC established the so-called SRES emission scenarios to account for different potential developments in the 21st century regarding population growth, economic and social developments, technological inventions, environmental management, and use of resources (IPCC, 2007c). For this thesis, the underlying assumption of socio-economic developments from the A1B and B1 scenarios are used in order to account for two different potential social and economic development paths. The A1B scenario is characterized by a rapid economic growth, yet with a balanced emphasis on all energy sources. B1 in turn is similar as A1B, but is considered to be more environmentally friendly, resulting in lower atmospheric CO2 concentrations by 2050[4] (Nakicenovic et al., 2000).

In ESIM, the macro data, such as population and income growth, are adjusted accordingly. The vegetation model LPJmL uses climate input data from the global circulation models ECHAM5, HadCM3, CSSM3, GFDL and ECHO_G[1], and the respective CO2 concentrations. The projection horizon is 45 years from 2005 to 2050. For each of the SRES scenarios three scenarios were specified: a baseline scenario without climate change which serves as reference scenario, one scenario which takes the CO2-fertilization effect into account and one which does not (further referred to as "with CO2" and "without CO2" scenario, respectively). The base technological progress shifter rates of the yield functions are equal for both baseline scenarios. All shifter rates for the baselines and each climate change scenario can be found in Annex B. Figure 7.1 depicts the scenarios developed for the study projections.

[4]With increasing CO2: 532ppm in 2050 in A1B, 488ppm in 2050 in B1. Without increasing CO2: constant CO2 concentration 370ppm.

[1]An overview of the institutional background and references of the circulation models, is provided in Chapter 6.5.

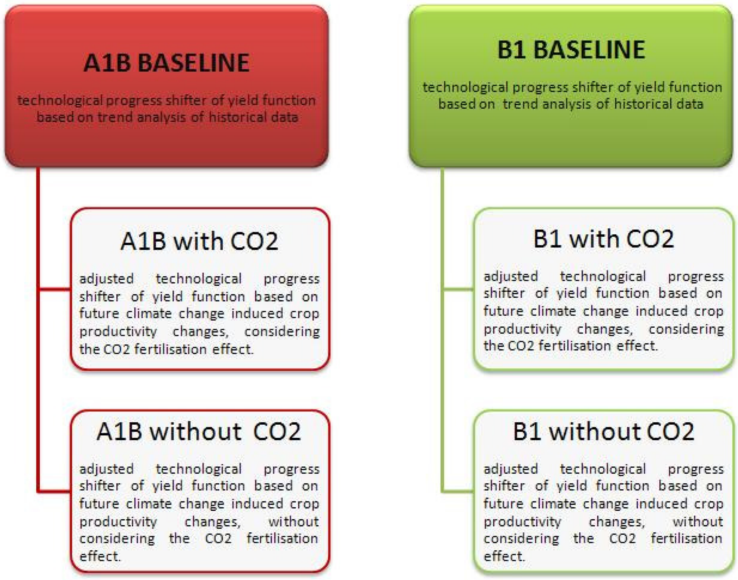


Figure 7.1: Overview of scenarios.

Source: Own compilation.

7.1 Baseline scenario

ESIM was first run for the two baseline scenarios which serves as a reference scenario projecting agricultural markets by 2050 assuming no climate change. The technological progress shifters ("trend") applied in the yield function of ESIM are based on a yield trend analysis from FAOSTAT data of the period 1992 to 2007. For each SRES emission scenario considered for this study (A1B and B1), a baseline scenario without climate change for the time period 2005 to 2050 is defined, driven by the different macro shifters for income and population growth rates (see Table 7.1).

		FR	UK	EU	ROW
A1B	Population	0.27	0.17	-0.1	0.78
	Income	1.91	1.91	3.28	5.09
B1	Population	0.27	0.17	-0.1	0.78
	Income	1.71	1.71	2.78	4.98

Table 7.1: Annual growth rate GDP and population for selected countries and regions for the A1B and B1 emission scenarios 2005 - 2050.

Source: Own compilation.

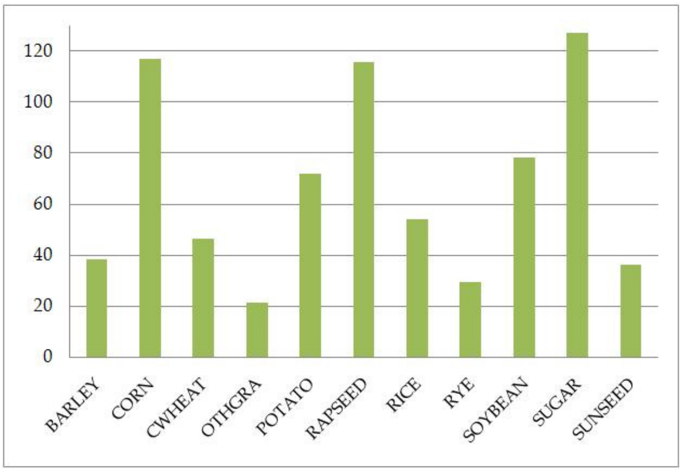


Figure 7.2: World average technological progress shifter indices per crop by 2050 "no CC".

Source: Own compilation.

The overall trend of world market prices under the baseline is calibrated to meet projections published by IFPRI for 2050 (Nelson et al., 2009a). Demand shifters in the aggregated non-European countries (NEU) are calibrated to approximate IFPRI world market price projections. Biofuel consumption is calibrated to maintain a share of 10% in total transportation fuels in the European Union (EU). For the aggregated world (WO), the consumption share is calibrated to 4% in 2050[5]. For this thesis, it is assumed that global agricultural markets are fully liberalized and no policies, such as tariffs or quotas, are implemented.

Figure 7.2 depicts the development of average world productivity shifters between 2005 and 2050 for selected crops in the baseline reference scenarios A1B and B1 without climate change ("no CC"). This is not a model result, but just a weighted average based on productivity growth rates presented in Table 4.1 in Chapter 4 (for EU, NEU and the WO) and Annex B (for all European countries and crops). Highest productivity increases can be seen for corn, rapeseed and sugar, which each have productivity increases by 117%, 116% and 127%. In contrast, lowest productivity changes can be observed for the category other grains (Othgra), rye and sunflower seed with increases of 21%, 30% and 36 %, respectively.

[5]Consumption of transport fuels in 2050 from the World Energy Outlook 2008, as cited in Fischer (2009).

7.2 Emission scenarios A1B and B1

The A1 family of scenarios is characterized by a rapid economic growth and a quick spread of new technologies. The subset A1B to the A1 family is characterized by a balanced emphasis on all energy sources. The B1 scenarios are of a more integrated and ecologically friendly world. The scenarios are characterized by the same rapid economic growth as in A1, but with a faster development towards a service and information economy. Also, material intensity is reduced and the introduction of clean and resource efficient technologies distinguishes the B1 from the A1 scenarios. The emphasis is on global solutions to economic, social and environmental stability. Population growth until 2050 is equal in both scenarios (Nakicenovic et al., 2000). The only difference between the A1B and B1 baseline scenarios in their implementation in ESIM is the development of income growth according to IPCC projections, with the A1B scenario having a more pronounced income growth rate compared to the B1 scenario (IPCC, 2007c). Selected macro shifters driving the baseline scenarios for both SRES emission scenarios are shown in Table 7.1.

Table 7.2 depicts the predicted global mean warming for the period 2046 to 2065 for the A1B and B1 scenario. The higher carbon dioxide emission under A1B (see Table 3.2 in Chapter 3) leads to a higher temperature increase of about 1.75 degree as compared to the B1 scenario under which global mean temperature is predicted to increase of around 1.29 degree by 2050.

	Global mean warming (C°) 2046-2065
A1B	1.75
B1	1.29

Table 7.2: Mean global warming for the A1B and B1 emission scenarios 2046-2065.

Source: IPCC (2007c).

7.3 Implementation of mean GCM-LPJmL outputs in ESIM

As described in Chapter 4, climate change is introduced in ESIM by adding an additional component to the technological progress shifters in the yield functions for any climate change scenario in order to incorporate productivity changes resulting from climate change. The vegetation model LPJmL delivered mean yield changes for the period 1996-2005 to 2046-2055 based on climate data from the five global circulation models CCSM3, ECHAM5, ECHO_G, GFDL and HadCM3. Based on the percentage yield changes from the LPJmL, an annual growth rate was derived and added to the technical progress shifter in ESIM. This scenario on the one hand delivers results based on the mean yield changes from the LPJmL (see Chapter 8.1), and further serves as a basis for the stochastic version of ESIM.

Figure 7.3 illustrates the average world productivity shifters by 2050 for selected crops under the emission scenarios A1B and B1 with and without CO2 relative to the baseline scenario without climate change. Again, this is just a weighted average based on productivity growth rates presented in Table 4.1 in Chapter 4 (for EU, NEU and the WO) and Annex B (for all European countries and crops). Highest productivity increases can be seen for sunflower seed and soybean for the two "with CO2" scenarios, which each have a productivity increase between 16% and 28%. Lowest productivity increases are estimated for corn and wheat under the "with

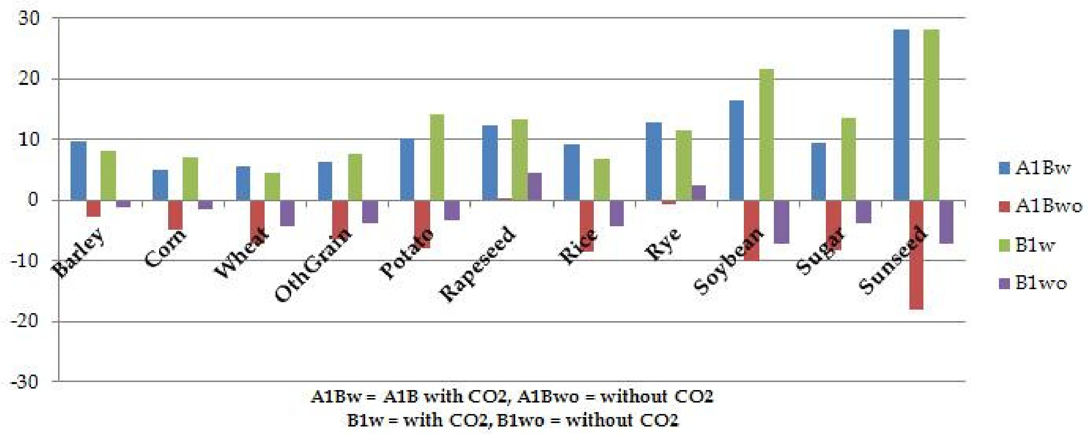


Figure 7.3: World average technological progress shifter indices per crop by 2050 vs. baseline scenario "no CC".

Source: Own compilation.

CO2" scenarios with around 5% each. In contrast, soybean and sunflower seed show declines of as much as 10% and 18 % respectively under the "without CO2" scenarios.

7.4 Increased variability based on Gaussian Quadratures

The method of Gaussian Quadratures described in former sections is a convenient and computational time saving approach to implement stochasticity in market models for applying sensitivity analysis. Climate change will most likely lead to an increased variability of crop yields. The GQ method as implemented in the standard stochastic version of ESIM (Artavia et al., 2009) uses variability based on historical yield analysis, and hence would potentially underestimate climate change induced variability in market model predictions. However, since it is not possible to exactly describe future climate variable distributions reliably, the variance of the historical stochastic term distribution of the market model's yield function is increased by 20% for the A1B "with CO2" scenario. If there was a concrete prediction of the variability increase in the future, one could simply use the GQ approach and adjust the time series data error terms to account for the variability increase. Unfortunately, to the best of the author's knowledge, as of now it is not possible to predict the potentially increased yield variability due to climate change (see Chapter 5.2). Therefore, an increase by 20% is assumed. New GQ were calculated and implemented into ESIM and the expected value and standard deviation of results were derived.

Figure 5.6 a) in Chapter 5 graphically illustrates the stochastic method of how uncertainty is accounted for.

7.5 Implementing outputs based on five individual GCM-LPJmL results in ESIM

Another approach to account for uncertainty from climate models is using the crop productivity changes from the LPJmL model which are based on the five GCMs CCSM3, ECHAM5, ECHO_G, HadCM and GFDL. Table 7.3 depicts their institutional origin.

Name	Organization	Author
ECHAM5	Max Planck Institut für Meteorologie (MPI), Germany	Jungclaus et al. (2006)
HadCm3	Hadley Center, UK	Cox et al. (1999)
CCSM3	National Center for Atmospheric Research, USA	Collins et al. (2006)
ECHO-G	Meteorological Institute, University of Bonn, Germany	Min et al. (2005)
GFDL	NOAA Geophysical Fluid Dynamics Labraory, USA	Delworth et al. (2006)

Table 7.3: Overview of the five global circulation models used for this study.

Source: Own compilation.

The LPJmL data used for this study where originally generated for the 2010 World Bank's World Development Report[2]. Due to Müller et al. (2009), whether the yield change results from the LPJmL model are negative or positive on a global scale is determined by the CO2 fertilisation effect. When CO2 is fully accounted for, mean crop yield changes from all GCMs and the emission scenarios used[3] are estimated to rise globally by 8%-22% in 2050 relative to 2000. However, all regions experience a decrease in crop yields between 0%-13%, if CO2 fertilization is not taken into account (Müller et al., 2009). It is important to notice, however, that at national and sub-national scale, differences in climate projections often have larger influence on changes in crop yields than the CO2 fertilization effect, emphasizing therefore the importance of selecting various climate projections to account for this major source of uncertainty for the assessment of national and sub-national climate change impacts on crop yields.

The technological progress trend shifter of the crop yield functions in ESIM where adjusted according to each of the five individual LPJmL results and solved for each GCM under the A1B and B1 scenarios, each "with CO2" and "without CO2" effect. This resulted in five outcomes for each of the emission scenarios, and all together in 20 different scenario runs. Figure 5.7 b) in Chapter five illustrates the method of generating results and their distribution for each emission scenario.

Results were first compared to the baseline scenario without climate change to exemplarily show the varying results of the GCMs. In a second step, the mean

[2]Climate change impacts on agricultural yields, background note to the World Development Report 2010, World Bank, 2009

[3]For the World Bank's Report the emission scenarios A1B, A2 and B1 were used.

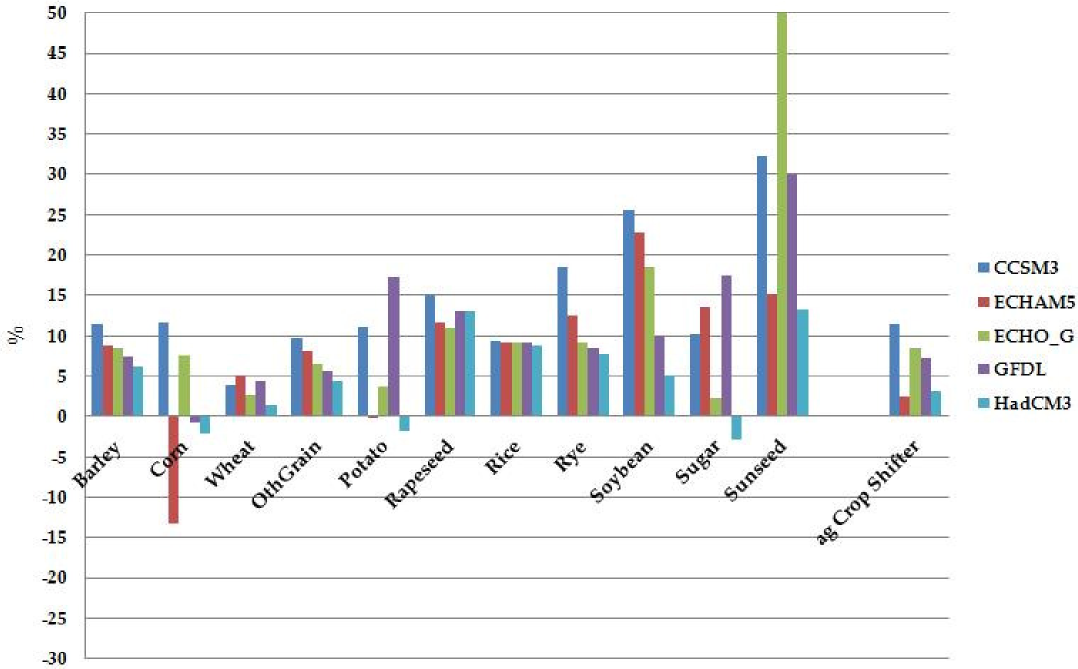
and standard deviation were taken from the five individual results of each emission scenario in order to obtain a distribution of results which accounts for the range of all GCM-LPJmL outcomes.

Figures 7.4 a) to d) show the world average technological progress shifter indices, weighted by supply quantity of the base year 2005, by 2050 for 12 selected crops for each of the climate models compared to the baseline scenario for both emission scenarios. First, the globally weighted technological progress shifter for the "with CO2" scenarios is considered (a) and (b). Under the A1B scenario, the aggregated changes of the technological progress shifters are positive for most crops in comparison to the baseline scenario without climate change.The highest productivity increases are for sunflower seed, ranging from 13% (HadCM3)to 53% (ECHO_G), which is also the crop with the most pronounced variation of shifter rates. The only crops showing productivity decreases in the A1B "with CO2" scenario are corn, which has a reduced productivity ranging from -1% (GFDL) and -13% (ECHAM3), potato (-0.1% and -1.8% (under ECHAM5 and HadCM3, respectively) and sugar (-3% under HadCM3).

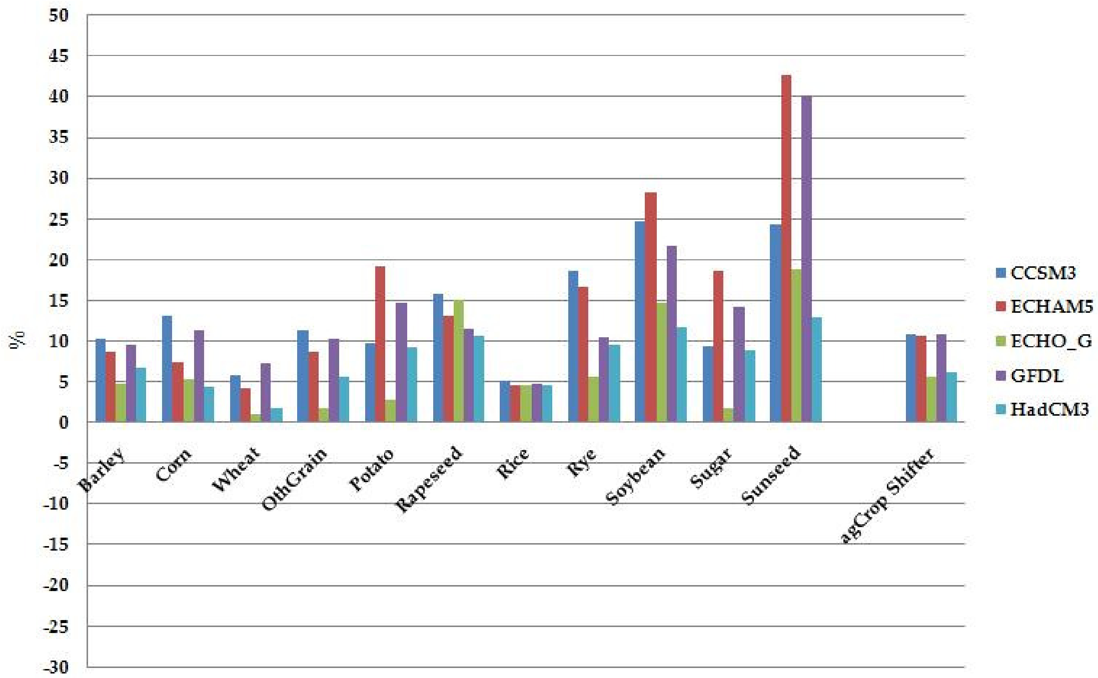
In the B1 scenario, all aggregated technological progress shifters are positive ranging from 1.1% for wheat under ECHO_G to as much as 43% for sunflower seed under ECHAM5. The weighted shifters for A1B and B1 on the right side in Figure 7.6 a) and b) imply that changes for all crops are most amplified under the CCSM3 scenario with an increase of about 11%. Figure c) and d) show the "without CO2" scenario results where aggregated shifters are negative for most crops. Exceptions in the A1B scenario are corn (CCSM3), rye (CCSM3, ECHAM5) and soybean (ECHO_G). Relative productivity shifter declines range from 26% for sunflower seed (ECHAM5) to 0.1% for rapeseed (ECHO_G). By contrast, productivity increases are highest for potato with 41% (CCSM3) and soybean with 25%(ECHO_G). The category of soybean in the A1B "without CO2" scenario also shows the biggest difference of GCM shifter results with productivity changes ranging from -26% under HadCM3 to 25% under ECHO_G. For the B1 "without CO2" scenario, relative changes are positive for more crops as compared to A1B, ranging from 0.1% for barley (CCSM3) to about 42% for sunflower seed (ECHAM5). As can be seen in Table d), productivity changes under the B1 scenario, indicate positive as well as negative productivity changes within most crop categories, with the most pronounced difference in sunflower seed, ranging from -13% ((ECHO_G) to 11% (ECHAM5). The weighted crop shifters for all GCM scenarios imply a decrease between -3% and -12% for A1B and -0.4% to -5% for B1 (both for CCSM3 and HadCM3, respectively).

In most GCM scenarios, the opposite direction of the shifter, as compared to the "with CO2" scenario, emphasises the fundamental disparities of results under varying CO2-fertilisation effect assumptions. Generally, most model runs are uniform in indicating increases in aggregated crop productivity by 2050 under both emission scenarios when the CO2 effect is considered. On the contrary, when the CO2 fertilization effect is not accounted for, results of the different GCMs are not as uniform in their direction as under the "with CO2" scenarios. The figures above underline the fact that one of the largest uncertainties is the effect of CO2 fertilization, which potentially can increase crop yields considerably. However, one has to keep in mind that the extend of the effect is still subject to debate.

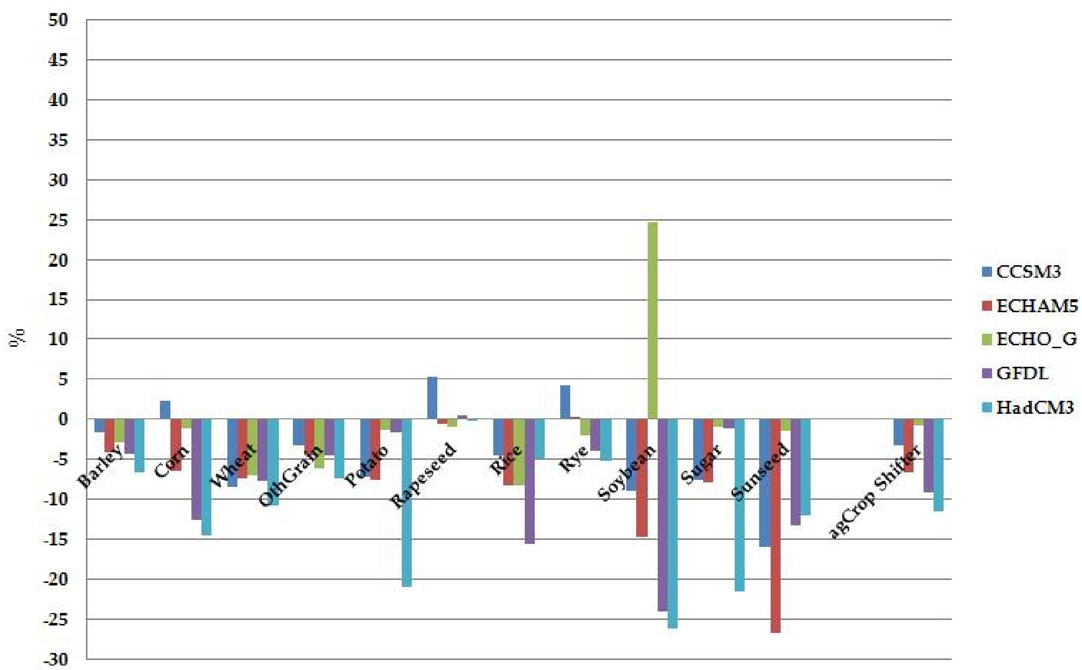
Figure 7.4: World average technological progress shifter indices by 2050 vs. baseline scenario "no CC" for both emission scenario "with CO2" and "without CO2" fertilization effect.



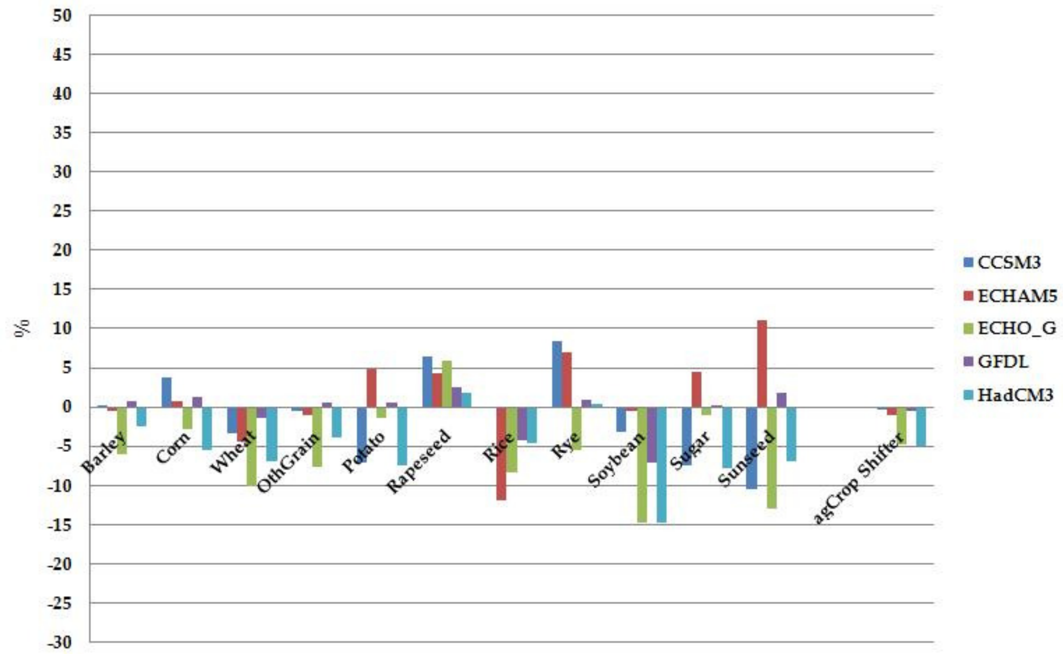
a) A1B "with CO2"



b) B1 "with CO2"



c) A1B "without CO2"



d) B1 "without CO2"

Source: Own compilation.

8 Results

8.1 Results based on mean GCM-LPJmL outputs

8.1.1 Change in crop supply and price indices by 2050

Climate change impacts on agricultural production vary widely among regions. Whereas for some regions and crops the changing agroclimatic conditions could potentially be beneficial, they can also lead to severe decreases in agricultural productivity elsewhere. These productivity changes will also have effects on global food prices. In order to present a first impression of the aggregated regional and global effects, Figure 8.1 shows crop supply and price index changes for the EU, NEU and the WO, for both SRES and CO2-scenarios compared to the baseline. The price indices are producer price indices for crops weighted with supply quantity, and supply indices are weighted with prices, both with values of the base year (2005).

Not surprisingly, crop supply indices are positive in the A1B and B1 "with CO2" scenario compared to the baseline scenario, and the relative supply increase for the EU (12% for A1B and 10% for B1) is greater than it is for the aggregate NEU

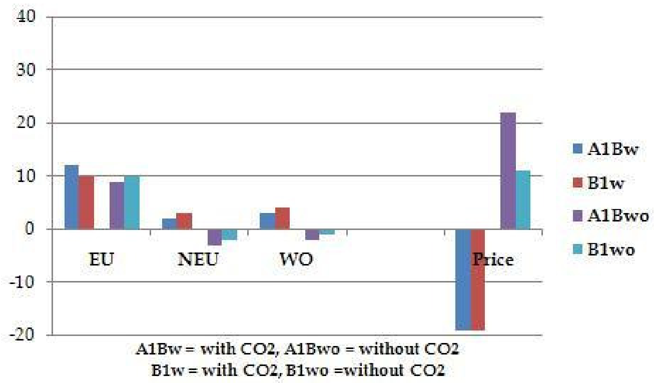


Figure 8.1: Supply and price indices by 2050 vs. baseline scenario "no CC".

Source: Own compilation.

(2% for A1B and 3% for B1). This results in a 3.1% and 3.7% aggregated supply increase in the WO under the A1B and B1 scenario, respectively. In the EU, the higher atmospheric CO2 concentration under A1B as compared to B1, explains the more pronounced productivity increases. However, the aggregated change in global crop supply is more positive under B1 in the "with CO2" scenario than it is under A1B. This can be explained by the fact, that outside the EU higher temperatures under A1B might limit productivity increases which are not outweighed by the CO2 fertilisation effect.

Due to the supply increase in world markets the price index for crops declines by 18.9% in the A1B scenario and by 18.5% in the B1 compared to the baseline scenario.

Generally, the relatively large price change compared to the small supply increase can be explained by the relatively low income and price elasticities of human demand incorporated in the model. As described in detail in Chapter 4, these demand elasticities have been modified because of the high income increase over the projection horizon of 45 years Table 4.1). Figure 8.7 depicts the globally weighted human demand elasticities with respect to price (elastDP), and the percentage share of human demand, feed use and demand for processing activities of total global use by 2050. Under the "without CO2" scenarios, increases in crop productivity, and hence crop supply, are smaller. In the A1B and B1 scenario the crop supply index for the EU is still positive (about 9% and 10%, respectively), but is less pronounced than it is under the "with CO2" scenario. For NEU, however, crop supply decreases relative to the baseline scenario by about 3% for A1B and 2% for B1. Comparing the results for A1B and B1 when CO2 effect is taken into account, as opposed to the results without CO2, exemplarily depicts the potential impact power of the CO2 fertilisation effect. It seems that under B1, the benefits of the CFE are stronger than under A1B.

Since aggregated supply in the WO declines by 2% and 1% under A1B and B1, the crop price index increases about 22% (A1B) and 11% (B1), as compared to the baseline scenario without climate change. These results indicate, that the rising temperature under the A1B scenario leads to more aggregated crop supply in the EU as compared to the B1 scenario. Especially countries in higher latitudes experience crop productivity increases. For the aggregated global crop supply instead, productivity is higher under the B1 scenario, indicating that for most regions outside the EU, the agroclimatic conditions under A1B are less favourable.

8.1.2 Change in crop yields in the EU by 2050

Higher temperatures tend to shorten the growing period, at low latitudes where crops are currently grown at higher temperatures and are nearer their limits of temperature tolerances for heat and water stress. Warmer conditions hence lead to yield decreases at low latitudes. In higher latitudes in contrast, an increase in temperature tends to potentially extend growing periods and hence increase yields (Parry et al., 1999). Whether increased temperature and a higher CO2 concentration in the countries and regions considered leads to net benefits for crop productivity, depends on which effect is dominating. The potential beneficial CO2 effect can be counterweight by increased temperatures which can lead to more water and heat stress.

Figure 8.2 shows the average weighted yield changes for selected crops in the EU for all scenarios. Yield increases are stronger for most grain crops in the A1B than the B1 "with CO2" scenario, with biggest changes for rice (26%), sunflower seed and rye (both about 20%). This is because the strong yield increases of the two major rice producing countries, namely Italy and Spain with 15% and 48%, respectively. The same applies to the category sunflower seed in Spain and France, where increases of 36% and 31% are simulated. For Poland, which produces about 40% of total European rye production, the yield increase of 24% is responsible for the high increase of that product. Simulated yield changes for rye are particularly high for countries in higher latitudes, such as Denmark (31%), Finland (22%), Sweden (26%) and Lithuania (35%).

For Corn and rapeseed in turn, increases are stronger under the B1 scenario. This is due to the higher yield increases under B1 for major rapeseed producers such as

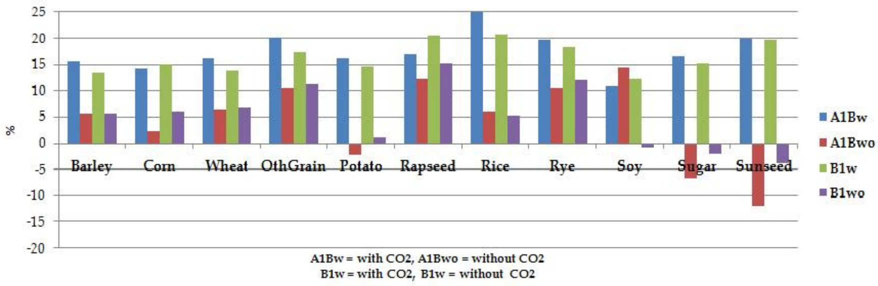


Figure 8.2: Average yield change EU in % by 2050 vs. baseline scenario "no CC", based on mean GCM-LPJmL outcomes.

Source: Own compilation.

Germany, Poland and France, with increases of 26%, 35% and 7%, respectively. Whereas for corn, the more pronounced positive effects under B1 stem from the yield increases of the big producers Hungary and Romania (14% and 10% under B1 as compared to 2% and -3% under A1B).

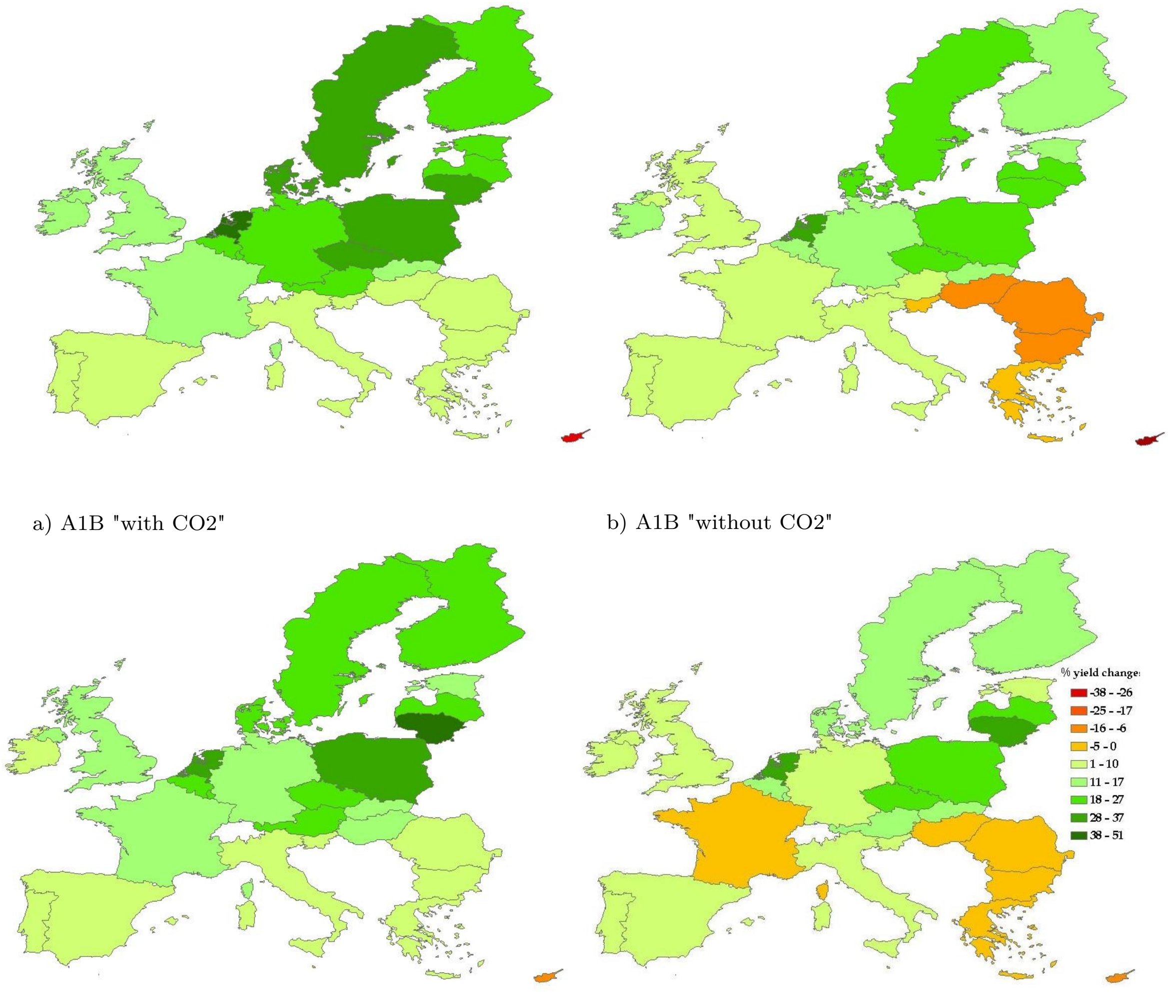
Yield effects are generally positive under both, the "with CO2" and "without CO2" scenario. In contrast, the only crops where yield is declining in the "without CO2" scenarios is potato (2%), soybean (0.8%), sugar (7%) and sunflower seed (12% for A1B and 4% for B1). The comparatively large yield decline for sunflower seed under A1B "without CO2", can be explained by the fact that simulation results for major sunflower seed producers in the EU such as Hungary, France, Romania and Belgium, are negative (between 19% for Romania and 24% for France). An overview of yield changes for all European countries is provided in Annex C.

8.1.3 Change in yields of grains and oilseeds at EU member state level by 2050

Figure 8.3 and 8.6 show the simulated changes in average national grain and oilseed yields for the A1B and B1 with and without the CO2 fertilisation effects on plant growth for European countries[1]. The maps for grains are derived from national average yield changes for wheat, corn, maize, rye, barley and the category other grains. Oilseed maps on the other hand where derived based on national average yield changes for rapeseed, sunflower seed and soybean.

When climate change is considered for grains "with CO2" as compared to the baseline scenario, yields increases by 2050 are positive in every country with the exception of Cyprus (-35% for A1B and -12% for B1) and Malta (around -4% for A1B and B1). Yield increases, however, vary widely among countries with more pronounced increases being simulated for countries in higher latitudes such as Denmark (33% A1B, 22% B1), Finland (26% A1B, 21% B1), Sweden (27% A1B, 22% B1) and Lithuania (34% A1B, 41% B1). The smallest increase is simulated for Bulgaria under A1B and Portugal under B1, both with 1%. By contrast the highest result is for the Netherlands under A1B and Lithuania under B1 (both 41%).

[1] Since in ESIM yield is only modelled for European countries, no yields changes are shown for countries and regions outside the EU.



a) A1B "with CO2" b) A1B "without CO2"

c) B1 "with CO2" d) B1 "without CO2"

Figure 8.3: Yield changes for grains in % by 2050 under the A1B and B1 emission scenario for mean GCM-LPJmL outcomes.

Source: Own compilation.

Not surprisingly, the scenarios without considering the CO2 effect causes average national grain yields to decline for more countries than compared to the "with CO2" scenario. Declines under A1B are simulated for Bulgaria (12%), Greece (3%), Cyprus (38%), Hungary (17%) and Romania (13%). Under the B1 emission scenario "without CO2", declines are less pronounced ranging from 1% for Malta to 13% for Cyprus. Increases for these scenarios in turn range from marginal changes for Malta, Bulgaria and France, up to 36 % for the Netherlands (A1B).

The simulated average grain supply effects (Figure 8.4) for grains in the EU of 16% and 1% in non European countries (NEU), lead to global grain supply increases of 2%. The grain production increase leads to a price decline of 17 % under the A1B,

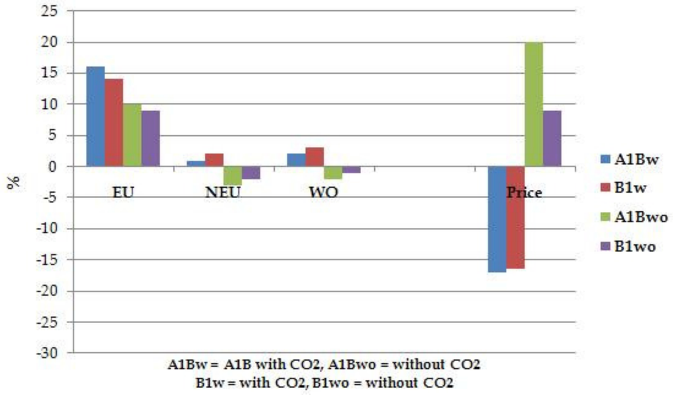


Figure 8.4: Grain supply and price developments in % by 2050 vs. baseline scenario "no CC".

Source: Own compilation.

and 16.5 % under the B1 "with CO2" scenario. The "without CO2" scenarios in contrast, show minor increases for the EU between 9% and 10% for B1 and A1B, respectively. For the NEU region, declines of 3% and 2% (A1B and B1, respectively), result in an aggregated supply decline of 2% under A1B and 1% under B1. Grain supply reduction hence leads to a price increase of about 20% and 9 %.

Biggest declines of supply on a global level are estimated for the category other grains (4%) under the A1B "without CO2" scenario, whereas largest global supply increases are estimated for rye (6%) under the B1 "with CO2", as compared to the baseline scenario without climate change.

Figure 8.5 illustrates developments of oilseed supply and price developments by 2050 compared to the no climate change scenario for the EU, NEU and the WO. Similar to developments of grains, aggregated supply changes for oilseeds are positive for the EU for all scenarios with smaller increases under the "without CO2" scenarios.

The aggregated global supply increases in the WO of 4.1% under A1B and 4.4% under B1 "with CO2", cause world market prices for oilseeds to decline by 25% and 30%, respectively. For both "without CO2" scenarios, supply changes in NEU are negative, with a more pronounced decline of 3% under A1B as compared to 1% under B1. This leads to aggregated global effects of -2% in the WO for the A1B and -1% for the B1 "without CO2" scenario. This global supply reductions lead to relative price increases of 23% and 14%, respectively. Within the oilseed sector, supply reductions are most severe under A1B "without CO2" for sunflower seed with a global decline of about 16%. In contrast, on a global level, soybean supply

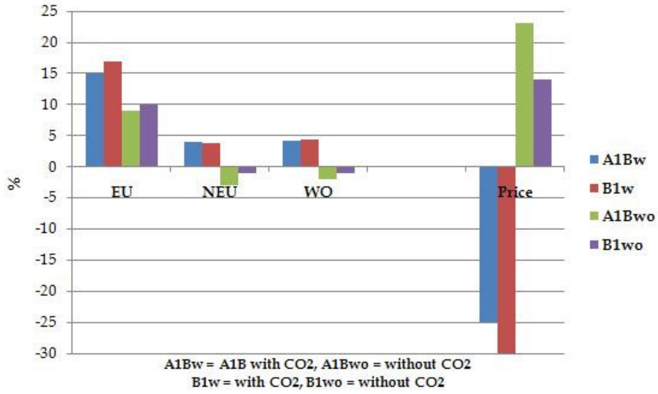
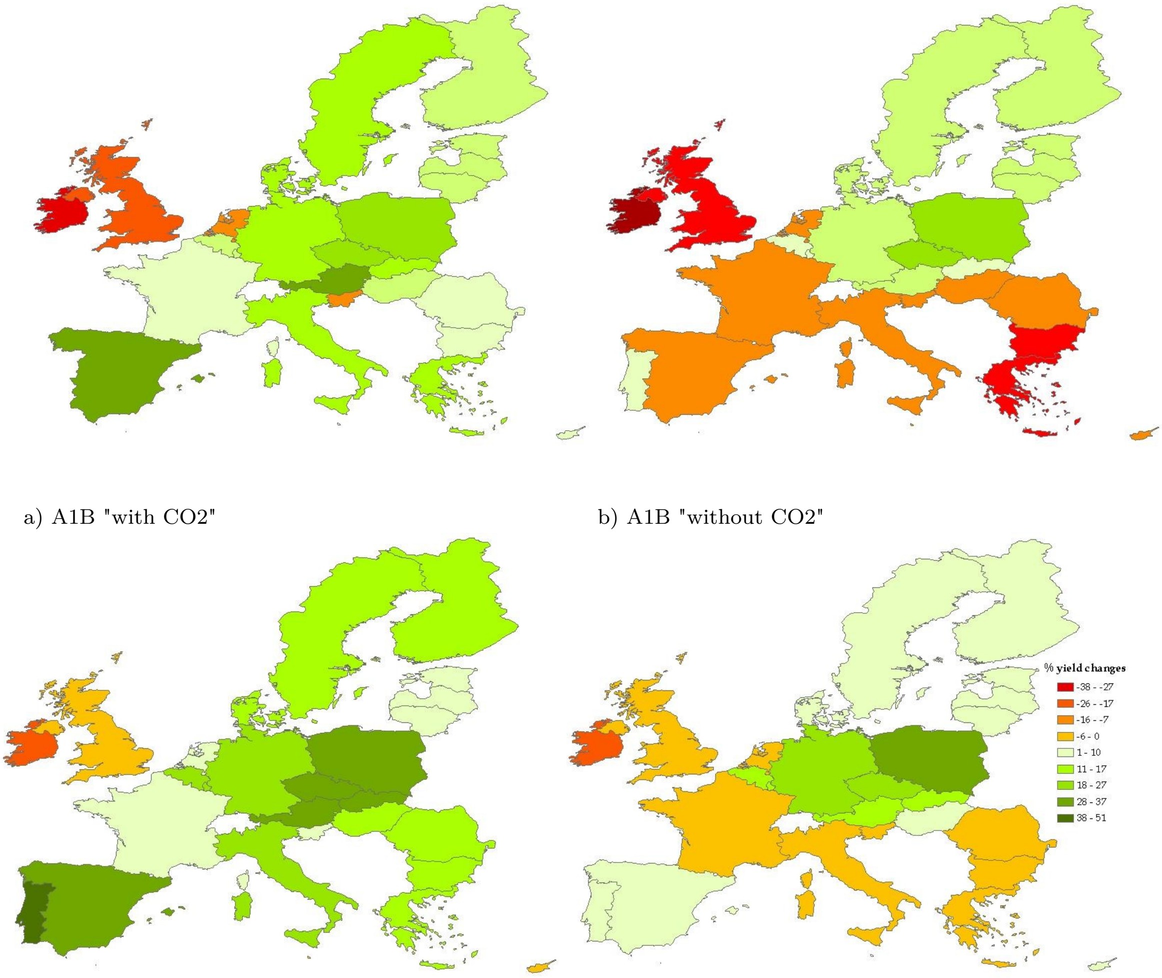


Figure 8.5: Oilseed supply and price developments in % by 2050 vs. baseline scenario "no CC".

Source: Own compilation.

reductions are estimated to decline by only 1%. The national changes of average yields of oilseeds are illustrated in Figure 8.6. Under the A1B "with CO2" scenario, yield changes vary as much as declining from 21% in Ireland, up to increases of 51% for Portugal. For most countries, however, yield increases between 9% and 25% can be observed. Under B1 "with CO2", with the exception of Ireland (-17%) and the UK (-2%), yield changes are positive ranging from 1% (Slovenia) to 39% (Portugal), as compared to the baseline scenario without climate change. For the "without CO2", as compared to the "with CO2" scenarios, more countries show yield reductions within a range of 2% for Spain and 26% for Ireland. Declines are also more pronounced for the A1B than the B1 scenario. Increases range from 2% in Slovenia to 28% in Poland.



a) A1B "with CO2"

b) A1B "without CO2"

c) B1 "with CO2"

d) B1 "without CO2"

Figure 8.6: Yield changes for oilseeds in % by 2050 under the A1B and B1 emission scenario for mean GCM-LPJmL outcomes.

Source: Own compilation.

8.1.4 Change in global crop supply and prices by 2050

Tables 8.1 and 8.2 indicate global supply and price changes by 2050 for selected crops. As expected under the "with CO2" scenarios aggregated crop supply increases for all crops. However, there is a huge disparity between the level of increases among the different crops, ranging from as little as 0.5% for wheat to as much as 22% for sunflower seed under B1. For most crops increases are more pronounced under the A1B scenario as compared to B1. This can be related to stronger CO2 fertilization effect, since atmospheric CO2 concentration under A1B is higher than under B1. Likewise, under the "without CO2" scenarios, supply decreases are stronger under A1B which is due to higher temperatures as compared to B1. Potential productivity declines are not outweighed by positive CO2 fertilization effects. Declines range from 1% for soybean to 16% for sunflower seed. Potato (the only crop which is modelled as a non-tradeable in ESIM) and rapeseed are the only crops for which supply increases are simulated under both "without CO2" scenarios. For rapeseed this is due to the strong supply increase within the EU which outweighs supply declines in NEU. Under B1, small increases are also estimated for rye.

World market prices by 2050 develop accordingly (Table 8.2) The supply increases under both "with CO2" scenarios lead to relative world market price declines of between 12% for sugar (A1B) to 32% for soybean (B1). Relative supply declines under the "without CO2" scenarios lead to world market price increases for most crops ranging from a marginal change for rapeseed (B1) to 26% for rice and soybean

	A1Bw	**A1Bwo**	**B1w**	**Bwo**
Barley	5	-2	4	-1
Corn	4	-3	5	-1
Wheat	1	-2	0.5	-1
OthGrain	4	-4	5	-3
Potato	0.3	0.1	0.8	0.2
Rapseed	7	0	8	2
Rice	1	-1	1	-1
Rye	6	-1	6	0.5
Soybean	2	-1.0	2	-1
Sugar	7	-6	10	-3
Sunseed	22	-16	22	-7

Table 8.1: Change in global supply in % by 2050 vs. "no CC".

Source: Own compilation.

	A1Bw	**A**1Bwo	**B**1w	**B**1wo
Barley	−21	13	−17	5
Corn	−14	16	−17	6
Wheat	−17	23	−15	12
OthGrain	−15	19	−16	10
Potato*	−20	23	−25	11
Rapeseed	−16	7	−16	0
Rice	−21	26	−18	12
Rye	−23	11	−21	3
Soy	−27	26	−32	17
Sugar	−12	13	−15	6
Sunseed	−22	18	−22	6

Table 8.2: Change in prices in % by 2050 vs. "no CC".

*Potato is a non-tradeable in ESIM, hence prices depicted here are average prices of the aggregate Rest of the World (ROW).

Source: Own compilation.

(A1B). The big price changes compared to relatively small supply changes, as can for example be seen for soybean, are related to the small price elasticities of demand (e.g. 0.001 for soybean, making the price more volatile to any given supply change. The relatively small aggregated global supply increase under A1B "with CO2" of about 2%, leads to a huge price decline of 27%.

Also wheat and rice supply increases (decreases) of up to 2% lead to price declines (increases) of as much as 23%. Both globally weighted price elasticities of demand are -0.075 (wheat) and -0.078 (rice). The strong price index development is further strengthened by the huge global production quantity of the two crops. Thus, price developments of other crops are also influenced. In contrast for sunflower seed, supply and price changes are approximately equal, stemming from the fact that major parts of sunflower seed demand originates from processing activities (94% for sunflower seed and 66% for sunoil).

Table 8.3 shows global weighted price elasticities of demand of crops and their percentage share of global demand. The marginal price change of rapeseed under B1 "without CO2" can be explained by the fact that processing demand for substitutes, such as sunflower seed and soybean, is declining due to rising prices and hence processing demand for rapeseed is increasing. The rising demand in turn leads to a higher rapeseed price and outweighs potential negative price developments which would be expected from the relative supply increase.

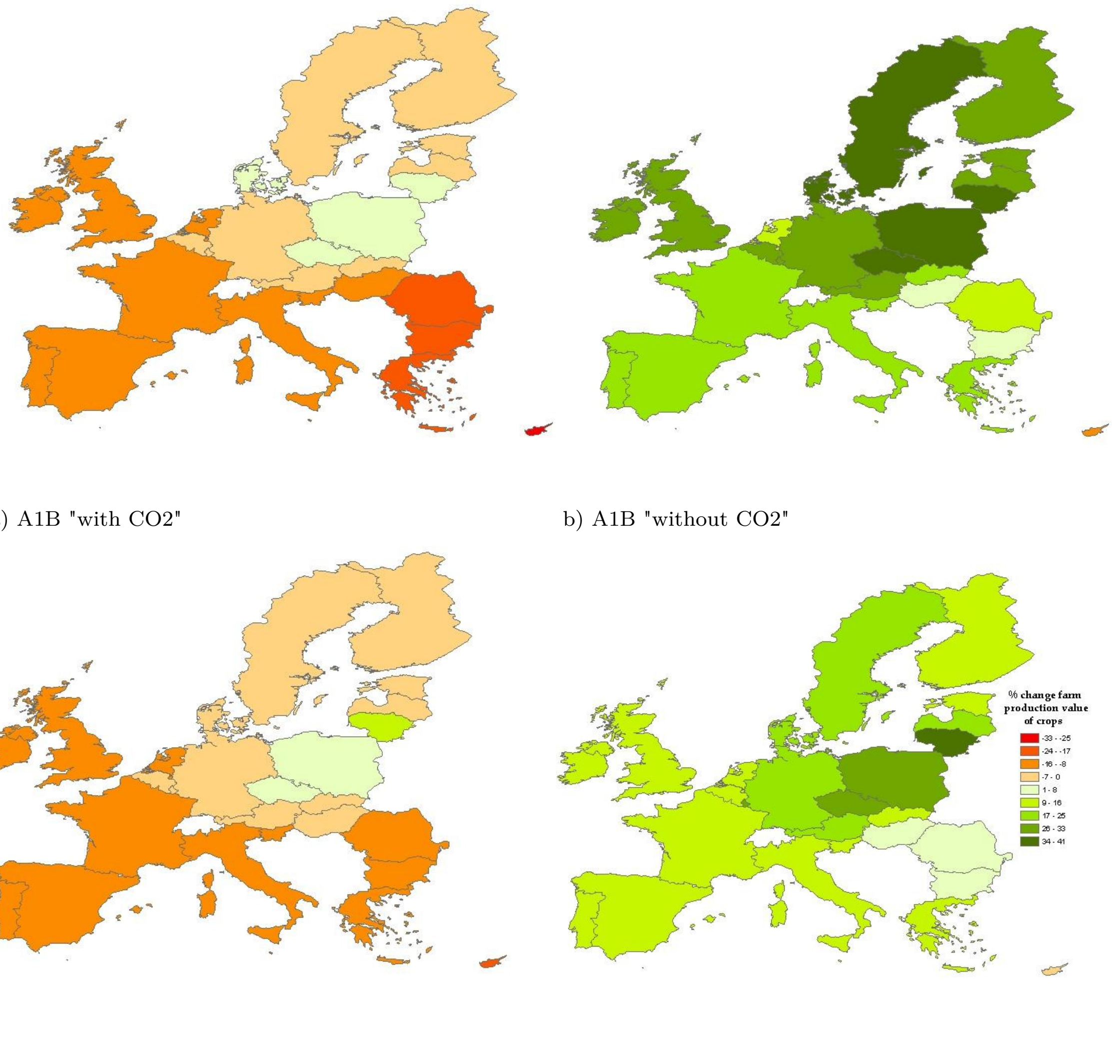
		share of global demand in %		
elastDP		human	feed	processing
Barley	-0.013	28	66	
Biodiesel	-1.500	100		
Corn	-0.027	51	42	4
Wheat	-0.075	80	14	0
Durum	-0.072	97		
Ethanol	-1.500	100		
Manioc	-0.076	59	41	
OthGrain	-0.016	47	50	
Potato	-0.056	73	16	
Rapoil	-0.026	8		92
Rice	-0.078	97		
Rye	-0.022	49	40	
Soybean	-0.001	48	3	45
Soyoil	-0.019	100		
Sugar	-0.147	52		48
Sunoil	-0.027	34		66
Sunseed	-0.002	3	3	94

Table 8.3: Global weighted price elasticities of demand and share of demand by 2050 for selected products (baseline scenario "no CC").

Source: Own compilation.

8.1.5 Change in farm production value at EU member state level by 2050.

The maps in Figure 8.7 indicate the climate change induced alterations of farm production value of crops for the European Union. As expected, the crop supply increase under the "with CO2" scenarios lead to decreasing production values for most countries because of world market price declines. Relative reductions range between 2% in Sweden and 22% in Romania. Cyprus is hardest hit with a simulated production value decline of 33% under the A1B "with CO2" scenario. However, despite the relative declines of world market prices, simulation results for some countries in Europe still deliver positive values. The Czech Republic, Poland, Lithuania and Denmark show increases in a range of 2-6% relative to the reference scenario without climate change. For Lithuania the increase is due to the very large projected supply increases of about 148% for corn and about 50% for most other grains, which outweighs the negative world market price developments. Also in the Czech Republic, the corn supply increase by 78%, leads to positive developments of farm production values. In contrast, with the exception of Cyprus, simulated changes for all European countries are positive for both "without CO2" scenarios due to world market price increases for most crops, since global supply is projected to decline under both "without CO2" emission scenarios. The higher world market prices under A1B deliver more pronounced relative farm production value increases as the B1 "without CO2" scenario. For the former scenario, an increase of up to 41% is estimated for Denmark, whereas under B1, highest value changes are estimated for Lithuania with an increase of 34%.



a) A1B "with CO2" b) A1B "without CO2"

c) B1 "with CO2" d) B1 "without CO2"

Figure 8.7: Changes of farm production value of crops in % by 2050 under both A1B and B1 emission scenarios for mean GCM-LPJmL outcomes.

Source: Own compilation.

Aggregated change in farm production value of crops by 2050

Results indicate that despite declining global productivity of the agricultural sector under the "without CO2" scenarios, the farm production value of crops increases due to higher world market prices. Particularly for Europe, such developments are as high as 24% (A1B) and 14% (B1) as compared to the no climate change scenario. this is because crop production in Europe is, at least until 2050, more positively affected by climate impacts than aggregated regions outside the EU. In non European regions the farm production value is in turn projected to increase only by 18% and 9% under both "without CO2" scenarios, respectively.

	EU	NEU	WO
A1Bw	-8	-17	-17
A1Bwo	24	18	18
B1w	-7	-18	-17
B1wo	14	9	9

Table 8.4: Aggregated change of farm production value of crops in % by 2050 vs. "no CC".

Source: Own compilation.

The aggregated supply increases lead to declines in world market prices under the scenarios "with CO2". Hence, production value changes are negative on aggregate levels. Declines for the EU are 8% for A1B and 7% under B1. In regions outside the EU declines are as much as 17% under A1B and 18% under B1. Those results indicate, that despite increasing productivity, farm production values are actually decreasing due to falling prices. However, effects are less pronounced for regions outside the EU. Table 8.4 depicts aggregated changes of farm production value of crops for the EU, regions outside the EU (NEU) and the world (WO).

8.1.6 Distribution of results based on Gaussian Quadratures

This section describes the distribution of results when stochasticity is introduced in ESIM as described in Chapter 6.3). By increasing the error terms of the yield function by 20%, a scenario which simulates the case of increasing the yield variability by the same value is generated. This simulation means, that the random variation of crop yields will be 20% greater than the historically observed variation. The stochastic simulations were solved for the year 2050 under the SRES A1B "with CO2" scenario to exemplarily demonstrate the effect of a climate change related increase of yield variability by 20%.

Table 8.5 shows the development between 2005 and 2050 of expected value and standard deviations for yield, supply and price developments in percent for the crops wheat, barley and rapeseed in Germany and the aggregated rest of the world (ROW).

GERMANY	**EV**	**SD***	**SD 20%**	**ROW**	**EV**	**SD***	**SD 20%**
Wheat				**Wheat**			
Yield	59	6.3	7.4	Supply	75	2.7	4.0
Supply	71	6.3	7.2	Price	13	7.5	9.4
				△ Price(%)**			**25.1**
Barley				**Barley**			
Yield	61	6.6	7.8	Supply	37	7.5	8.1
Supply	69	6.1	6.6	Price	10	6.1	9.7
				△ Price(%)**			**58.5**
Rapeseed				**Rapeseed**			
Yield	191	10.1	11.8	Supply	157	4.6	4.5
Supply	165	9.3	8.9	Price	-9	3.5	5.4
				△Price(%)**			**53.7**

*Standard deviation in 2050 when ESIM is run with historical error term.
**Changed price volatility when error term is increased by 20%.

Table 8.5: Yield, supply and price development of expected value and standard deviation in % between 2005 and 2050 under the A1B "with CO2" scenario for wheat, barley and rapeseed in Germany and ROW.
in %

Source: Own compilation.

It is important to notice, that the expected values are percentage changes between 2005 and 2050, and not relative changes compared to the no climate change scenario. Numbers presented in the third column show the standard deviation based on historical error terms. The fourth column shows the effect of an increased variance by 20% and its impacts on yield, supply and price variability. Price variability is increased by 25% for wheat and even as much as 58% for barley. The higher price variability for barley is attributable to the lower price elasticity of demand, which is 0.014 for Barley as compared to 0.077 for wheat in ROW. Results indicate, that an increase of yield variability has large impacts on future crop price volatility, and does hence highlight the importance of undertaking stochastic analysis of climate change impact assessments.

8.2 Results and distribution based on five individual GCM - LPJmL outputs

8.2.1 Change in crop supply and price indices by 2050

Firstly, results for aggregated supply and price index changes within the EU, non European regions, and the world by 2050 compared to the baseline scenario without climate change, are presented (Figure 8.8). Those indices are similar to the ones described for the scenarios in Chapter 8.1 (Figure 8.1), where only one model run per emission scenario based on mean GCM-LPJmL outcomes, was conducted. Generally, the crop supply indices for the second approach presented in this section, are smaller for all "with CO2" scenarios. The biggest difference between the two approaches is under the A1B "with CO2" scenario, where the crop supply index change for the EU is about 10% for the second approach, and about 12% for the first approach. Regarding price indices, the changes for the "with CO2" scenarios are hence less pronounced for the second approach (around -16%) as compared to the first approach (around -19%). This is due to the fact, that aggregated supply index changes for the world for the second approach are with around 2% (A1B) and 3% (B1) smaller than the supply index changes for the first approach (3% under A1B and 4% under B1). For the "without CO2" scenario, the supply declines for the aggregated world are more pronounced for the second approach under A1B (around 3%) compared to the first approach (2.5%), and hence the price index change under A1B (25%) is by 3.6 percentage points higher than for the first approach (22%).

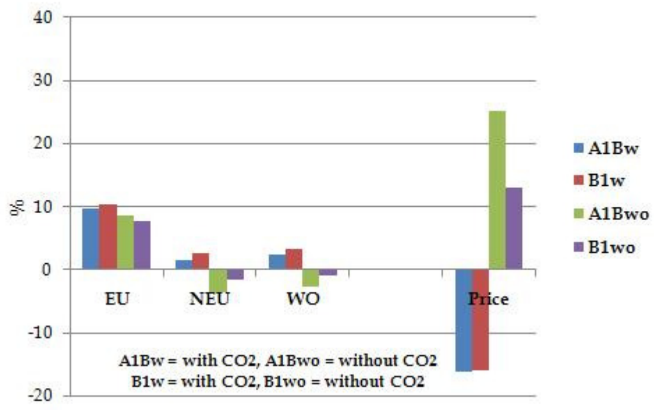


Figure 8.8: Supply and price indices by 2050 vs. baseline scenario "no CC".

Source: Own compilation.

8.2.2 Change in crop yields in the EU by 2050

In Figure 8.9, results for average yield changes for the EU by crop are presented. When comparing simulation results of both modelling approaches used for this study, they show a great similarity. The only significant difference can be observed for the category potato under the A1B "with CO2" scenario with a 3.7 percentage point difference between the two approaches. This can be explained by the fact that major potato producing countries tend to have greater yield increases when results are based on the mean LPJ-mL inputs. Differences can also be observed for soybean under the A1B "without CO2" scenario with a difference of about 3 percentage points, caused by a larger yield increase in Romania for the mean GCM-LPJmL outputs.

In order to illustrate the strong regional differences of yield results between the outputs based on five GCMs, Figure 8.10 shows exemplarily the individual yield change results for the crops corn, wheat and rapeseed in France. Results are presented for the A1B "without CO2" emission scenario and indicate relative yield changes in percent by 2050 compared to the baseline scenario without climate change.

Corn yields in ESIM for example are projected to decline in one out of five simulations, namely by 8% for the HadCM3 scenario. Results based on the CCSM3, ECHAM5, ECHO_G and GFDL model inputs, however, indicate corn yield increases varying from 1% (ECHAM5) to as much as 21% (CCSM3). This offsets the projected declines of the HadCM3 scenario, and results in a change in the multi-

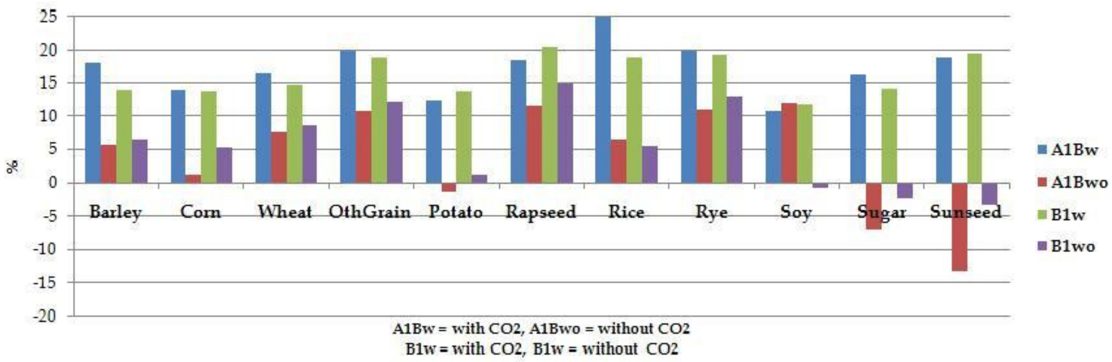


Figure 8.9: Average yield change EU in % by 2050 vs. baseline scenario "no CC", based on mean of five individual GCMs-LPJmL results.

Source: Own compilation.

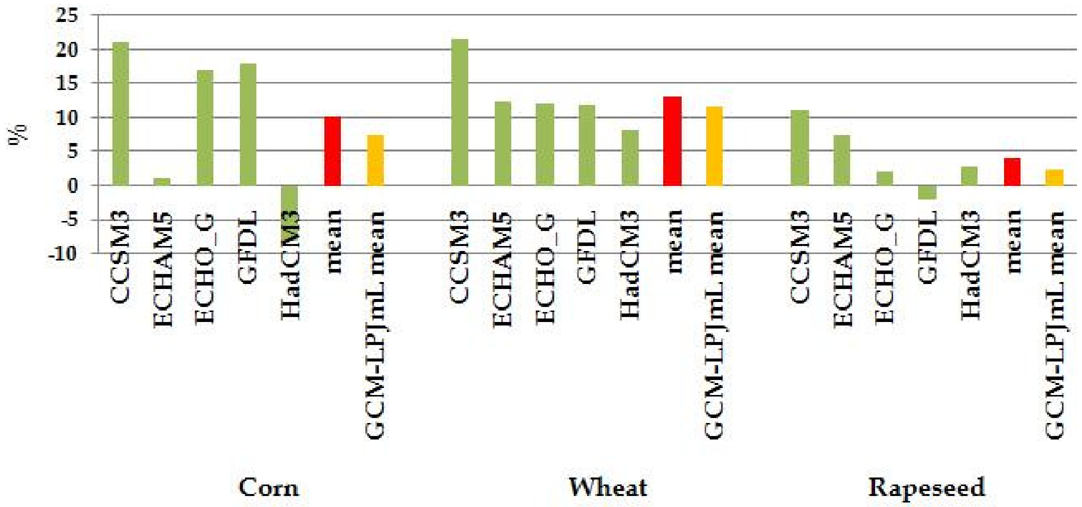


Figure 8.10: Yield change projections under A1B "with CO2" by 2050 vs. baseline scenario "no CC" for corn, wheat and rapeseed in France.

Source: Own compilation.

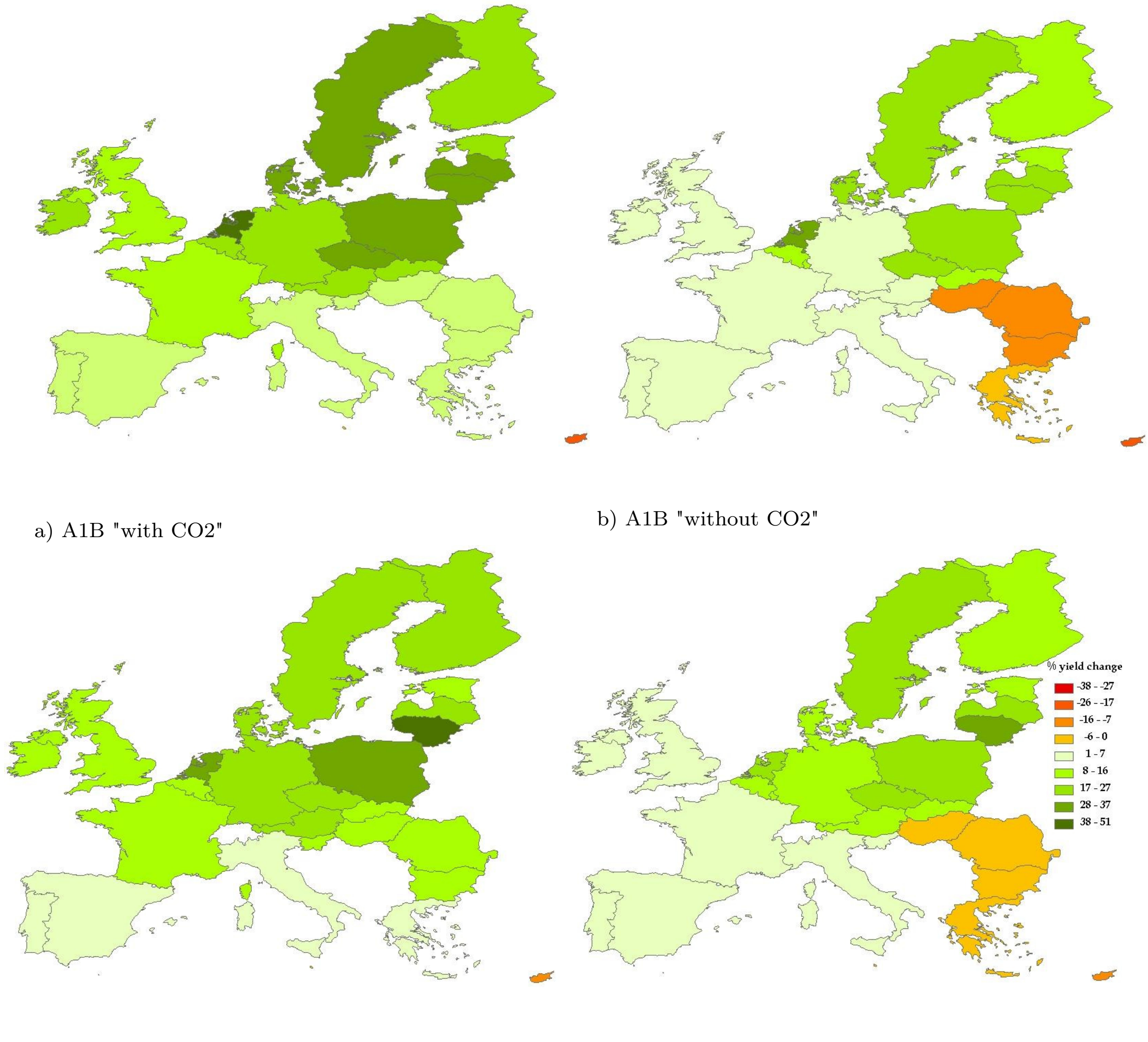
GCM mean of 10% (indicated by the red bar). For comparison, results of the yield changes based on mean GCM-LPJmL outputs, as described in Chapter 8.1, are also presented in the graph by the orange bars.

Disparities are also simulated for rapeseed with deviations between −2% (GFDL) and 11% (CCSM3) of individual results. These different projections highlight the source of uncertainty from different climate predictions and underline the necessity to consider multiple potential climate developments.

8.2.3 Change in yields of grains and oilseeds at EU member state level by 2050

Also for the aggregated grain and oilseed sector, the approach of implementing five individual LPJmL results based on five GCM outcomes into ESIM and taking an average of simulated ESIM results, delivers very similar outcomes as compared to the method of using the mean yield changes from LPJmL (Figure 8.11 and 8.12). Differences for oilseed and grain yields for the EU vary on average only up to 3%. The only exception is the grain sector in Cyprus, where differences between both A1B scenarios is about as much as 10%.

Whereas the first approach used delivers relative yield declines for barley and the category other grains of 35% and 38% for both A1B scenarios in Cyprus, the second method described in this chapter, delivers yield declines of about 24% for the same crop categories and scenarios. An explanation for the different results could be the standard deviation for barley and the category other grains, which is as high as 28% of the mean value of all five individual results in Cyprus. Compared to other crops, this standard deviation is rather high. For most countries and crop yields, the average standard deviation is around 6% for the category grains. The relatively high standard deviation indicates the high inconsistency of model results for Cyprus for the two crop categories.



a) A1B "with CO2"

b) A1B "without CO2"

c) B1 "with CO2"

d) B1 "without CO2"

Figure 8.11: Yield changes for grains in % by 2050 under the A1B and B1 emission scenario for five individual GCM-LPJmL outcomes.

Source: Own compilation.

For the category oilseeds, the two approaches agree also within a range of 1% to 3% for all scenarios. Within the category oilseed, the highest standard deviation can be observed for sunflower seed in France, Slovenia and Italy with deviations of 34%, 28% and 22%, respectively.

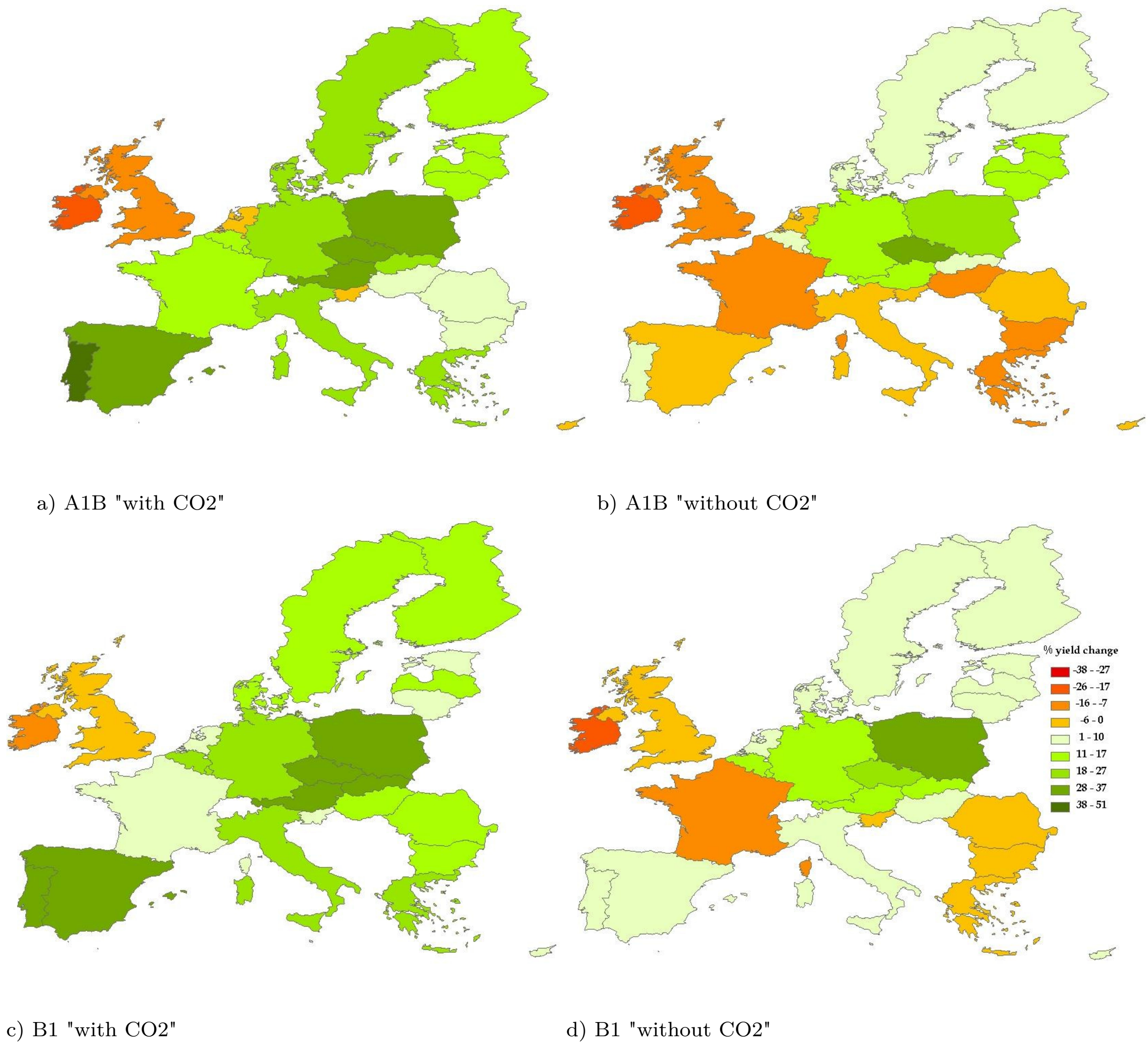


Figure 8.12: Yield changes for oilseeds in % by 2050 under the A1B and B1 emission scenario for 5 individual GCM-LPJmL outcomes.

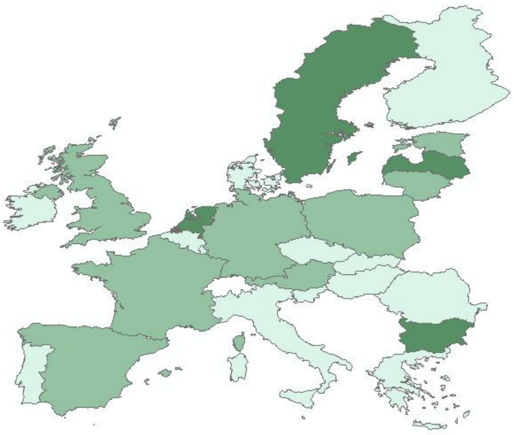
Source: Own compilation.

Figures 8.13 and 8.14 show the difference of yield change results in percentage points between both approaches for the categories grains and oilseed. Highest discrepancy is under both A1B scenarios for grains in Cyprus, with differences of 11 and 12 percentage points, respectively[2]. For most other countries, however, the differences are much smaller with a range of zero to four percentage points. As can be

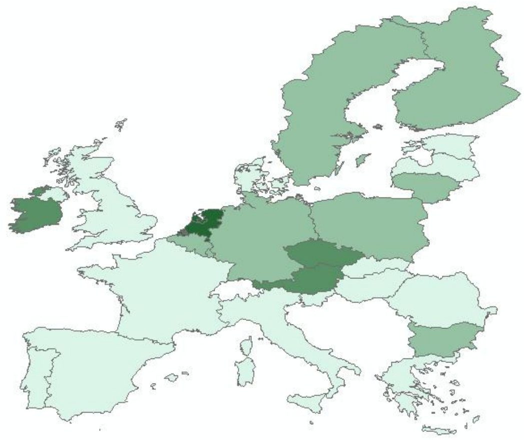
[2]For a better illustration, Cyprus is not depicted in those Figures.

seen in the maps, the best agreement is under the grains B1 "without CO2" scenario (Figure 8.13 d), where over 60% of all depicted countries show a difference of between zero and one percentage points. By contrast, for the oilseed A1B "with CO2" scenario, the same applies only for 36% of all countries (Figure 8.14 a). Generally, more than 50% of the yield change results show a small difference of between zero and one percentage points between both approaches. This implies, that simulations effects from the market model do not lead to big alterations when deriving the mean of the individual market model results, as compared to the method where only one vegetation model output, the mean of the 5 individual climate-LPJmL results, serves as input for the market model.

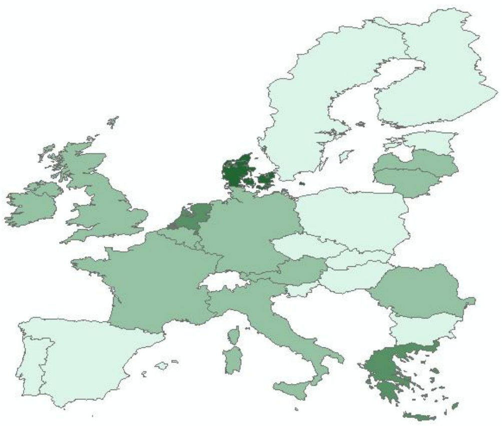
On country level, best agreement of both approach results are for Finland, Hungary, Poland and Slovenia, where most scenario results of both approaches disagree within a range of around one percentage point. The Netherlands is, apart from Cyprus, the country with the highest deviation of results, with an average of 2.6 percentage points of all scenarios. A particularly high discrepancy can be observed for the grains scenarios in the Netherlands. This is explained by the fact, that the 5 individual yield change results for corn vary between -1% (HadCM3) and 144% (CCSM3), resulting in a comparatively lower mean change as compared to the method, where the mean of the GCM-LPJmL output was used.



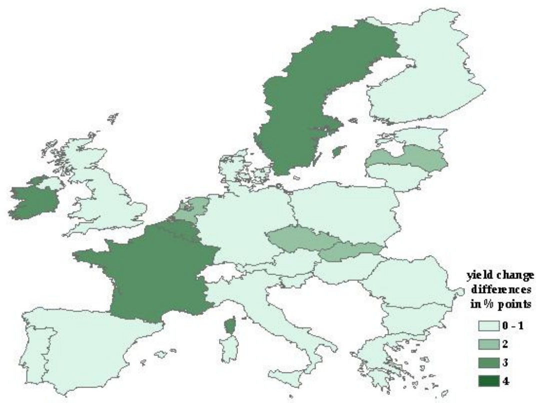
a) A1B "with CO2"



b) A1B "without CO2"



c) B1 "with CO2"

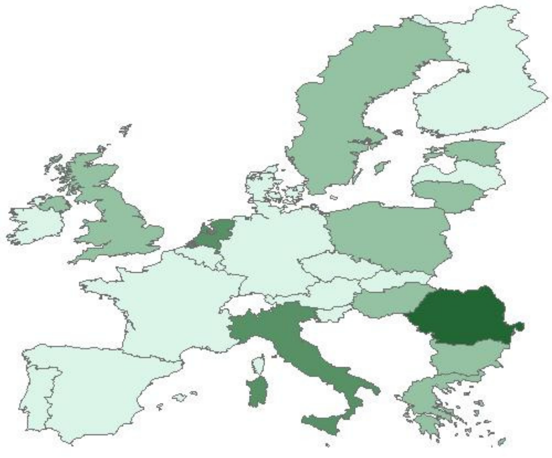


d) B1 "without CO2"

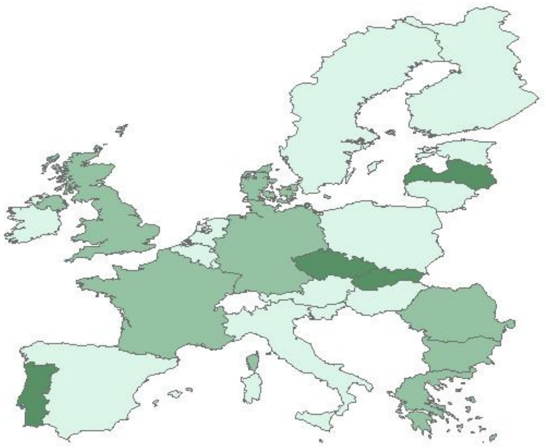
Figure 8.13: Difference of grain yield changes in percentage points, between both approaches, by 2050 under the A1B and B1 emission scenario.

Source: Own compilation.

a) A1B "with CO2"



b) A1B "without CO2"



c) B1 "with CO2"

d) B1 "without CO2"

Figure 8.14: Difference of oilseed yield changes in percentage points, between both approaches, by 2050 under the A1B and B1 emission scenario.

Source: Own compilation.

8.2.4 Change in global crop supply and prices by 2050

As next step, the mean and the standard deviation have been derived from the five individual GCM-LPJmL results of each emission scenario run. Mean values were than compared to the baseline scenario without climate change, and standard deviation is depicted in percentage change of the mean value which is the coefficient of variation (CV). Table 8.6 to 8.8 show supply differences and standard deviations by 2050 for selected crops for the EU, non European countries (NEU) and the world (WO). Under the A1B "with CO2" scenario in the EU supply increases for most crops range between 3% for potato and 22% for rice. Only for sugar and soy supply declines can be observed for the EU (both about 1%). The comparatively high standard deviation of 8% for rapeseed, and 14% for soybean and sunflower seed, indicates that the five GCM-LPJmL outputs disagree more for those crops as compared to e.g. potato (2%) and sugar (1%).

Standard deviations are particularly high for the A1B and B1 "without CO2" scenario, ranging from 1% for potato and sugar, to as much as 24% for soybean. Within the EU, the only supply decline is estimated for sunflower seed with 15% and 4% for A1B and B1. Increases for other crops in contrast range between 1% (potato) and 26% (soybean) (Table 8.6). By contrast, for NEU (Table 8.7), supply declines are between 1% for potatoes, 7% for rye and 4% for barley, as compared to the baseline scenario. Also in NEU, standard deviations are highest for corn with up to 7% and 14% for sunflower seed (both under A1B "with CO2"). Sunflower seed is also the category with the highest supply increases for both, the A1B and B1 "with CO2" scenario, as compared to the baseline scenario (24% and 23%, respectively).

In contrast, declines are most pronounced for barley (11%), rye (13%) and sunflower seed (13%) for the A1B "without CO2" scenario (Table 8.7). The aggregated global supply effects under A1B and B1 "with CO2" scenarios, are all positive by as much as 22% for sunflower seed and 1% for corn. Exception are the crops wheat and potatoes where changes are only marginal. Declines on a global level for the A1B "without CO2" scenario are as high as 13% for sunflower seed. Marginal changes are simulated for potato, rapeseed (A1B) and corn (B1). The standard deviations are similar to the ones in NEU with sunflower seed and sugar being the most amplified (Table 8.8).

Table 8.9 illustrates the relative global price changes by 2050 compared to the no climate change scenario. Results are similar to the ones described in Chapter 8.1.4 for the mean GCM-LPJmL outputs, yet with slight disparities. Also here, due to global supply increases for all crops under both "with CO2" scenarios, estimated price declines range between 6% for corn (A1B) up to as much as 30% for soybean (B1). For the "without CO2" scenarios, price changes range from a marginal change for rapeseed (B1) to as much as 20% for soybean (A1B).

The deviations of price results for the A1B and B1 "with CO2" results range between 2% for rice up to 14% for corn, potato and soybean. However, the CV is highest amongst all crops under all scenarios with up to 39% for soybean under the A1B "without CO2" scenario. This development is due to the very low price elasticity of demand for soybean (-0.001), which makes prices more volatile to any given supply change. For potato in contrast, the high CV can be explained by the fact that potato is a non-tradeable crop in ESIM, meaning that no equalizing trade effects affect its price development.

EU								
	A1B CO2		A1B no CO		B1 CO2		B1 no CO2	
Crop	**△Supply %**	**SD%**	**△Supply %**	**SD%**	**△Supply %**	**SD%**	**△Supply %**	**SD%**
Barley	15	4	8	4	13	2	7	1
Corn	18	7	3	9	14	6	6	7
Wheat	17	5	17	5	15	3	14	3
Othgrain	21	5	13	6	19	5	13	5
Potato	3	2	1	1	3	1	1	1
Rapeseed	17	8	15	9	20	6	16	6
Rice	22	4	11	9	19	2	10	6
Rye	18	6	11	9	19	2	10	6
Soy	-1	14	26	24	-3	9	9	12
Sugar	-1	1	3	2	-1	1	1	1
Sunseed	11	14	-15	17	15	9	-4	13

Table 8.6: Supply change EU in % by 2050 vs. baseline scenario, based on mean of five individual GCM-LPJmL outputs.

Source: Own compilation.

NEU								
	A1B CO2		A1B no CO		B1 CO2		B1 no CO2	
Crop	**△Supply %**	**SD%**	**△Supply %**	**SD%**	**△Supply %**	**SD%**	**△Supply %**	**SD%**
Barley	-4	3	-11	3	-3	2	-8	4
Corn	0	7	-5	6	6	3	-1	3
Wheat	-3	2	-6	2	-2	1	-5	2
Othgrain	0	1	-8	2	0	3	-6	3
Potato	-1	0	0	1	0	0	0	1
Rapeseed	4	3	-5	3	4	3	-3	3
Rice	1	0	-1	1	1	0	-1	1
Rye	-7	4	-13	4	-6	3	-11	4
Soy	2	1	-1	2	2	1	-1	1
Sugar	6	7	-7	7	7	5	-2	4
Sunseed	24	11	-13	10	23	9	-4	10

Table 8.7: Supply change NEU in % by 2050 vs. baseline scenario, based on mean of five individual GCM-LPJmL outputs.

Source: Own compilation.

Crop	A1B CO2 ΔSupply %	SD%	A1B no CO ΔSupply %	SD%	B1 CO2 ΔSupply %	SD%	B1 no CO2 ΔSupply %	SD%
	WO							
Barley	5	1	-3	1	4	1	-2	2
Corn	1	7	-4	6	6	2	0	2
Wheat	0	1	-2	1	0	1	-2	1
Othgrain	4	1	-3	1	4	2	-2	2
Potato	0	1	0	1	1	0	0	1
Rapeseed	7	2	0	2	7	1	2	2
Rice	1	0	-1	1	1	0	-1	1
Rye	5	2	-1	2	6	2	0	3
Soy	2	1	-1	2	2	1	-1	1
Sugar	6	7	-6	7	7	5	-2	4
Sunseed	22	10	-13	9	22	9	-4	9

Table 8.8: Supply change WORLD in % by 2050 vs. baseline scenario, based on mean of five individual GCM-LPJmL outputs.

Source: Own compilation.

Crop	A1B CO2 ΔPrice%	SD%	A1B no CO ΔPrice %	SD%	B1 CO2 ΔPrice %	SD%	B1 no CO2 ΔPrice %	SD%
	WO							
Barley	-15	8	9	15	-15	5	8	7
Corn	-6	14	13	18	-17	7	6	8
Wheat	-13	4	18	17	-13	7	15	9
Othgrain	-13	4	12	14	-15	7	10	8
Potato	-14	14	17	29	-19	11	9	8
Rapseed	-15	3	1	10	-15	3	0	3
Rice	-20	2	13	17	-13	2	17	11
Rye	-19	7	7	15	-20	8	4	10
Soybean	-25	14	20	39	-30	11	20	14
Sugar	-9	8	10	18	-13	7	5	5
Sunseed	-21	9	8	18	-21	8	4	7

Table 8.9: Price changes in % by 2050 vs. baseline scenario based on mean of five individual GCM-LPJmL outputs.

Source: Own compilation.

Comparison of yield shifter variance and supply variance

In a third step, it is exemplarily analysed for the emission scenario A1B "with CO2", to what extent the variance of the productivity shifters ("trend") in the crop yield function in ESIM between the five individual GCM-LPJmL results is transmitted in the variation of crop supply[3]. Therefore, the coefficients of variation of the five individual GCM-LPJmL based crop supply results of ESIM are compared to the CVs of the individual supply function's shifter rates of all crops and countries depicted in ESIM. This procedure is graphically depicted in Figure 8.15.

Comparing the values of the CVs between the shifter rates and the supply changes shows, that their variances are similar. About 60% of the shifter and supply CVs

[3]Text of this section is partly based on Moeller et al.(2011):
"Modelling Climate Change Impacts on European Agriculture: Does the Choice of Global Circulation Model Matter?", accepted at the EAAE 2011 Congress "Change and Uncertainty, Challenges for Agriculture, Food and Natural Resources", August 30 2011, Zurich, Switzerland

Figure 8.15: Graphical depiction of the comparison between the coefficients of variation of shifter rates and crop supply.

Source: Own compilation.

are bigger than 5%.

One would expect that the variation of the shifter rates, and hence their CVs, are bigger than those of the crop supply CVs. This is because input shifters' impact should be smoothed by various equilibrium processes in the model. However, when the crop supply CVs are subtracted from the the shifter rates' CVs, only 49% of result values are equal or smaller than that of the shifter rates. This implies, that the variation for more than 50% of the supply shifter rates is bigger than that of the shifter rates. One explanation for this result is the low demand elasticities in this version of ESIM.

Testing the CVs with the higher standard demand elasticities, shows that 54% of the supply CVs are equal or smaller than that of the shifter rates, implying that the variation of shifter rates based on the five climate models is higher than those of their supply results.

Table 8.10 depicts the average shifter rates and crop supply CVs for the EU, NEU, and the WO for the A1B "with CO2" scenario. An overview of all coefficients of variation for the A1B "with CO2" scenario can be found in Annex F.

Taking a closer look at a more aggregate level, such as the aggregated crop supply indices for each European country, the CVs between the five individual GCM-LPJmL results are lower (Figure 8.16). This is because many effects at the level of indi-

	EU		**NEU**		**WO**	
Crop	sifter	supply	sifter	supply	sifter	supply
Barley	1%	4%	4%	6%	3%	5%
Corn	3%	8%	7%	14%	5%	11%
Wheat	1%	6%	4%	7%	3%	6%
Durum	1%	5%	4%	8%	3%	7%
Othgrain	6%	6%	7%	7%	6%	7%
Potato	4%	2%	7%	1%	5%	1%
Rapseed	9%	10%	17%	6%	13%	8%
Rice	9%	4%	14%	7%	11%	5%
Rye	1%	7%	4%	7%	3%	7%
Soybean	6%	17%	23%	22%	14%	20%
Sugar	7%	1%	12%	8%	9%	5%
Sunseed	4%	17%	8%	19%	6%	18%

Table 8.10: Coefficient of variation of shifter rates and crop supply for selected crops in the EU, NEU and WO for the A1B "with CO2" scenario.

Source: Own compilation.

vidual crops are compensated by opposite effects for other crops, resulting in lower variability in the aggregate. The European average of the supply indices CVs is about 6%, whereas by contrast on country level, the highest CVs are estimated for Hungary with 11% and Denmark and Cyprus both around 10%. In Hungary, the high deviation from the mean stems from the high variance of supply results for the categories corn and sunflower seed (21% and 10%, respectively). In Denmark the relatively high standard deviation of the crop supply indices originate from the high variance between the model results for the categories wheat and barley (16% and 14%, respectively). In Cyprus, in turn, the high variance stems from the category barley with 29%.

Those different projections highlight the source of uncertainty from different climate projections, and underline the necessity of considering a range of climate models in order to be able to provide a comprehensive interpretation of results for climate impact assessments.

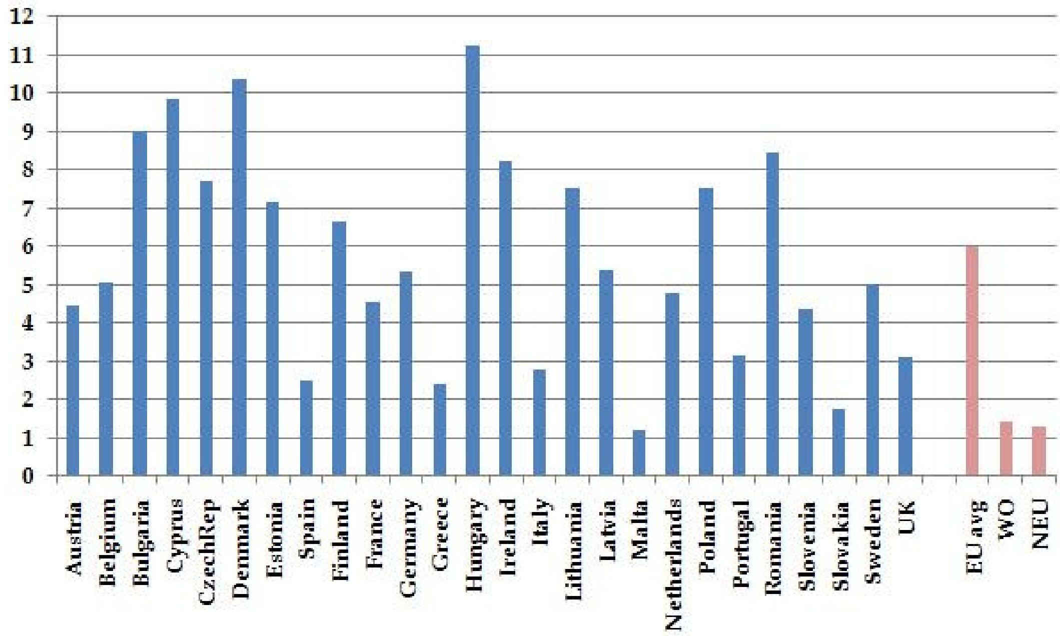


Figure 8.16: Coefficients of variation of crop supply indices by 2050 for all regions depicted in ESIM under the A1B "with CO2" scenario, based on mean of five individual GCMs-LPJmL results.

Source: Own compilation.

9 Summary of Results

The main objective of this study is to assess potential economic effects of climate change on European agricultural markets at the member state level. The future scenarios include socio- as well as economic developments derived from the emission scenarios A1B and B1 (Nakicenovic et al., 2000). Crop productivity changes are based from simulations using the dynamic vegetation model LPJmL (Bondeau et al. 2009; Müller et al. 2009; Waha et al. 2011). Changes of crop yields, production quantity, crop prices and farm crop production values by the year 2050 are modelled with the European Simulation Model (ESIM) (Banse et al., 2005). The results of this thesis indicate that at least up to the year 2050, agricultural productivity in most European countries will be positively affected. For regions outside the EU however, supply declines are projected particularly when the CO2-effect is not taken into consideration.

A closely connected purpose of this study is to consider climate change induced adaptation of farmers to changes in the relative profitability of crops. This is done by shifting area allocation functions based on yield trends and elasticities with respect to yield trends. These elasticities were derived based on yield driven cost changes generated by the farm level model FARMIS (Offermann et al., 2005). The aggregated crop supply and price results with and without the added trend to the area allocation function indicate, that aggregated global crop supply is increased by adding the trend. The world market prices decrease accordingly. Thereby it is shown, that without accounting for farmers' adaptational behaviour regarding relative profitability, results would underestimate production effects of climate change.

In this thesis two approaches to account for the uncertainty inherent in climate impact assessments are presented. First, the mean result of yield changes from the vegetation model LPJmL is used for simulations, which also serve for the introduction of Gaussian Quadratures. Gaussian Quadratures are a convenient and computational time saving way to approximate the distribution of historical error terms when stochasticity is implemented into ESIM. The yield variability is expanded by increasing the historical error terms of the yield function by 20%. This simulation means that the random variation of crop yields will be 20% greater than the historically observed yield variations. Stochastic simulations were exemplaryily solved for the year 2050 under the SRES A1B "with CO2" to demonstrate the effect of a climate change related increase of yield variability by 20%, leading to an increased price variability of 25% for wheat, and even as much as 58% for barley. Given the fact that so far there is no reliable accurate prediction of future climate change induced yield variability, the main focus of this thesis regarding uncertainty, is on the following approach. Therefore, the mean value and standard deviation of five different ESIM outcomes, which are based on five individual climate- and crop model results, are derived. This delivers a distribution of projected results which enables for a more comprehensive interpretation.

The following summary of climate change induced changes of crop yields, supply, world market prices and farm production value, is only presented for the first method, the mean LPJmL outputs. This is because simulation results based on the five individual GCM-LPJmL outputs show a high agreement. For the second method, where ESIM results are based on five individual GCM-LPJmL outputs, only their distributions, as well as a comparison of the coefficients of variation among yield shifter rates and simulated supply results, is provided in the last section of this chapter.

Change in European crop yields by 2050

It is demonstrated, that productivity changes vary substantially by country and crop categories. Comparing model results of projected yields to the baseline scenario without climate change, delivers relative productivity changes of crops caused by climate change impacts. Results indicate that countries in higher latitudes experience crop productivity increases under both emission scenarios, with more pronounced effects under the A1B scenario. When CO2 fertilisation effects are accounted for, average yield increases are strongest for rice (26%), sunflower seed and rye (both 20%). In contrast for the B1 scenario, impacts are more pronounced for the crop categories corn (15%) and rapeseed (20%). Whereas in Europe for most crops effects are positive for both emission and CO2 scenarios, the only crops where yield is declining in the scenarios without CO2-fertilisation effetc is potato (-2% under A1B), soybean (1% under B1), sugar (7% under A1B and 2% under B1) and sunflower seed (12% for A1B and 4% for B1).

Change in European grain yields and world market prices

Average national grain yields within the EU are positive for all countries under the CO2-fertilisation scenario with the exception of Cyprus and Malta where declines of up to 35% are projected. However, productivity increases vary greatly among countries, with particularly strong effects for regions in higher latitudes, such as Denmark, Sweden, Finland and Lithuania. If the CO2 fertilisation effect is not accounted for, the average national grain yields are estimated to decline for some countries with the strongest effect being estimated under A1B for Cyprus (38%). Under the B1 emission scenario without CO2-fertilisation, declines are less pronounced. Also here, Cyprus shows the biggest decline with 13%. For most countries within the EU, however, increases are positive. Highest inclines are estimated for the Netherlands (36%) under A1B.

Whereas aggregated supply effects of grains in the EU is more positive under A1B, the projected aggregated supply changes for regions outside the EU are higher under the B1 scenario. This can be attributed to the CO2-fertilisation effect which is particularly effective for grains, making potential losses due to higher temperatures within the EU smaller. By contrast in aggregted regions outside the EU, effects of higher temperatures under A1B are not compensated by potential benefits of the CFE. This leads to aggregated relative supply changes of grains of 3% under A1B and 4% under B1 with CO2 fertilisation effect, and -2% under A1B and -1% under B1 when fertilisation effects are not accounted for. This indicates that under the A1B scenario, agroclimatic conditions within the EU are more favourable for grain productivity under A1B, as compared to regions outside the EU, were projected effects are more positive under the B1 scenario.

Quantity weighted grain prices change as follows. Global supply increases under both CO2-fertilisation scenarios, lead to price declines of around 17%, whereas global supply declines under the no fertilisation effect scenarios increase by 20% (A1B) and 9% (B1).

Change in European oilseed yields and world market prices

Similar to the climate change induced developments of grains, aggregated supply changes for oilseeds are positive for the EU for all scenarios with smaller increases for the no CO2-fertilisation scenarios. However, in contrast to the simulation results of the grain sector described above, for the EU increases are stronger under the B1 scenario. For regions outside the EU, in turn, effects are slightly more positive under the A1B "with CO2" scenario. The aggregated global supply increases in the WO of 4.1% under A1B and 4.4% under the B1 CO_2-fertilization scenario, cause world market prices for oilseeds to decline by 25% and 30%, respectively. For regions outside the EU without the fertilisation effect, supply changes are negative, with a more pronounced decline of 3% under A1B as compared to 1% under B1. This leads to aggregated global effects of -2% for the A1B and -1% for the B1 scenario. This global supply reductions lead to relative price increases of 23% and 14%, respectively. Within the oilseed sector, supply reductions are most severe under A1B when CO2-fertilisation is not considered for sunflower seed, with a global decline of about 16%. In contrast, on a global level, soybean supply reductions are estimated to decline by only 1%.

Under the A1B with CO2-fertilisation effect scenario, yield changes of oilseeds vary as much as declining from 21% in Ireland, up to increases of 51% for Portugal. For most countries, however, yield increases between 9% and 25% can be observed. For the B1 scenario, except Ireland (-17%)and the UK (-2%), yield changes are positive ranging from 1% to 39% as compared to the baseline scenario without climate change. For the scenarios without CO2-fertilisation, more countries show oilseed yield reductions within a range of 2% for Spain and 26% for Ireland. Declines are also more pronounced for the A1B than the B1 scenario. Increases range from 2% in Slovenia to 28% in Poland.

Change in global crop supply and world market prices

Aggregated global crop supply changes are positive for for all crops with CO2-fertilisation under both emission scenarios. However, there is a huge disparity between the level of increases among the different crops, ranging from as little as 0.5% for wheat to as much as 22% for sunflower seed under B1. For most crops increases are more pronounced under the A1B scenario as compared to B1. This can be related to stronger CO2 fertilization effect, since atmospheric CO2 concentration under A1B is higher than under B1. Likewise under the scenarios without climate change, supply decreases are stronger under A1B which is due to higher temperatures as compared to B1. Potential productivity declines are not outweighed by positive CO2 fertilization effects. Declines range from 1% for soybean to 16% for sunflower seed. Potato and rapeseed are the only crops for which supply increases are estimated under both scenarios.

World market prices by 2050 develop accordingly. The supply increases under both CO2-fertilisation scenarios lead to relative world market price declines of up to 32% for soybean (B1). Relative supply declines when CO2-fertilisation is not accounted for, lead to world market price increases for most crops, with biggest inclines of 26% for rice and soybean (A1B).

Change in farm production value of crops

Due to changing crop supply and prices, the production value of crops is also changing depending on quantity and price developments. Results indicate that despite declining productivity of the agricultural sector under the no CO2-fertilisation scenarios, farm production value of crops are positive due to relative increases of world market prices. Particularly for Europe such developments are as high as 24% (A1B) and 14% (B1) as compared to the no climate change scenario as crop production in Europe is, at least up to 2050, more positively affected by climate impacts as aggregated regions outside the EU. In non European regions the farm production value is in turn projected to increase only by 18% and 9% under A1B and B1 scenarios when CO2-fertilisation is not accounted for. In regions outside the EU declines for the CO2-fertilisation effect scenarios are as much as 17% under A1B and 18% under B1. Those results indicate, despite increasing productivity, farm production values are actually decreasing due to relative price declines. However, effects are more positive for the EU with -8% under A1B and -7% under B1.

Distribution of results based on five individual GCM-LPJmL-outputs

The mean value and standard deviation of five different ESIM outcomes which are based on five individual climate- and crop model results, is analysed in order to account for uncertainty by considering a wide range of potential future climate scenarios. Mean values were than compared to the baseline scenario without climate change, and standard deviation is depicted in percentage change of the mean value (CV).

Under the A1B CO2-fertilisation scenario in the EU, comparatively high CVs of 8% for rapeseed, and 14% for soybean and sunflower seed are simulated. CVs are particularly high for the A1B and B1 scenario without CO2-fertilisation scenario, ranging from 1% for potato and sugar to as much as 24% for soybean. Also in regions outside the EU the CVs are highest for corn with up to 7% and 14% for sunflower seed (both under A1B with CO2-fertilisation). In the aggregated world, the standard deviations are similar to the once in non European regions with sunflower seed and sugar being the most amplified. Higher CVs indicate that the five GCM-LPJmL outputs disagree more for those crops.

The CVs of price results for the A1B and B1 CO2-fertilisation effetc scenarios range between 2% for rice up to 14% for corn, potato and soybean. However, the

CV is highest amongst all crops and scenarios for soybean with up to 39% under the A1B with CO2-fertilisation scenario. This develoment can be explanation by the very low price elasticity of demand for soybean, which makes prices more volatile to any given supply change.

Finally, it is exemplarily analysed to what extent the variance of the climate change shifters in the crop yield function in ESIM between the five individual GCM-LPJmL results is transmitted in the variation of crop supply. Therefore, the CVs of the five individual GCM-LPJmL crop supply results is compared to the CVs of the individual shifter rates of all crops of all countries and regions depicted in ESIM. Comparing the values of the CVs between the shifter rates and the supply changes shows, that their variances are similar. About 60% of the shifter and supply CVs are above 5%. By subtracting the values of the crop supply CVs from values of the shifter rates' CVs shows that only 49% are equal or smaller than that of the shifter rates. Although one would expect that the impact of input shifters is smoothed by various equilibrium processes in the model, the results show a different outcome. This is due to the low price elasticities of demand in the model.

Taking a closer look at a more aggregate level, such as the aggregated crop supply index for each European country, the CVs between the five individual GCM-LPJmL results is less pronounced. This is because many effects at the level of individual crops are compensated by opposite effects for other crops, resulting in lower variability in the aggregate.

The degree of variation among the five individual ESIM results, highlight the source of uncertainty from different climate projections and it is shown that it s necessary to consider a range of climate models projections, in order to be able to assert the potential range of results for climate impact assessments.

Comparison of results with other studies

Comparing the results of different climate change studies assessing impacts on agricultural markets is not straight forward due to different aggregation of regions, crop categories, different projection horizons and certainly diverging scenario assumptions. Comparing yield changes of the present study by 2050 under the B1 HadCM scenario with Parry et al. (2004), as described in Chapter 6.3.1, shows, that simulation results for the aggregated crops wheat, rice and soybean in Western Europe[1] are much more positive as compared to study results in Parry et al. (2004). When CO2 fertilization is considered, an increase of 15 % as compared to the scenario

[1]Excluding results of the new member states in ESIM.

without climate change is predicted. Also when CO2 fertilization is not accounted for, yield changes for Western Europe are still positive with 7%. By contrast, for the same emission and climate scenario (B1 and HadCM), Parry et al. (2004) project an increase by only 5% for the CO2 scenario, and a decline by 2.5% when CO2 is not accounted for. Since simulation results for yields of the present study incorporate economic adjustments, whereas yield change results of Parry et al. (2004) are estimated with yield transfer functions derived from crop simulation models, the comparison is not unproblematic. However, the general conclusion that especially countries in higher latitudes tend to experience crop productivity increases, are equal for both studies.

Iglesias et al. (2009) project climate change impacts on European yields by 2020 and 2080, with underlying emission scenarios (A2 and B2). Hence, the differing assumptions from the present study, makes a direct comparison even more difficult. Additionally, their estimates are not on country level, but are provided in nine aggregated agro-climatic zones for Europe. Further, results provided in the study are only for yield change aggregates including the crops winter wheat, spring wheat, rice, grassland, maize and soybean. As described in Chapter 3.6.1, those yield changes are not the results from an agricultural market model, but are direct results of crop models and derived production functions not including any economic adjustments e.g regarding responses to changing prices. Yet, they draw the similar conclusion regarding directions of productivity changes for Northern and Southern Europe.

Comparing results for global production changes by 2050 derived by Nelson et al. (2009a), the mean changes for the crops rice, wheat and corn under the A2 emission forcing "without CO2" for the climate projections CSIRO and NCAR are -12% (rice), -25% (wheat) and -0.1% (corn), as compared to the scenario without climate change. Global production changes for the same crops of the present study by contrast, based on the mean GCM-LPJmL outputs under the A1B scenario, delivers quite differing results. Simulated global changes by 2050 are -1% (rice), -2% (wheat) and -3% (corn). However, one has to keep in mind that the underlying climate predictions are based on different GCMs, and different emission scenarios are assumed. Since for both emission scenarios, the atmospheric CO2 concentration and predicted increase of surface temperature by 2050 do not differ to a great extend, the variation of results for the three crops considered might be due to different climate projections and the different crop growth models used for each study.

Ambiguous developments of world market prices for the above considered crops, act accordingly. Whereas Nelson et al. (2009a) predict mean price changes for rice of +35% by 2050 under A2, as compared to the no climate change scenario, the present study projects a price increase for rice under A1B of 26%. Also for soybean, a difference of 10 percentage points lies between both predicted changes (13% by Nelson et al. (2009a) as compared to 26% by the present study). Corn price developments vary more, with an increase of 54% by Nelson et al. (2009a) and 16% by the present study. Biggest difference, however, is for the category wheat, were Nelson et al. (2009a) predict a high price increase of 103% as compared to 23% by the underlying work. Price result changes of different studies depend, amongst others, on the different structure and driving parameters of the market models. Parameters such as demand elasticities influence economic effects profoundly, but due to missing data availability, it is hardly possible to draw conclusions on the differing modelling results.

The above presented comparison of climate impact studies on agricultural markets clearly show that variations in variable results, such as yield, are unavoidable unless the input data are based on the same assumptions and modelling framework. Impacts are different in terms of regions, impact sectors as well as social-economic and climate scenarios, which makes it difficult to form a consistent picture of global climate change impacts. Yet, it is necessary to include all study results in the discussion on climate change impacts, since non of the studies is likely to be more realistic than others. They each have a different focus, whether regarding crops or regions, and they have advantages inherent in their particular modelling approach. Since non of the climate or emission scenarios are more likely to occur, the presented results open a wide corridor of interpretation. Ideally, it should be tried to compare studies using similar inputs assumptions to build an adequate evidence base for formulating adaptation and mitigation strategies.

10 Conclusion

Modelling economic effects of climate change on agricultural markets is not a straight forward task and involves climate forecasts, crop responses and finally economically adjusted impacts derived with market models. This inheres a huge range of uncertainty, increasing from emission paths to climate change, from climate change to possible impacts and finally to formulating adequate adaptation and mitigation measures and policies (Iglesias et al., 2009).

Regarding the underlying uncertainty, it is important to consider different social and economic developments and involve them in the modelling systems, since they do not only impact future emission scenarios, but also have implications for future adaptive capacity of a society. The present work covers the two emission paths of the A1B and B1 scenarios and thus takes different social and economic developments into account. However, as they can be classified as rather moderate scenarios regarding their future CO2 concentration, modelling impacts for fossil fuel intensive scenarios, such as the A1F1 emission scenario, would deliver less positive impacts due to higher surface temperature developments. With regards to the CO2-fertilisation effect, this study indicates that, for most GCM scenarios, the direction of the technological progress shifters tend to develop in opposite directions for the "with CO2" and "without CO2" scenarios. This emphasises the fundamental disparities of results under varying CO2-fertilisation effect assumptions. Generally, most model runs are uniform in indicating increases in aggregated crop productivity by 2050 under both emission scenarios when the CO2 effect is considered. On the contrary, when the CO2 fertilization effect is not accounted for, results of the different GCMs are not as uniform in their direction as under the "with CO2" scenarios. This disparity highlights additionally the uncertainty around the CO2-fertilization effect. Further research has to be undertaken about its actual impact, as productivity outcomes highly vary depending on underlying fertilisation-effect assumptions. Yet, until today there is ambiguity in science about its dimension and this has to be kept in mind when evaluating climate change impacts on agricultural markets. This gives also reason to assume, that the optimistic assumption of a full CO2-fertilization effect in this study leads to overestimated productivity increases. Also, more research needs to be done about the potential impacts of climate change on pests and diseases which will certainly impact future productivity of crops. From this point of view, the simulation results of this study probably understate potential losses, since neither the climate, crop, nor the market model in this study, explicitly deal with increased damage from pests or more frequent and severe extreme weather events. Impacts by the middle of this century could thus easily involve more damage than actually projected.

Another important issue is the change in land use and the shift of suitable agricultural area due to changing agro-climatic conditions. In this study, within the crop model, area allocation is kept constant over the projection horizon and also area allocation in the market model is a) only modelled for the EU, and b) constrained to a certain amount. Thus, simulated losses particularly outside the EU could be much larger. The aggregated global impacts simulated in this work might be benign under the CO2 effect scenarios, but it would be a mistake to conclude from this analysis that little should be done to curb climate change. This is especially given the fact that this modelling approach takes a snapshot of time at the year 2050, yet impacts can certainly be expected to continue. Beyond 2050 agroclimatic conditions will worsen and thus reduce global crop productivity to a greater degree by then.

Further, it is shown in this study, that incorporating adaptation in the assessment has substantial effects on the modelling results, highlighting the importance of including adaptation in climate change impact studies. Adaptation refers to all those responses to climate change that may be used to reduce vulnerability or to actions designed to take advantage of new opportunities that may arise as a result of climate change (Burton, 2005). While most adaptation to climate change is characterised by responses at the farm level, implemented policies have the capability to encourage the speed and extent of adoption (Iglesias et al., 2009). Therefore, it can be concluded that policy makers should focus on fostering measures for an adequate adaptation. This should include increasing research efforts for improved and adapted crop varieties in line with the changing agroclimatic conditions, or provide incentive for alternative farm management practices. This is particularly important for most developing countries, especially in lower latitudes, where temperatures are already very high. Considering that agriculture accounts for a bigger fraction of their economy, and their ability for adaptation regarding resources and technology is limited, climate change is likely to cause greater damage.

Another important issue is the effect of extreme events. There is little agreement among models as to whether variability will increase or decrease, indicating the need for further research in this area. Since extreme events are considered to be a major cause of yield variability, one needs to know to which extent extreme weather events are likely to occur in the future. As described above, there are no unambiguous assumptions. Stochastic simulation modelling is capable of capturing the uncertainty attached to variables, such as yields. However, most studies miss to consider climate change as causing changes in the distribution of random variables (Schimmelpfennig, 1990). This thesis closes that gap, by implementing stochasticity in the market model, for the A1B "with CO2" scenario, with an assumed increase of the historical error terms of 20%. However, more research needs to be undertaken in order to be able to predict extreme events more accurately. According to Moriondo et al. (2011), if the role of extreme events is neglected in future impact assessments, the potential impact of a warmer climate on yield losses could be underestimated and hence also lead to inappropriately applied adaptation measures. This emphasizes the necessity to further investigate the potential increase of extreme weather events and implement adequate mitigation measures in order to minimize future damages. Further, examining the results based on five individual climate projections in this work shows that projections from a suite of alternative climate forecasts need to be considered in order to cover a range of possible climate scenarios.

Regarding the adjustments of economic models over a projection horizon of 50 years poses several challenges. As described in Chapter 4.3.1., price and income elasticities of demand have to be in line with population and economic developments. A number of forces in the developing and the developed countries are driving changes in global food consumption patterns, with income growth being one of the most important (Seale and Regmi, 2006). Despite the fact, that making accurate assumptions on future demand elasticities is a difficult task, it is important to include future consumer responsiveness to changes in food prices and income into economic models. In this study, demand elasticities are multiplied by 0.5 since global income growth by 2050 is based on rather optimistic assumptions, and hence, price developments for certain crops might be overstated. Since estimation of demand elasticities for such a long projection horizon is scarce in literature, further research is needed in order to evaluate climate change induced price developments and their impact on global demand of agricultural products.

Another important issue is the inclusion of future global demand for biofuels in the year 2050 and its underlying processing technology. Which technology will be used for converting biomass and particularly which crops will be processed will also have major implications for agricultural markets. Biofuel consumption is calibrated to maintain a share of 10% in total transportation fuels in the European Union. For the aggregated world, the consumption share is calibrated to 4% in 2050. This assumption was based on extensive literature review, but one has to keep in mind that especially with regards to biofuel production, the model in this study is based on current technologies. Therefore, the resulting area use for biofuel production is likely to allow for higher shares in total fuel consumption in 2050 as new technologies would allow for higher yields.

For this thesis, it is assumed that global agricultural markets are fully liberalized and no policies, such as tariffs or quotas, are implemented. Agricultural trade flows depend on the interaction between comparative advantage in agriculture, determined by climate and resource endowments, and a wide range of local, regional, national and international trade policies (Nelson et al., 2009b). Since climate change leads to alterations in agro-climatic conditions, agricultural comparative advantage also changes. This will in turn lead to changes in trade flows as producers respond to potential arising constraints and opportunities. According to Nelson et al. (2009b), liberal international trade allows comparative advantage to be more fully exploited. Thus, assuming restrictions on trade in climate impact modelling would worsen the simulated effects of climate change by reducing the ability of producers and consumers to adjust.

Over the past two decades, a variety of literature on the economics of climate change impacts on agricultural markets has evolved. However, due to the underlying assumptions such as the different implemented emission and climate scenarios, their results are difficult to compare. Nevertheless, one gets a good idea of potential future impacts of climate change, and even though countries in northern latitudes will tend to benefit over the next four decades, this does not mean one can neglect measures to adapt and mitigate to the changing climate.

In the light of the additional challenges European and global agricultural markets are to face in the coming decades, such as competition for water and soil resources, growing population and urbanity, it is essential to improve the understanding of climate change and its potential effects. It is also crucial to quantify the potential damages and benefits that may arise from climate change regionally, as well as globally, since the assessments will affect domestic and international policies, trading patterns, resource use, regional planning , and the welfare of its people (Tubiello, 2007).

Climate change effects are already, and certainly will in the long run, impact policy making substantially. The more accurate estimates of future climate change impacts are, the better is the chance to mitigate and adapt to future threats or take advantage of possible benefits.

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Appendix A

Groupings of countries and adjusted macro shifter in ESIM

WHEAT	BARLEY	RAPESEED	Deterministic		
			Wheat	**Barley**	**Rapeseed**
Germany	Germany	Germany	Cyprus	Cyprus	Cyprus
France	France	France	Malta	Malta	Malta
UK Ireland	UK Ireland	UK Ireland	Slovenia	Slovenia	Slovenia
Spain Portugal	Spain Portugal	Poland	Baltic States	Baltic States	Baltic States
Italy	Denmark Sweden	Cz.Republic Slovakia			Belgium
Poland	Poland	Denmark Sweden Finland			Luxembourg
Cz.Republic Slovakia	Cz.Republic Slovakia	Hungary			Netherlands
Romania Bulgaria	Romania Bulgaria	Austria			Spain
Hungary	Finland	ROW			Portugal
Denmark Sweden Finland	Austria			Italy	
Greece	Hungary				Romania
Netherlands Belgium Luxembourg	Italy				Bulgaria
Austria	Netherlands Belgium Luxembourg				Greece
Turkey	Greece				Turkey
US	Turkey				US
ROW	US				
	ROW				

Table 1: Groupings of countries with identical stochastic term in yield function of wheat, barley and rapeseed.

	Population	GDP /A1B	GDP /B1
Austria	-0.23	1.71	1.91
Belgium	-0.3	1.71	1.91
Bulgaria	-0.88	3.78	5.46
Cyprus	0.42	3.78	1.91
CzechRep	-0.15	5	5.46
Denmark	0.07	1.71	1.91
Estonia	-0.86	3.78	5.46
Finland	-0.01	1.71	1.91
France	0.27	1.71	1.91
Germany	-0.08	1.71	1.91
Greece	-0.14	1.71	1.91
Hungary	-0.32	5	5.46
Ireland	0.82	1.71	1.91
Italy	-0.38	1.71	1.91
Latvia	-0.28	1.71	5.46
Lithuania	-0.05	5	5.46
Malta	0.22	3.78	1.91
Netherlands	0.16	1.71	1.91
Poland	-0.06	3.78	5.46
Portugal	-0.05	1.71	1.91
Romania	-0.21	5.12	5.46
Slovakia	-0.08	3.78	5.46
Slovenia	-0.26	3.78	5.46
Spain	-0.29	1.71	1.91
Sweden	-0.04	1.71	1.91
UK	0.17	1.71	1.91
Turkey	0.86	4.98	1.91
US	0.63	2.15	1.5
ROW	0.78	5.09	4.98

Table 2: Annual growth rates of the macro shifters population and GDP in ESIM, based on IPCC projections by 2050.

Appendix B

Rates of technical progress for different groups of agricultural products and regions for all emission scenarios and GCM-LPJmL outputs

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.22	0.90	0.40	0.22	0.80	0.30	1.73	0.80	0.20	0.80	0.22	0.22	1.20	0.22	1.73
BARLEY	0.24	1.40	0.24	0.24	0.40	1.00	1.94	0.50	0.60	0.80	0.24	0.30	1.10	0.24	1.94
CORN	1.90	2.30	2.00	1.98	2.50	1.98	1.98	1.98	0.60	1.30	0.49	2.50	1.98	0.49	1.98
RYE	0.28	2.27	1.20	1.13	1.60	0.50	2.27	0.28	1.10	0.30	0.60	1.20	1.13	0.60	2.27
OTHGRA	0.27	1.30	1.06	1.06	0.27	1.06	0.90	0.27	0.27	0.30	1.70	1.06	1.06	1.06	1.30
RICE	1.20	1.20	2.40	1.20	1.20	1.20	1.20	1.20	0.70	0.30	0.30	2.30	1.20	0.90	1.20
SUGAR	1.60	1.99	2.50	1.99	2.50	1.60	1.99	1.70	1.30	1.40	0.50	1.99	1.90	0.70	2.50
POTATO	1.80	0.33	2.50	1.90	2.20	0.70	0.70	1.20	1.70	1.40	0.33	2.50	2.00	0.70	0.40
SOYBEAN	1.70	1.96	2.50	1.96	2.50	1.96	1.96	1.96	0.70	1.96	0.49	1.10	1.96	0.49	1.96
RAPSEED	1.10	2.00	2.50	1.85	1.50	2.50	2.50	0.00	0.60	2.20	1.85	2.50	1.90	0.46	2.50
SUNSEED	0.40	1.17	1.50	1.17	0.80	1.17	1.17	1.17	0.90	0.29	0.70	2.30	1.17	0.29	1.17
SMAIZE	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	0.70	1.81	1.81	2.50	1.81	1.81	1.81

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	1.73	1.73	0.22	1.20	0.22	0.22	0.22	0.40	1.73	0.40	0.40	0.71	0.60	1.00	1.00
BARLEY	1.94	1.94	0.24	1.00	1.50	0.24	0.10	0.90	2.30	0.90	0.30	0.87	0.40	1.20	0.50
CORN	1.98	1.98	2.50	1.90	2.40	0.80	0.50	2.10	2.50	1.98	1.98	1.79	1.80	2.50	1.90
RYE	1.90	1.13	0.28	0.40	1.10	2.00	0.28	0.70	1.94	1.10	1.20	1.14	0.28	1.80	0.60
OTHGRA	0.27	1.06	1.06	0.50	1.06	1.06	1.06	2.12	2.12	1.40	0.30	0.96	1.06	0.27	0.27
RICE	1.20	1.20	1.20	1.20	0.50	0.30	1.20	1.20	0.80	1.20	1.20	1.11	1.60	2.40	1.00
SUGAR	2.50	0.50	0.60	2.40	2.50	2.50	2.50	1.99	2.50	1.00	1.10	1.78	1.60	1.50	2.00
POTATO	0.33	0.33	0.10	1.00	0.33	0.90	1.00	2.50	2.50	0.33	0.33	1.15	1.40	1.20	1.30
SOYBEAN	1.96	1.96	1.96	1.96	1.96	2.50	0.50	2.50	2.10	1.96	1.96	1.79	0.90	2.50	1.70
RAPSEED	1.00	1.85	0.46	2.50	1.85	2.50	0.60	0.46	2.50	1.90	0.90	1.63	0.50	2.50	1.90
SUNSEED	1.17	1.17	1.17	1.17	2.34	0.29	1.60	1.90	2.30	1.17	1.17	1.19	0.50	1.20	0.60
SMAIZE	1.81	1.81	1.81	2.50	1.81	1.81	0.45	1.81	1.81	1.81	1.81	1.77	1.30	1.81	0.90

Table 3: Rates of technical progress for different groups of agricultural products and regions baseline scenario "No CC".

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.5	1.2	0.6	-0.7	1.3	1.0	2.2	1.4	0.5	1.2	0.5	0.5	1.6	0.5	2.3
BARLEY	0.5	1.7	0.5	-0.7	0.9	1.7	2.4	1.1	0.9	1.2	0.5	0.6	1.5	0.5	2.6
RYE	0.5	2.6	1.4	0.2	2.1	1.2	2.7	0.8	1.4	0.7	0.9	1.5	1.5	0.8	2.9
OTHGRA	0.5	1.6	1.3	0.1	0.8	1.8	1.4	0.8	0.6	0.7	2.0	1.3	1.5	1.3	1.9
CORN	2.6	3.3	1.9	2.0	3.8	4.5	4.3	4.9	0.8	2.5	0.5	2.6	2.0	0.6	3.4
SMAIZE	2.6	2.8	1.8	1.8	3.1	4.3	4.1	4.7	0.9	3.0	1.8	2.6	1.8	2.0	3.3
RICE	1.2	1.2	3.0	1.2	1.2	1.2	1.2	1.2	1.6	0.3	0.5	3.2	1.2	1.3	1.2
SUGAR	1.8	2.3	2.6	2.0	3.0	2.4	2.0	4.2	1.4	1.8	0.7	2.0	2.5	1.0	3.4
POTATO	2.0	0.6	2.6	1.9	2.7	1.5	0.7	3.7	1.8	1.8	0.5	2.5	2.6	1.0	1.3
SOYBEAN	2.9	2.0	2.2	2.0	3.7	2.0	2.0	2.0	1.0	2.0	0.5	1.3	2.0	0.9	5.0
RAPSEED	1.4	2.3	2.5	1.9	2.2	3.0	2.9	0.4	0.7	2.7	1.9	2.5	1.4	0.7	2.9
SUNSEED	0.9	3.3	1.8	1.2	1.7	1.2	1.2	1.2	1.6	1.2	1.4	2.7	1.2	1.1	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.5	1.7	0.6	1.8	0.4	0.6	0.6	0.6	2.0	1.0	0.8	1.0	1.1	1.3	1.0
BARLEY	2.7	1.9	0.6	1.6	1.6	0.6	0.5	1.1	2.5	1.5	0.7	1.2	0.9	1.5	0.5
RYE	2.7	1.1	0.7	1.0	1.2	2.3	0.7	0.9	2.2	1.7	1.6	1.4	0.7	2.1	0.6
OTHGRA	1.0	1.1	1.5	1.1	1.2	1.4	1.4	2.3	2.4	2.0	0.7	1.3	1.5	0.6	0.2
CORN	3.8	2.0	4.2	3.5	2.4	0.8	1.0	2.3	2.6	2.0	4.4	2.6	1.9	2.7	2.0
SMAIZE	3.6	1.8	3.5	4.1	1.8	1.8	0.9	2.0	2.0	1.8	4.2	2.7	1.4	2.0	1.0
RICE	1.2	1.2	1.2	1.2	1.4	0.4	1.2	1.2	1.8	1.2	1.2	1.3	2.0	3.0	1.2
SUGAR	3.2	0.5	1.1	2.8	2.6	2.5	2.7	2.2	2.8	1.9	1.7	2.1	1.7	1.6	2.2
POTATO	1.1	0.3	0.6	1.4	0.5	0.9	1.2	2.7	2.8	1.2	0.9	1.5	1.5	1.3	1.5
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.6	1.9	2.5	2.3	2.0	2.0	2.0	1.2	3.7	2.1
RAPSEED	1.4	1.9	0.4	3.2	1.9	2.6	1.2	0.5	2.7	2.4	0.7	1.8	1.9	2.5	2.1
SUNSEED	1.2	1.2	1.2	1.8	3.4	0.7	2.2	2.4	3.1	1.2	1.2	1.6	0.8	1.9	1.2

Table 4: Rates of technical progress for different groups of agricultural products and regions A1B with CO2 effect (GCM-LPJmL mean).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.2	0.9	0.3	-0.9	1.0	0.7	2.0	1.0	0.2	0.9	0.2	0.2	1.4	0.2	2.1
BARLEY	0.2	1.4	0.2	-0.9	0.6	1.4	2.2	0.7	0.6	0.9	0.2	0.3	1.3	0.2	2.3
RYE	0.3	2.3	1.1	0.0	1.8	0.9	2.5	0.5	1.1	0.4	0.6	1.2	1.3	0.6	2.6
OTHGRA	0.2	1.3	1.0	-0.1	0.5	1.5	1.1	0.5	0.3	0.4	1.7	1.0	1.2	1.1	1.6
CORN	2.2	2.9	1.2	2.0	3.4	4.3	4.1	4.7	0.5	2.2	0.4	1.8	2.0	0.5	3.2
SMAIZE	2.2	2.5	1.0	1.8	2.7	4.2	3.9	4.5	0.6	2.7	1.7	1.8	1.8	1.8	3.0
RICE	1.2	1.2	2.4	1.2	1.2	1.2	1.2	1.2	1.1	0.3	-0.1	2.7	1.2	0.8	1.2
SUGAR	1.3	1.7	2.1	2.0	2.5	1.9	2.0	3.8	0.7	1.3	0.3	1.1	2.1	0.4	3.0
POTATO	1.5	0.1	2.1	1.9	2.2	1.0	0.7	3.3	1.1	1.3	0.1	1.6	2.2	0.4	0.9
SOYBEAN	2.4	2.0	2.4	2.0	3.7	2.0	2.0	2.0	1.0	2.0	0.5	0.5	2.0	0.3	5.1
RAPSEED	1.2	2.1	2.3	1.9	2.0	2.7	2.7	0.2	0.5	2.5	1.9	2.3	1.2	0.5	2.7
SUNSEED	0.2	2.7	1.1	1.2	1.2	1.2	1.2	1.2	0.2	0.6	0.2	2.0	1.2	-0.1	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.2	1.7	0.4	1.5	0.1	0.2	0.3	0.4	1.7	0.8	0.5	0.8	0.8	1.0	0.7
BARLEY	2.4	1.9	0.4	1.3	1.3	0.2	0.2	0.9	2.3	1.3	0.4	0.9	0.6	1.2	0.2
RYE	2.4	1.1	0.5	0.7	0.9	2.0	0.4	0.7	1.9	1.5	1.3	1.1	0.4	1.8	0.3
OTHGRA	0.7	1.1	1.3	0.8	0.9	1.0	1.2	2.1	2.1	1.8	0.4	1.0	1.2	0.3	-0.1
CORN	3.6	2.0	4.1	3.4	2.4	0.2	0.9	2.0	2.5	2.0	4.3	2.4	1.5	2.4	1.9
SMAIZE	3.4	1.8	3.4	4.0	1.8	1.2	0.9	1.7	1.8	1.8	4.2	2.5	1.0	1.7	0.9
RICE	1.2	1.2	1.2	1.2	1.0	-0.1	1.2	1.2	1.2	1.2	1.2	1.1	1.0	2.4	0.8
SUGAR	2.8	0.5	0.6	2.5	2.4	1.6	2.3	1.6	2.4	1.5	1.2	1.7	1.1	1.3	1.8
POTATO	0.7	0.3	0.1	1.1	0.2	0.0	0.8	2.1	2.4	0.9	0.4	1.1	0.9	1.0	1.1
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.9	1.3	2.5	2.4	2.0	2.0	2.0	0.4	2.7	1.6
RAPSEED	1.2	1.9	0.3	3.0	1.9	2.3	0.9	0.2	2.5	2.1	0.6	1.6	1.6	2.5	1.8
SUNSEED	1.2	1.2	1.2	1.1	2.4	-0.3	1.3	1.4	2.2	1.2	1.2	1.1	0.3	0.9	0.1

Table 5: Rates of technical progress for different groups of agricultural products and regions A1B without CO2 effect (GCM-LPJmL mean).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.5	1.2	0.6	0.0	1.3	0.8	2.1	1.3	0.5	1.1	0.4	0.5	1.4	0.4	2.3
BARLEY	0.5	1.7	0.4	0.0	0.9	1.5	2.3	1.0	0.9	1.1	0.4	0.5	1.3	0.4	2.6
RYE	0.5	2.6	1.4	0.9	2.1	1.0	2.6	0.8	1.4	0.6	0.8	1.4	1.4	0.8	2.9
OTHGRA	0.5	1.6	1.3	0.8	0.8	1.6	1.3	0.7	0.5	0.6	1.9	1.3	1.3	1.3	1.9
CORN	2.5	3.0	2.3	2.0	3.4	4.1	4.3	5.1	0.8	2.3	0.6	2.9	2.0	0.6	3.4
SMAIZE	2.4	2.5	2.1	1.8	2.7	3.9	4.1	4.9	0.9	2.8	1.9	2.9	1.8	2.0	3.2
RICE	1.2	1.2	2.9	1.2	1.2	1.2	1.2	1.2	1.4	0.3	0.6	3.0	1.2	1.2	1.2
SUGAR	1.9	2.2	2.7	2.0	2.9	2.3	2.0	4.2	1.4	1.8	0.7	2.4	2.3	1.0	3.4
POTATO	2.1	0.5	2.7	1.9	2.6	1.4	0.7	3.7	1.8	1.8	0.5	2.9	2.4	1.0	1.3
SOYBEAN	2.7	2.0	2.6	2.0	3.4	2.0	2.0	2.0	1.0	2.0	0.5	1.6	2.0	0.9	5.1
RAPSEED	1.4	2.5	2.6	1.9	2.2	2.9	2.8	0.4	0.8	2.8	1.9	2.5	1.5	0.7	2.8
SUNSEED	1.0	3.0	2.0	1.2	1.6	1.2	1.2	1.2	1.2	1.0	1.3	2.8	1.2	1.1	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.6	1.7	0.6	1.8	0.3	0.5	0.6	0.6	1.9	0.9	0.7	1.0	1.0	1.2	1.0
BARLEY	2.8	1.9	0.6	1.6	1.6	0.5	0.5	1.1	2.5	1.4	0.6	1.2	0.8	1.4	0.5
RYE	2.8	1.1	0.6	1.0	1.2	2.3	0.7	0.9	2.1	1.6	1.5	1.4	0.7	2.0	0.6
OTHGRA	1.2	1.1	1.4	1.1	1.1	1.3	1.4	2.3	2.3	1.9	0.6	1.2	1.4	0.5	0.3
CORN	3.3	2.0	3.9	3.0	2.4	1.1	0.8	2.3	2.6	2.0	3.8	2.5	2.0	2.7	2.0
SMAIZE	3.1	1.8	3.3	3.6	1.8	2.1	0.7	2.0	1.9	1.8	3.6	2.6	1.5	2.0	1.0
RICE	1.2	1.2	1.2	1.2	1.2	0.5	1.2	1.2	1.6	1.2	1.2	1.2	2.0	3.0	1.2
SUGAR	3.2	0.5	1.0	2.8	2.6	2.8	2.7	2.3	2.7	1.8	1.5	2.1	1.9	1.6	2.3
POTATO	1.1	0.3	0.5	1.4	0.4	1.2	1.2	2.8	2.7	1.2	0.7	1.5	1.7	1.3	1.6
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.8	1.5	3.0	2.3	2.0	2.0	2.0	1.3	3.6	2.2
RAPSEED	1.3	1.9	0.6	3.3	1.9	2.6	1.2	0.5	2.7	2.2	0.9	1.8	1.6	2.5	2.1
SUNSEED	1.2	1.2	1.2	1.6	3.2	0.9	2.4	2.6	3.0	1.2	1.2	1.6	0.9	1.8	1.2

Table 6: Rates of technical progress for different groups of agricultural products and regions B1 with CO2 effect (GCM-LPJmL mean).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.2	1.0	0.4	-0.2	1.1	0.6	1.9	1.0	0.2	0.9	0.2	0.2	1.2	0.2	2.1
BARLEY	0.3	1.5	0.2	-0.1	0.7	1.3	2.1	0.7	0.6	0.9	0.2	0.3	1.1	0.2	2.3
RYE	0.3	2.3	1.2	0.7	1.9	0.8	2.4	0.5	1.1	0.4	0.6	1.2	1.2	0.6	2.7
OTHGRA	0.3	1.4	1.0	0.7	0.5	1.4	1.1	0.5	0.3	0.4	1.7	1.0	1.1	1.1	1.7
CORN	2.3	2.8	1.9	2.0	3.2	4.0	4.3	4.9	0.5	2.1	0.4	2.4	2.0	0.5	3.3
SMAIZE	2.2	2.3	1.7	1.8	2.5	3.8	4.1	4.8	0.6	2.6	1.8	2.4	1.8	1.8	3.1
RICE	1.2	1.2	2.5	1.2	1.2	1.2	1.2	1.2	1.0	0.3	0.1	2.6	1.2	0.8	1.2
SUGAR	1.5	1.8	2.3	2.0	2.6	1.9	2.0	3.9	0.9	1.4	0.4	1.7	2.0	0.6	3.1
POTATO	1.7	0.1	2.3	1.9	2.3	1.0	0.7	3.4	1.3	1.4	0.2	2.2	2.1	0.6	1.0
SOYBEAN	2.2	2.0	2.2	2.0	3.0	2.0	2.0	2.0	0.6	2.0	0.5	0.9	2.0	0.4	4.8
RAPSEED	1.3	2.3	2.4	1.9	2.0	2.7	2.6	0.2	0.7	2.6	1.9	2.4	1.4	0.5	2.7
SUNSEED	0.5	2.5	1.4	1.2	1.2	1.2	1.2	1.2	0.3	0.6	0.5	2.3	1.2	0.3	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.4	1.7	0.4	1.6	0.1	0.2	0.4	0.4	1.7	0.7	0.5	0.8	0.8	1.0	0.8
BARLEY	2.6	1.9	0.5	1.4	1.4	0.2	0.2	0.9	2.3	1.2	0.4	0.9	0.6	1.2	0.3
RYE	2.6	1.1	0.5	0.8	1.0	2.0	0.4	0.7	1.9	1.4	1.3	1.2	0.4	1.8	0.4
OTHGRA	0.9	1.1	1.3	0.9	0.9	1.0	1.2	2.1	2.1	1.7	0.4	1.0	1.2	0.3	0.0
CORN	3.1	2.0	3.8	2.9	2.4	0.7	0.8	2.2	2.5	2.0	3.8	2.4	1.7	2.4	1.9
SMAIZE	3.0	1.8	3.2	3.5	1.8	1.7	0.7	1.9	1.8	1.8	3.6	2.5	1.2	1.7	0.9
RICE	1.2	1.2	1.2	1.2	0.9	0.1	1.2	1.2	1.2	1.2	1.2	1.1	1.3	2.5	0.9
SUGAR	2.9	0.5	0.6	2.6	2.4	2.1	2.5	1.9	2.4	1.5	1.2	1.8	1.5	1.3	1.9
POTATO	0.8	0.3	0.1	1.2	0.2	0.5	1.0	2.4	2.4	0.9	0.4	1.2	1.3	1.0	1.2
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.3	1.1	2.4	2.0	2.0	2.0	1.9	0.6	3.3	1.6
RAPSEED	1.1	1.9	0.4	3.1	1.9	2.4	1.0	0.3	2.5	2.0	0.8	1.7	1.4	2.5	1.9
SUNSEED	1.2	1.2	1.2	1.1	2.4	0.2	1.8	2.0	2.3	1.2	1.2	1.2	0.6	1.1	0.4

Table 7: Rates of technical progress for different groups of agricultural products and regions B1 without CO2 effect (GCM-LPJmL mean).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.6	1.3	0.5	-1.6	1.7	1.4	2.2	1.3	0.7	1.4	0.3	0.4	1.7	0.4	2.3
BARLEY	0.6	1.8	0.3	-1.5	1.3	2.1	2.4	1.0	1.1	1.4	0.4	0.5	1.6	0.5	2.5
RYE	0.7	2.7	1.3	-0.7	2.5	1.6	2.7	0.8	1.6	0.9	0.7	1.4	1.6	0.8	2.9
OTHGRA	0.6	1.7	1.1	-0.7	1.1	2.2	1.3	0.8	0.7	0.9	1.8	1.3	1.5	1.3	1.9
CORN	3.0	3.5	2.5	2.0	4.1	2.0	2.0	2.0	1.1	2.7	0.6	3.1	2.0	0.7	2.0
SMAIZE	2.9	3.0	2.3	1.8	3.4	1.8	1.8	1.8	1.2	3.2	1.9	3.1	1.8	2.1	1.8
RICE	1.2	1.2	2.9	1.2	1.2	1.2	1.2	1.2	1.4	0.3	0.5	3.1	1.2	1.2	1.2
SUGAR	1.9	2.3	2.6	2.0	3.1	2.5	2.0	4.5	1.6	1.8	0.7	2.1	2.4	1.2	3.4
POTATO	2.1	0.7	2.6	1.9	2.8	1.6	0.7	4.0	2.0	1.8	0.5	2.6	2.5	1.2	1.3
SOYBEAN	2.7	2.0	2.2	2.0	3.5	2.0	2.0	2.0	1.0	2.0	0.5	1.7	2.0	1.2	5.1
RAPSEED	1.5	2.5	2.5	1.9	2.5	3.3	2.9	0.4	0.9	2.9	1.9	2.5	1.8	0.6	2.9
SUNSEED	1.2	3.1	1.9	1.2	2.0	1.2	1.2	1.2	2.5	1.4	1.8	2.9	1.2	1.9	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.5	1.7	0.7	2.2	0.5	0.3	0.7	0.6	2.1	1.1	0.9	1.1	1.1	1.1	0.9
BARLEY	2.7	1.9	0.7	2.0	1.8	0.3	0.6	1.1	2.7	1.6	0.8	1.2	0.9	1.3	0.4
RYE	2.6	1.1	0.8	1.4	1.4	2.0	0.8	0.9	2.3	1.8	1.7	1.4	0.8	1.9	0.5
OTHGRA	1.0	1.1	1.6	1.5	1.3	1.1	1.5	2.3	2.5	2.1	0.8	1.3	1.6	0.4	0.2
CORN	3.3	2.0	4.7	3.5	2.4	0.9	1.1	2.5	2.7	2.0	2.0	2.3	2.2	2.9	2.0
SMAIZE	3.1	1.8	4.0	4.1	1.8	1.9	1.1	2.2	2.0	1.8	1.8	2.4	1.7	2.2	1.0
RICE	1.2	1.2	1.2	1.2	1.1	0.3	1.2	1.2	1.5	1.2	1.2	1.5	2.2	3.0	2.1
SUGAR	3.2	0.5	1.1	2.9	2.7	2.3	2.7	2.4	2.8	2.0	1.6	2.2	1.8	1.7	2.2
POTATO	1.0	0.3	0.6	1.5	0.5	0.7	1.2	2.9	2.8	1.3	0.9	1.6	1.6	1.4	1.5
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.5	1.6	3.0	2.3	2.0	2.0	2.5	1.5	2.6	2.2
RAPSEED	1.4	1.9	0.6	3.4	1.9	2.4	1.4	0.5	2.8	2.4	0.7	1.9	1.7	2.5	2.1
SUNSEED	1.2	1.2	1.2	2.2	3.4	0.8	2.2	3.2	3.1	1.2	1.2	1.7	1.1	2.2	1.2

Table 8: Rates of technical progress for different groups of agricultural products and regions A1B with CO2 effect (GCM-LPJmL, CCSM).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.3	1.1	0.1	-1.8	1.4	1.1	1.9	1.1	0.4	1.1	0.0	0.1	1.4	0.2	2.1
BARLEY	0.3	1.6	0.0	-1.7	1.0	1.8	2.1	0.8	0.8	1.1	0.1	0.2	1.3	0.2	2.3
RYE	0.3	2.4	0.9	-0.8	2.2	1.3	2.5	0.5	1.3	0.6	0.4	1.1	1.4	0.6	2.6
OTHGRA	0.3	1.5	0.8	-0.9	0.9	1.9	1.1	0.5	0.5	0.6	1.5	0.9	1.3	1.0	1.6
CORN	2.6	3.0	1.9	2.0	3.7	2.0	2.0	2.0	0.8	2.3	0.4	2.2	2.0	0.6	2.0
SMAIZE	2.5	2.5	1.7	1.8	3.0	1.8	1.8	1.8	0.9	2.8	1.7	2.2	1.8	1.9	1.8
RICE	1.2	1.2	2.4	1.2	1.2	1.2	1.2	1.2	0.9	0.3	-0.2	2.6	1.2	0.7	1.2
SUGAR	1.3	1.7	2.1	2.0	2.6	2.0	2.0	4.1	0.8	1.4	0.3	1.2	2.0	0.6	2.9
POTATO	1.5	0.1	2.1	1.9	2.3	1.1	0.7	3.6	1.2	1.4	0.1	1.7	2.1	0.6	0.8
SOYBEAN	2.0	2.0	1.7	2.0	2.8	2.0	2.0	2.0	0.4	2.0	0.5	0.8	2.0	0.6	4.6
RAPSEED	1.3	2.3	2.2	1.9	2.3	3.0	2.7	0.2	0.6	2.7	1.9	2.3	1.6	0.4	2.6
SUNSEED	0.3	2.2	1.0	1.2	1.3	1.2	1.2	1.2	1.0	0.6	0.8	1.9	1.2	0.8	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.2	1.7	0.5	1.9	0.2	-0.1	0.4	0.4	1.9	0.9	0.7	0.8	0.8	0.8	0.6
BARLEY	2.4	1.9	0.6	1.7	1.5	-0.1	0.3	0.9	2.4	1.4	0.6	0.9	0.6	1.0	0.1
RYE	2.3	1.1	0.6	1.1	1.1	1.6	0.4	0.7	2.1	1.6	1.5	1.2	0.5	1.6	0.2
OTHGRA	0.7	1.1	1.4	1.2	1.0	0.7	1.2	2.1	2.2	1.9	0.6	1.0	1.3	0.1	-0.1
CORN	2.9	2.0	4.5	3.3	2.4	0.4	0.9	2.2	2.6	2.0	2.0	2.0	1.9	2.6	1.9
SMAIZE	2.7	1.8	3.8	3.9	1.8	1.4	0.9	1.9	1.9	1.8	1.8	2.1	1.4	1.9	0.9
RICE	1.2	1.2	1.2	1.2	0.7	-0.3	1.2	1.2	0.9	1.2	1.2	1.0	1.1	2.4	0.9
SUGAR	2.7	0.5	0.6	2.6	2.4	1.4	2.3	1.7	2.5	1.6	1.1	1.7	1.3	1.3	1.8
POTATO	0.5	0.3	0.1	1.2	0.2	-0.2	0.8	2.2	2.5	0.9	0.3	1.1	1.1	1.0	1.1
SOYBEAN	2.0	2.0	2.0	2.0	2.0	1.8	0.9	2.1	1.9	2.0	2.0	1.8	0.8	1.7	1.4
RAPSEED	1.1	1.9	0.4	3.2	1.9	2.1	1.2	0.2	2.6	2.2	0.6	1.7	1.4	2.5	1.9
SUNSEED	1.2	1.2	1.2	1.4	2.2	-0.2	1.2	1.8	2.3	1.2	1.2	1.2	0.7	1.4	0.1

Table 9: Rates of technical progress for different groups of agricultural products and regions A1B without CO2 effect (GCM-LPJmL, CCSM).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.4	1.2	0.7	0.0	1.6	1.2	2.2	1.3	0.4	1.2	0.4	0.3	1.4	0.3	2.6
BARLEY	0.4	1.7	0.5	0.0	1.2	1.9	2.5	1.0	0.8	1.2	0.5	0.4	1.3	0.4	2.8
RYE	0.5	2.6	1.5	0.9	2.4	1.4	2.8	0.8	1.3	0.7	0.8	1.3	1.3	0.7	3.1
OTHGRA	0.5	1.6	1.4	0.9	1.0	1.9	1.4	0.8	0.4	0.7	1.9	1.2	1.3	1.2	2.1
CORN	2.4	2.7	2.6	2.0	3.3	2.0	2.0	2.0	0.6	2.4	0.5	3.0	2.0	0.6	2.0
SMAIZE	2.3	2.2	2.4	1.8	2.6	1.8	1.8	1.8	0.7	2.9	1.9	3.0	1.8	1.9	1.8
RICE	1.2	1.2	2.8	1.2	1.2	1.2	1.2	1.2	1.5	0.3	0.5	2.8	1.2	1.2	1.2
SUGAR	1.8	2.0	2.6	2.0	2.9	2.2	2.0	4.0	1.1	1.7	0.6	2.2	2.4	0.9	3.2
POTATO	2.0	0.3	2.6	1.9	2.6	1.3	0.7	3.5	1.5	1.7	0.5	2.7	2.5	0.9	1.1
SOYBEAN	2.7	2.0	2.9	2.0	3.4	2.0	2.0	2.0	0.7	2.0	0.5	1.7	2.0	0.6	4.4
RAPSEED	1.5	2.6	2.7	1.9	2.4	3.1	2.9	0.6	1.0	2.9	1.9	2.6	1.7	0.7	2.9
SUNSEED	1.2	2.4	2.2	1.2	1.9	1.2	1.2	1.2	0.4	1.1	0.9	3.0	1.2	0.9	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.9	1.7	0.7	2.2	0.1	0.5	0.6	0.6	1.9	1.0	0.8	1.1	1.1	1.3	1.0
BARLEY	3.1	1.9	0.8	2.0	1.4	0.5	0.5	1.1	2.4	1.5	0.7	1.2	0.9	1.5	0.5
RYE	3.1	1.1	0.8	1.4	1.0	2.3	0.7	0.9	2.1	1.7	1.6	1.4	0.8	2.1	0.6
OTHGRA	1.4	1.1	1.6	1.5	1.0	1.3	1.5	2.3	2.2	2.0	0.7	1.3	1.6	0.5	0.3
CORN	2.7	2.0	4.4	3.1	2.5	1.1	0.6	2.3	2.7	2.0	2.0	2.1	2.3	2.8	2.0
SMAIZE	2.6	1.8	3.7	3.7	1.9	2.1	0.6	2.0	2.0	1.8	1.8	2.2	1.8	2.1	1.0
RICE	1.2	1.2	1.2	1.2	1.4	0.5	1.2	1.2	1.7	1.2	1.2	1.4	2.3	2.8	1.8
SUGAR	3.0	0.5	0.9	2.7	2.5	2.4	2.7	2.2	2.7	1.8	1.5	2.0	2.0	1.6	2.2
POTATO	0.8	0.3	0.4	1.3	0.4	0.8	1.2	2.7	2.7	1.1	0.7	1.4	1.8	1.3	1.5
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.7	1.4	3.1	2.2	2.0	2.0	2.4	1.6	3.1	2.1
RAPSEED	1.4	1.9	0.6	3.6	1.9	2.6	1.4	0.5	2.6	2.2	0.9	1.9	1.7	2.5	2.1
SUNSEED	1.2	1.2	1.2	1.7	3.2	1.2	2.9	3.0	3.1	1.2	1.2	1.6	1.1	1.5	1.1

Table 10: Rates of technical progress for different groups of agricultural products and regions B1 with CO2 effect (GCM-LPJmL, CCSM).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.1	1.0	0.4	-0.2	1.3	0.9	2.1	1.1	0.1	1.0	0.2	0.0	1.2	0.1	2.3
BARLEY	0.2	1.5	0.3	-0.1	0.9	1.6	2.3	0.8	0.5	1.0	0.2	0.1	1.1	0.2	2.6
RYE	0.2	2.4	1.2	0.8	2.1	1.1	2.6	0.6	1.0	0.5	0.6	1.0	1.1	0.5	2.9
OTHGRA	0.2	1.4	1.1	0.7	0.8	1.7	1.2	0.5	0.2	0.5	1.7	0.9	1.0	1.0	1.9
CORN	2.1	2.3	2.1	2.0	2.9	2.0	2.0	2.0	0.4	2.0	0.4	2.4	2.0	0.4	2.0
SMAIZE	2.0	1.8	1.9	1.8	2.2	1.8	1.8	1.8	0.5	2.6	1.8	2.4	1.8	1.8	1.8
RICE	1.2	1.2	2.4	1.2	1.2	1.2	1.2	1.2	1.1	0.3	0.0	2.4	1.2	0.8	1.2
SUGAR	1.4	1.5	2.3	2.0	2.5	1.8	2.0	3.7	0.6	1.3	0.3	1.5	2.0	0.4	2.8
POTATO	1.6	-0.2	2.3	1.9	2.2	0.9	0.7	3.2	1.0	1.3	0.1	2.0	2.1	0.4	0.7
SOYBEAN	2.2	2.0	2.4	2.0	2.8	2.0	2.0	2.0	0.2	2.0	0.5	1.0	2.0	0.1	4.0
RAPSEED	1.3	2.4	2.5	1.9	2.2	2.9	2.7	0.4	0.8	2.7	1.9	2.4	1.6	0.5	2.7
SUNSEED	0.6	1.8	1.5	1.2	1.4	1.2	1.2	1.2	-0.7	0.6	0.3	2.4	1.2	0.0	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.6	1.7	0.6	2.0	-0.1	0.2	0.3	0.4	1.6	0.8	0.5	0.8	0.9	1.0	0.8
BARLEY	2.8	1.9	0.6	1.8	1.2	0.2	0.2	0.9	2.2	1.3	0.4	1.0	0.7	1.2	0.3
RYE	2.8	1.1	0.6	1.2	0.8	1.9	0.4	0.7	1.9	1.5	1.3	1.2	0.6	1.8	0.4
OTHGRA	1.2	1.1	1.4	1.3	0.8	1.0	1.2	2.1	2.0	1.8	0.4	1.1	1.4	0.3	0.0
CORN	2.4	2.0	4.2	2.9	2.5	0.7	0.6	2.0	2.6	2.0	2.0	1.9	2.0	2.5	1.9
SMAIZE	2.3	1.8	3.5	3.5	1.9	1.7	0.5	1.7	1.9	1.8	1.8	2.0	1.5	1.8	0.9
RICE	1.2	1.2	1.2	1.2	1.1	0.1	1.2	1.2	1.3	1.2	1.2	1.2	1.5	2.4	1.0
SUGAR	2.6	0.5	0.5	2.5	2.3	1.7	2.4	1.7	2.4	1.5	1.1	1.7	1.6	1.4	1.8
POTATO	0.4	0.3	0.0	1.1	0.1	0.1	0.9	2.2	2.4	0.8	0.4	1.1	1.4	1.1	1.1
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.2	0.9	2.3	1.9	2.0	2.0	1.9	1.0	2.9	1.5
RAPSEED	1.2	1.9	0.5	3.4	1.9	2.3	1.2	0.3	2.4	2.0	0.7	1.7	1.5	2.5	1.9
SUNSEED	1.2	1.2	1.2	1.0	2.3	0.3	2.1	2.0	2.4	1.2	1.2	1.1	0.8	0.8	0.3

Table 11: Rates of technical progress for different groups of agricultural products and regions B1 without CO2 effect (GCM-LPJmL, CCSM).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.6	1.3	0.7	-0.4	1.3	1.0	2.0	1.2	0.5	1.2	0.6	0.6	1.3	0.5	2.3
BARLEY	0.6	1.8	0.6	-0.4	0.9	1.7	2.2	0.9	0.9	1.2	0.6	0.7	1.2	0.5	2.5
CORN	2.1	2.6	0.5	2.0	3.4	2.0	2.0	2.0	0.6	2.2	0.5	2.0	2.0	0.5	2.0
SMAIZE	2.1	2.1	0.3	1.8	2.7	1.8	1.8	1.8	0.7	2.7	1.8	2.0	1.8	1.8	1.8
RYE	0.6	2.7	1.5	0.5	2.1	1.2	2.5	0.7	1.4	0.7	1.0	1.6	1.3	0.9	2.8
OTHGRA	0.6	1.7	1.4	0.4	0.8	1.8	1.2	0.7	0.6	0.7	2.1	1.4	1.2	1.3	1.8
RICE	1.2	1.2	3.0	1.2	1.2	1.2	1.2	1.2	1.6	0.3	0.6	3.2	1.2	0.9	1.2
SUGAR	1.7	2.3	2.5	2.0	2.9	2.6	2.0	4.2	1.3	1.9	0.7	1.7	2.6	0.7	3.6
POTATO	1.9	0.7	2.5	1.9	2.6	1.7	0.7	3.7	1.7	1.9	0.5	2.2	2.7	0.7	1.5
SOYBEAN	2.5	2.3	1.6	2.0	3.2	2.0	2.0	2.0	0.8	2.0	0.5	0.7	2.0	0.7	5.3
RAPSEED	1.5	2.5	2.6	1.9	2.4	3.0	2.8	0.3	0.8	2.9	1.9	2.6	1.9	0.7	2.8
SUNSEED	0.7	1.2	1.4	1.2	1.4	1.2	1.2	1.2	0.4	1.0	0.6	2.5	1.2	0.0	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.5	1.7	0.7	1.8	0.3	0.7	0.6	0.7	1.8	0.9	0.7	1.0	1.0	1.3	1.0
BARLEY	2.7	1.9	0.7	1.6	1.6	0.8	0.5	1.2	2.4	1.4	0.6	1.2	0.8	1.5	0.5
CORN	3.4	2.0	4.2	3.1	2.4	0.3	0.8	2.2	2.6	2.0	2.0	1.9	1.9	2.5	2.0
SMAIZE	3.2	1.8	3.5	3.7	1.9	1.4	0.8	1.9	1.9	1.8	1.8	1.8	1.4	1.8	1.0
RYE	2.7	1.1	0.7	1.0	1.2	2.5	0.7	1.0	2.0	1.6	1.5	1.4	0.7	2.1	0.6
OTHGRA	1.1	1.1	1.5	1.1	1.1	1.6	1.5	2.4	2.2	1.9	0.6	1.3	1.4	0.6	0.3
RICE	1.2	1.2	1.2	1.2	1.7	0.5	1.2	1.2	2.0	1.2	1.2	1.8	1.9	3.1	2.0
SUGAR	3.5	0.5	1.2	2.9	2.7	2.4	2.7	2.0	2.7	2.1	1.8	2.2	1.8	1.6	2.3
POTATO	1.3	0.3	0.7	1.5	0.5	0.8	1.2	2.6	2.7	1.4	1.0	1.6	1.6	1.3	1.6
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.4	1.4	2.1	2.3	2.0	2.0	1.9	1.2	4.6	2.3
RAPSEED	1.3	1.9	0.5	3.4	1.9	2.8	1.3	0.7	2.6	2.2	0.9	1.8	1.9	2.5	2.0
SUNSEED	1.2	1.2	1.2	1.8	3.6	0.4	2.0	2.1	2.6	1.2	1.4	1.4	0.8	1.2	1.0

Table 12: Rates of technical progress for different groups of agricultural products and regions A1B with CO2 effect (GCM-LPJmL, ECHAM).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.3	1.0	0.4	-0.6	1.1	0.7	1.8	0.8	0.2	0.9	0.3	0.3	1.1	0.2	2.0
BARLEY	0.3	1.5	0.2	-0.6	0.7	1.4	2.0	0.5	0.6	0.9	0.3	0.4	1.0	0.2	2.2
CORN	1.7	2.6	-0.4	2.0	3.0	2.0	2.0	2.0	0.3	1.9	0.4	1.1	2.0	0.3	2.0
SMAIZE	1.6	2.1	-0.6	1.8	2.3	1.8	1.8	1.8	0.4	2.4	1.7	1.1	1.8	1.7	1.8
RYE	0.4	2.4	1.2	0.3	1.9	0.9	2.3	0.3	1.1	0.4	0.7	1.3	1.0	0.6	2.5
OTHGRA	0.3	1.4	1.1	0.2	0.6	1.4	1.0	0.3	0.3	0.4	1.8	1.1	1.0	1.1	1.6
RICE	1.2	1.2	2.5	1.2	1.2	1.2	1.2	1.2	1.0	0.3	0.0	2.8	1.2	0.9	1.2
SUGAR	1.2	1.8	2.0	2.0	2.4	2.1	2.0	3.8	0.6	1.4	0.3	0.6	2.2	0.1	3.2
POTATO	1.4	0.1	2.0	1.9	2.1	1.2	0.7	3.3	1.0	1.4	0.1	1.1	2.3	0.1	1.1
SOYBEAN	1.8	2.0	1.0	2.0	2.6	2.0	2.0	2.0	0.2	2.0	0.5	-0.4	2.0	0.1	4.8
RAPSEED	1.3	2.3	2.4	1.9	2.2	2.5	2.5	0.0	0.6	2.7	1.9	2.4	1.7	0.5	2.5
SUNSEED	-0.1	1.2	0.5	1.2	0.8	1.2	1.2	1.2	-1.0	0.4	-0.4	1.7	1.2	-1.2	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.2	1.7	0.5	1.6	0.0	0.4	0.4	0.5	1.5	0.7	0.4	0.8	0.7	1.0	0.7
BARLEY	2.4	1.9	0.5	1.4	1.3	0.4	0.2	1.0	2.1	1.2	0.3	0.9	0.5	1.2	0.2
CORN	3.1	2.0	4.1	3.0	2.4	-0.4	0.7	1.9	2.4	2.0	2.0	1.7	1.6	2.1	1.8
SMAIZE	2.9	1.8	3.4	3.6	1.8	0.6	0.7	1.6	1.7	1.8	1.8	1.8	1.1	1.4	0.8
RYE	2.4	1.1	0.5	0.8	0.9	2.1	0.4	0.8	1.7	1.4	1.2	1.1	0.4	1.8	0.3
OTHGRA	0.8	1.1	1.3	0.9	0.8	1.2	1.2	2.2	1.9	1.7	0.3	1.0	1.1	0.3	0.0
RICE	1.2	1.2	1.2	1.2	1.3	0.0	1.2	1.2	1.4	1.2	1.2	1.3	1.1	2.5	0.8
SUGAR	3.1	0.5	0.7	2.6	2.4	1.4	2.4	1.5	2.3	1.7	1.2	1.7	1.3	1.3	1.8
POTATO	0.9	0.3	0.2	1.2	0.2	-0.2	0.9	2.0	2.3	1.0	0.4	1.1	1.1	1.0	1.1
SOYBEAN	2.0	2.0	2.0	2.0	2.0	1.8	0.7	1.4	1.9	2.0	2.0	1.6	0.4	4.6	1.4
RAPSEED	1.0	1.9	0.3	3.2	1.9	2.5	1.1	0.4	2.3	2.0	0.7	1.6	1.5	2.5	1.7
SUNSEED	1.2	1.2	1.2	1.1	2.7	-1.0	0.7	1.0	1.9	1.2	1.2	0.5	-0.2	1.0	-0.1

Table 13: Rates of technical progress for different groups of agricultural products and regions A1B without CO2 effect (GCM-LPJmL, ECHAM).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.6	1.2	0.5	-0.1	1.4	0.8	2.0	1.1	0.4	1.2	0.3	0.6	1.0	0.4	2.4
BARLEY	0.6	1.7	0.4	0.0	1.0	1.5	2.2	0.8	0.8	1.2	0.3	0.7	0.9	0.5	2.6
CORN	2.7	2.6	1.7	2.0	3.6	2.0	2.0	2.0	0.9	2.4	0.5	3.1	2.0	0.7	2.0
SMAIZE	2.6	2.1	1.5	1.8	2.9	1.8	1.8	1.8	1.0	2.9	1.8	3.1	1.8	2.0	1.8
RYE	0.7	2.5	1.3	0.9	2.2	1.0	2.5	0.6	1.3	0.7	0.6	1.6	0.9	0.8	2.9
OTHGRA	0.6	1.6	1.2	0.8	0.9	1.5	1.2	0.6	0.5	0.7	1.7	1.5	0.8	1.3	2.0
RICE	1.2	1.2	3.0	1.2	1.2	1.2	1.2	1.2	1.3	0.3	0.6	3.0	1.2	0.9	1.2
SUGAR	1.9	2.4	2.6	2.0	3.0	2.4	2.0	4.9	1.6	1.8	0.7	2.4	2.4	1.1	3.8
POTATO	2.1	0.7	2.6	1.9	2.7	1.5	0.7	4.4	2.0	1.8	0.5	2.9	2.5	1.1	1.7
SOYBEAN	2.6	2.3	2.3	2.0	3.3	2.0	2.0	2.0	1.1	2.0	0.5	1.8	2.0	1.1	5.8
RAPSEED	1.5	2.5	2.5	1.9	2.2	2.8	2.7	0.2	0.7	2.8	1.9	2.6	1.9	0.6	2.7
SUNSEED	1.0	1.2	1.9	1.2	1.5	1.2	1.2	1.2	1.4	0.9	1.1	2.9	1.2	1.3	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	3.0	1.7	0.4	2.1	0.5	0.6	0.7	0.7	1.9	0.9	0.6	1.0	0.8	1.3	1.0
BARLEY	3.2	1.9	0.5	1.9	1.8	0.6	0.6	1.2	2.5	1.4	0.5	1.1	0.6	1.5	0.5
CORN	3.4	2.0	3.9	2.9	2.4	1.4	0.8	2.5	2.6	2.0	2.0	2.1	2.0	2.6	2.0
SMAIZE	3.3	1.8	3.2	3.5	1.8	2.4	0.8	2.2	1.9	1.8	1.8	1.8	1.5	1.9	1.0
RYE	3.1	1.1	0.5	1.3	1.4	2.4	0.8	1.0	2.1	1.6	1.4	1.4	0.5	2.1	0.6
OTHGRA	1.5	1.1	1.3	1.4	1.3	1.5	1.6	2.4	2.3	1.9	0.5	1.2	1.3	0.6	0.3
RICE	1.2	1.2	1.2	1.2	1.1	0.6	1.2	1.2	1.6	1.2	1.2	1.6	1.9	3.0	1.6
SUGAR	3.4	0.5	1.1	2.8	2.6	3.0	2.7	2.5	2.8	1.9	1.6	2.3	2.1	1.6	2.4
POTATO	1.2	0.3	0.6	1.4	0.5	1.4	1.2	3.0	2.8	1.3	0.8	1.7	1.9	1.3	1.7
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.9	1.6	3.3	2.3	2.0	2.0	2.1	1.3	4.4	2.4
RAPSEED	1.2	1.9	0.8	3.4	1.9	2.7	1.3	0.6	2.7	2.1	1.1	1.8	1.1	2.5	2.1
SUNSEED	1.2	1.2	1.2	1.7	3.4	0.8	2.6	2.9	3.2	1.2	1.2	1.8	1.0	1.8	1.5

Table 14: Rates of technical progress for different groups of agricultural products and regions B1 with CO2 effect (GCM-LPJmL, ECHAM).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.4	0.9	0.4	-0.2	1.2	0.5	1.8	0.8	0.2	1.0	0.0	0.4	0.8	0.2	2.2
BARLEY	0.4	1.4	0.2	-0.2	0.8	1.2	2.0	0.5	0.6	1.0	0.0	0.4	0.7	0.2	2.4
CORN	2.4	2.6	1.4	2.0	3.3	2.0	2.0	2.0	0.7	2.2	0.4	2.6	2.0	0.6	2.0
SMAIZE	2.3	2.1	1.3	1.8	2.6	1.8	1.8	1.8	0.8	2.7	1.7	2.6	1.8	1.9	1.8
RYE	0.4	2.3	1.2	0.7	2.0	0.7	2.4	0.3	1.1	0.5	0.4	1.3	0.7	0.6	2.7
OTHGRA	0.4	1.3	1.1	0.6	0.7	1.3	1.0	0.3	0.3	0.5	1.5	1.2	0.6	1.1	1.7
RICE	1.2	1.2	2.6	1.2	1.2	1.2	1.2	1.2	1.0	0.3	0.1	2.7	1.2	0.9	1.2
SUGAR	1.6	2.0	2.2	2.0	2.6	2.0	2.0	4.6	1.2	1.5	0.3	1.7	2.2	0.7	3.5
POTATO	1.8	0.3	2.2	1.9	2.3	1.1	0.7	4.1	1.6	1.5	0.2	2.2	2.3	0.7	1.4
SOYBEAN	2.2	2.0	1.9	2.0	2.8	2.0	2.0	2.0	0.6	2.0	0.5	1.2	2.0	0.6	5.5
RAPSEED	1.3	2.3	2.3	1.9	2.1	2.5	2.5	0.0	0.5	2.6	1.9	2.4	1.7	0.5	2.5
SUNSEED	0.6	1.2	1.4	1.2	1.0	1.2	1.2	1.2	0.7	0.4	0.4	2.5	1.2	0.7	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.7	1.7	0.3	1.9	0.2	0.3	0.5	0.5	1.7	0.7	0.4	0.8	0.6	1.1	0.8
BARLEY	2.9	1.9	0.3	1.7	1.5	0.3	0.4	1.0	2.3	1.2	0.3	1.0	0.4	1.3	0.3
CORN	3.3	2.0	3.8	2.9	2.4	1.0	0.8	2.4	2.5	2.0	2.0	2.0	1.8	2.4	1.9
SMAIZE	3.1	1.8	3.1	3.5	1.8	2.0	0.7	2.1	1.8	1.8	1.8	1.8	1.3	1.7	0.9
RYE	2.9	1.1	0.3	1.1	1.1	2.1	0.5	0.8	1.9	1.4	1.2	1.2	0.2	1.9	0.4
OTHGRA	1.2	1.1	1.1	1.2	1.1	1.2	1.3	2.2	2.1	1.7	0.3	1.0	1.0	0.4	0.1
RICE	1.2	1.2	1.2	1.2	0.9	0.3	1.2	1.2	1.2	1.2	1.2	1.3	1.2	2.6	0.7
SUGAR	3.1	0.5	0.8	2.6	2.4	2.4	2.5	2.2	2.5	1.7	1.2	2.0	1.8	1.3	2.1
POTATO	0.9	0.3	0.3	1.2	0.3	0.8	1.0	2.7	2.5	1.0	0.4	1.4	1.6	1.0	1.4
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.4	1.2	2.8	2.1	2.0	2.0	1.9	0.7	4.1	1.8
RAPSEED	1.0	1.9	0.6	3.2	1.9	2.4	1.1	0.6	2.5	2.0	0.9	1.7	1.4	2.5	1.9
SUNSEED	1.2	1.2	1.2	1.1	2.6	0.2	1.8	2.4	2.4	1.2	1.2	1.2	0.7	1.3	0.9

Table 15: Rates of technical progress for different groups of agricultural products and regions B1 without CO2 effect (GCM-LPJmL, ECHAM).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.5	1.1	0.7	-0.6	1.0	1.1	2.1	1.3	0.5	1.1	0.5	0.6	2.0	0.5	2.4
BARLEY	0.5	1.6	0.6	-0.5	0.6	1.8	2.3	1.0	0.9	1.1	0.6	0.7	1.9	0.5	2.6
RYE	0.5	2.5	1.5	0.3	1.8	1.3	2.6	0.8	1.4	0.6	0.9	1.6	1.9	0.8	2.9
OTHGRA	0.5	1.5	1.4	0.3	0.5	1.9	1.2	0.8	0.5	0.6	2.0	1.4	1.8	1.3	2.0
CORN	2.7	3.8	2.5	2.0	3.6	2.0	2.0	2.0	1.0	2.7	0.5	2.9	2.0	0.7	2.0
SMAIZE	2.7	3.3	2.3	1.8	2.9	1.8	1.8	1.8	1.1	3.2	1.8	2.9	1.8	2.0	1.8
RICE	1.2	1.2	2.9	1.2	1.2	1.2	1.2	1.2	1.6	0.3	0.6	3.2	1.2	1.4	1.2
SUGAR	2.0	2.3	2.8	2.0	3.0	2.0	2.0	3.3	1.5	1.8	0.7	2.4	2.5	1.0	3.1
POTATO	2.2	0.6	2.8	1.9	2.7	1.1	0.7	2.8	1.9	1.8	0.6	2.9	2.6	1.0	1.0
SOYBEAN	3.1	2.0	2.6	2.0	3.9	2.0	2.0	2.0	1.1	2.0	0.5	1.6	2.0	1.0	4.9
RAPSEED	1.3	2.3	2.4	1.9	1.9	3.1	2.8	0.4	0.7	2.6	1.9	2.4	1.7	0.6	2.7
SUNSEED	1.0	4.0	2.2	1.2	1.7	1.2	1.2	1.2	1.4	1.2	1.7	2.9	1.2	1.1	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.8	1.7	0.6	1.7	0.2	0.7	0.6	0.6	1.9	1.1	0.7	1.0	1.1	1.5	0.9
BARLEY	3.0	1.9	0.6	1.5	1.5	0.7	0.5	1.1	2.5	1.6	0.6	1.2	0.9	1.7	0.4
RYE	2.9	1.1	0.7	0.9	1.1	2.5	0.7	0.9	2.1	1.8	1.5	1.4	0.8	2.3	0.5
OTHGRA	1.3	1.1	1.4	1.0	1.1	1.6	1.4	2.3	2.3	2.1	0.6	1.3	1.6	0.8	0.2
CORN	3.1	2.0	4.2	3.0	2.4	1.2	0.9	2.4	2.7	2.0	2.0	2.2	2.0	2.8	2.0
SMAIZE	3.0	1.8	3.5	3.6	1.8	2.2	0.9	2.1	2.0	1.8	1.8	2.3	1.5	2.1	1.0
RICE	1.2	1.2	1.2	1.2	1.4	0.5	1.2	1.2	1.9	1.2	1.2	1.3	2.0	3.0	1.2
SUGAR	3.1	0.5	1.0	2.7	2.6	3.0	2.8	2.4	2.7	1.5	1.6	2.1	1.8	1.6	2.0
POTATO	0.9	0.3	0.5	1.3	0.5	1.4	1.3	2.9	2.7	0.8	0.8	1.5	1.6	1.3	1.3
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.8	2.3	2.7	2.3	2.0	2.0	2.1	1.3	3.2	2.1
RAPSEED	1.2	1.9	0.6	3.0	1.9	2.7	1.0	0.4	2.6	2.3	0.9	1.8	1.7	2.5	2.1
SUNSEED	1.2	1.2	1.2	1.7	3.4	1.1	2.3	2.4	2.9	1.2	1.2	1.6	0.8	2.0	1.7

Table 16: Rates of technical progress for different groups of agricultural products and regions A1B with CO2 effect (GCM-LPJmL, ECHO).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.2	0.8	0.4	-0.8	0.8	0.8	1.9	1.0	0.2	0.8	0.3	0.3	1.7	0.2	2.1
BARLEY	0.2	1.3	0.3	-0.7	0.4	1.5	2.1	0.7	0.6	0.8	0.3	0.3	1.6	0.2	2.3
RYE	0.2	2.2	1.2	0.1	1.6	1.0	2.4	0.5	1.1	0.3	0.7	1.2	1.7	0.6	2.7
OTHGRA	0.2	1.2	1.1	0.1	0.2	1.5	1.0	0.5	0.3	0.3	1.8	1.1	1.6	1.1	1.7
CORN	2.5	3.6	1.8	2.0	3.4	2.0	2.0	2.0	0.7	2.6	0.3	2.3	2.0	0.5	2.0
SMAIZE	2.4	3.1	1.6	1.8	2.7	1.8	1.8	1.8	0.8	3.1	1.7	2.3	1.8	1.8	1.8
RICE	1.2	1.2	2.4	1.2	1.2	1.2	1.2	1.2	1.1	0.3	-0.1	2.7	1.2	0.9	1.2
SUGAR	1.5	1.9	2.3	2.0	2.6	1.6	2.0	3.0	0.9	1.4	0.3	1.6	2.2	0.4	2.8
POTATO	1.7	0.2	2.3	1.9	2.3	0.7	0.7	2.5	1.3	1.4	0.2	2.1	2.3	0.4	0.7
SOYBEAN	3.1	2.0	4.4	2.0	5.4	2.0	2.0	2.0	2.6	2.0	0.5	1.0	2.0	0.4	6.7
RAPSEED	1.1	2.0	2.3	1.9	1.6	2.8	2.5	0.2	0.5	2.4	1.9	2.3	1.5	0.4	2.5
SUNSEED	0.4	3.6	1.6	1.2	1.2	1.2	1.2	1.2	0.2	0.8	0.5	2.2	1.2	-0.2	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.5	1.7	0.4	1.4	0.0	0.3	0.3	0.4	1.6	0.9	0.4	0.8	0.8	1.2	0.7
BARLEY	2.7	1.9	0.4	1.2	1.2	0.4	0.2	0.9	2.2	1.4	0.3	0.9	0.6	1.4	0.2
RYE	2.7	1.1	0.5	0.6	0.8	2.1	0.4	0.7	1.8	1.6	1.2	1.1	0.5	2.0	0.3
OTHGRA	1.0	1.1	1.2	0.7	0.8	1.2	1.2	2.1	2.0	1.9	0.3	1.0	1.3	0.5	-0.1
CORN	3.1	2.0	4.1	2.9	2.4	0.7	0.9	2.2	2.5	2.0	2.0	2.0	1.7	2.5	1.9
SMAIZE	2.9	1.8	3.4	3.5	1.8	1.7	0.8	1.9	1.8	1.8	1.8	2.1	1.2	1.8	0.9
RICE	1.2	1.2	1.2	1.2	1.0	0.0	1.2	1.2	1.4	1.2	1.2	1.1	1.1	2.4	0.8
SUGAR	2.7	0.5	0.6	2.5	2.4	2.2	2.5	1.9	2.4	1.1	1.2	1.7	1.3	1.3	2.0
POTATO	0.6	0.3	0.1	1.1	0.2	0.6	1.0	2.4	2.4	0.5	0.4	1.1	1.1	1.0	1.3
SOYBEAN	2.0	2.0	2.0	2.0	2.0	4.9	1.8	4.3	3.7	2.0	2.0	2.5	1.1	2.5	2.4
RAPSEED	1.0	1.9	0.4	2.8	1.9	2.4	0.8	0.2	2.4	2.1	0.8	1.6	1.5	2.5	1.8
SUNSEED	1.2	1.2	1.2	1.2	2.5	0.3	1.5	1.7	2.2	1.2	1.2	1.2	0.4	1.0	0.6

Table 17: Rates of technical progress for different groups of agricultural products and regions A1B without CO2 effect (GCM-LPJmL, ECHO).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.5	1.1	0.5	-0.6	1.1	0.8	1.8	1.1	0.5	1.1	0.4	0.4	1.6	0.4	2.1
DURUM	0.4	0.7	0.3	-0.7	0.7	0.7	0.9	0.7	0.4	0.7	0.3	0.3	1.0	0.3	1.2
BARLEY	0.5	1.6	0.3	-0.5	0.7	1.5	2.0	0.8	0.9	1.1	0.4	0.5	1.5	0.4	2.3
RYE	0.6	2.5	1.3	0.3	1.9	1.0	2.3	0.6	1.4	0.6	0.8	1.4	1.6	0.8	2.6
OTHGRA	0.5	1.5	1.1	0.3	0.6	1.6	1.0	0.6	0.6	0.6	1.9	1.3	1.5	1.2	1.6
CORN	2.6	3.4	2.0	2.0	3.2	2.0	2.0	2.0	0.9	2.4	0.6	2.9	2.0	0.7	2.0
SMAIZE	2.5	2.9	1.8	1.8	2.5	1.8	1.8	1.8	1.0	2.9	1.9	2.9	1.8	2.1	1.8
RICE	1.2	1.2	2.9	1.2	1.2	1.2	1.2	1.2	1.3	0.3	0.6	3.3	1.2	1.2	1.2
SUGAR	2.0	2.1	2.7	2.0	3.0	2.1	2.0	3.5	1.3	1.8	0.7	2.5	2.4	1.1	3.5
POTATO	2.2	0.5	2.7	1.9	2.7	1.2	0.7	3.0	1.7	1.8	0.6	3.0	2.5	1.1	1.4
SOYBEAN	2.8	2.0	2.5	2.0	3.5	2.0	2.0	2.0	1.1	2.0	0.5	1.6	2.0	1.0	4.5
RAPSEED	1.4	2.4	2.4	1.9	1.9	3.0	2.6	0.2	0.9	2.7	1.9	2.5	2.0	0.7	2.6
SUNSEED	0.9	3.1	1.9	1.2	1.5	1.2	1.2	1.2	1.3	1.0	1.2	2.7	1.2	1.6	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.4	1.7	0.4	1.5	0.2	0.3	0.5	0.5	1.9	0.8	0.7	0.9	1.0	1.2	0.9
DURUM	1.5	0.9	0.3	0.9	0.1	0.2	0.4	0.3	1.0	0.6	0.5	0.6	0.7	0.7	0.4
BARLEY	2.6	1.9	0.5	1.3	1.5	0.3	0.4	1.0	2.4	1.3	0.6	1.0	0.8	1.4	0.4
RYE	2.6	1.1	0.5	0.7	1.1	2.1	0.6	0.8	2.1	1.5	1.5	1.3	0.7	2.0	0.5
OTHGRA	0.9	1.1	1.3	0.8	1.0	1.1	1.4	2.2	2.3	1.8	0.6	1.1	1.5	0.4	0.1
CORN	3.5	2.0	4.1	2.7	2.4	1.0	0.8	2.4	2.6	2.0	2.0	2.1	1.9	2.7	2.0
SMAIZE	3.3	1.8	3.4	3.3	1.8	2.0	0.8	2.1	2.0	1.8	1.8	2.2	1.4	2.0	1.0
RICE	1.2	1.2	1.2	1.2	1.2	0.5	1.2	1.2	1.6	1.2	1.2	1.2	1.8	3.0	1.1
SUGAR	3.2	0.5	0.9	2.7	2.7	2.8	2.7	2.4	2.8	1.7	1.4	2.1	1.6	1.6	2.0
POTATO	1.0	0.3	0.4	1.3	0.5	1.2	1.2	3.0	2.8	1.0	0.6	1.5	1.4	1.3	1.3
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.7	1.8	3.0	2.3	2.0	2.0	2.0	1.1	3.5	2.1
RAPSEED	1.1	1.9	0.5	2.9	1.9	2.4	1.1	0.4	2.6	2.2	0.9	1.7	1.8	2.5	2.2
SUNSEED	1.2	1.2	1.2	1.6	3.0	0.7	2.2	2.4	2.8	1.2	1.2	1.5	0.8	1.5	1.0

Table 18: Rates of technical progress for different groups of agricultural products and regions B1 with CO2 effect (GCM-LPJmL, ECHO).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.2	0.9	0.2	-0.7	0.9	0.6	1.6	0.8	0.3	0.8	0.2	0.1	1.5	0.2	1.9
BARLEY	0.3	1.4	0.1	-0.7	0.5	1.3	1.8	0.5	0.7	0.8	0.2	0.2	1.4	0.2	2.1
RYE	0.3	2.3	1.0	0.2	1.7	0.8	2.2	0.2	1.2	0.3	0.5	1.1	1.4	0.6	2.4
OTHGRA	0.3	1.3	0.9	0.1	0.4	1.3	0.8	0.2	0.4	0.3	1.6	1.0	1.3	1.0	1.4
CORN	2.4	3.2	1.5	2.0	3.0	2.0	2.0	2.0	0.7	2.2	0.5	2.5	2.0	0.6	2.0
SMAIZE	2.3	2.7	1.4	1.8	2.3	1.8	1.8	1.8	0.8	2.7	1.8	2.5	1.8	1.9	1.8
RICE	1.2	1.2	2.5	1.2	1.2	1.2	1.2	1.2	1.0	0.3	0.1	2.9	1.2	0.9	1.2
SUGAR	1.6	1.8	2.4	2.0	2.7	1.7	2.0	3.3	0.8	1.4	0.4	1.9	2.1	0.7	3.1
POTATO	1.8	0.1	2.4	1.9	2.4	0.8	0.7	2.8	1.2	1.4	0.2	2.4	2.2	0.7	1.0
SOYBEAN	2.4	2.0	2.2	2.0	3.1	2.0	2.0	2.0	0.7	2.0	0.5	0.9	2.0	0.6	4.2
RAPSEED	1.2	2.2	2.3	1.9	1.7	2.7	2.4	0.0	0.7	2.5	1.9	2.3	1.9	0.5	2.4
SUNSEED	0.5	2.8	1.5	1.2	1.2	1.2	1.2	1.2	0.5	0.6	0.5	2.3	1.2	0.9	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	1.3	0.9	0.2	0.7	-0.1	-0.1	0.2	0.2	0.8	0.5	0.3	0.3	0.5	0.4	0.1
BARLEY	2.4	1.9	0.3	1.1	1.3	0.0	0.2	0.9	2.2	1.2	0.4	0.8	0.6	1.1	0.1
RYE	2.4	1.1	0.4	0.5	0.9	1.8	0.4	0.7	1.9	1.4	1.3	1.1	0.5	1.7	0.2
OTHGRA	0.7	1.1	1.1	0.6	0.8	0.8	1.1	2.1	2.1	1.7	0.4	0.9	1.2	0.2	-0.1
CORN	3.4	2.0	4.0	2.7	2.4	0.6	0.8	2.3	2.6	2.0	2.0	2.0	1.6	2.5	1.9
SMAIZE	3.2	1.8	3.3	3.3	1.8	1.6	0.7	2.0	1.9	1.8	1.8	2.1	1.1	1.8	0.9
RICE	1.2	1.2	1.2	1.2	0.9	0.1	1.2	1.2	1.2	1.2	1.2	1.1	1.1	2.6	0.8
SUGAR	2.9	0.5	0.5	2.5	2.4	2.2	2.5	2.1	2.5	1.4	1.0	1.8	1.2	1.3	2.0
POTATO	0.7	0.3	0.0	1.1	0.3	0.6	1.0	2.6	2.5	0.7	0.3	1.2	1.0	1.0	1.3
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.2	1.3	2.5	2.1	2.0	2.0	1.9	0.4	3.2	1.4
RAPSEED	0.9	1.9	0.4	2.8	1.9	2.1	0.9	0.2	2.4	2.0	0.7	1.6	1.6	2.5	2.0
SUNSEED	1.2	1.2	1.2	1.1	2.3	0.1	1.6	2.1	2.3	1.2	1.2	1.2	0.4	1.0	0.2

Table 19: Rates of technical progress for different groups of agricultural products and regions B1 without CO2 effect (GCM-LPJmL, ECHO).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.4	1.2	0.6	0.2	1.1	0.5	2.3	1.7	0.5	1.1	0.2	0.4	1.6	0.5	2.3
BARLEY	0.4	1.7	0.5	0.2	0.7	1.2	2.6	1.4	0.9	1.1	0.2	0.5	1.5	0.5	2.5
RYE	0.4	2.5	1.4	1.1	1.9	0.7	2.9	1.1	1.4	0.6	0.6	1.4	1.6	0.9	2.8
OTHGRA	0.4	1.6	1.3	1.1	0.5	1.3	1.5	1.1	0.6	0.6	1.7	1.2	1.5	1.3	1.8
CORN	2.6	3.4	1.8	2.0	3.7	2.0	2.0	2.0	1.0	1.3	0.5	2.8	2.0	0.7	2.0
SMAIZE	2.6	2.9	1.6	1.8	3.1	1.8	1.8	1.8	1.1	1.8	1.8	2.8	1.8	2.1	1.8
RICE	1.2	1.2	3.1	1.2	1.2	1.2	1.2	1.2	1.7	0.3	0.6	3.3	1.2	1.4	1.2
SUGAR	1.9	2.5	2.7	2.0	3.0	2.4	2.0	3.9	1.7	1.9	0.8	2.4	2.6	1.1	3.3
POTATO	2.1	0.9	2.7	1.9	2.7	1.5	0.7	3.4	2.1	1.9	0.6	2.9	2.7	1.1	1.2
SOYBEAN	3.0	2.0	2.4	2.0	3.8	2.0	2.0	2.0	1.0	2.0	0.5	1.4	2.0	1.0	4.4
RAPSEED	1.4	2.2	2.5	1.9	2.0	2.8	3.2	0.7	0.6	2.5	1.9	2.4	-1.9	0.7	3.0
SUNSEED	1.0	2.7	1.8	1.2	1.7	1.2	1.2	1.2	1.9	1.1	1.6	2.8	1.2	0.9	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.2	1.7	0.6	1.6	0.2	0.5	0.5	0.5	2.0	0.9	0.7	1.0	1.1	1.0	1.0
BARLEY	2.4	1.9	0.6	1.4	1.5	0.5	0.3	1.0	2.6	1.4	0.6	1.1	0.9	1.2	0.5
RYE	2.4	1.1	0.7	0.8	1.1	2.3	0.5	0.8	2.2	1.6	1.5	1.4	0.8	1.8	0.6
OTHGRA	0.8	1.1	1.4	0.9	1.1	1.3	1.3	2.2	2.4	1.9	0.6	1.2	1.6	0.3	0.2
CORN	2.0	2.0	2.5	1.9	2.4	1.1	1.0	2.2	2.7	2.0	2.0	1.9	1.7	2.8	1.9
SMAIZE	1.8	1.8	1.8	2.5	1.8	2.1	1.0	1.9	2.0	1.8	1.8	2.0	1.2	2.1	0.9
RICE	1.2	1.2	1.2	1.2	1.2	0.5	1.2	1.2	1.8	1.2	1.2	1.3	2.0	3.1	1.2
SUGAR	3.4	0.5	1.2	2.8	2.7	3.0	2.7	2.2	2.8	1.8	1.9	2.2	1.3	1.7	2.4
POTATO	1.2	0.3	0.7	1.4	0.5	1.4	1.2	2.7	2.8	1.2	1.1	1.6	1.1	1.4	1.7
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.7	2.1	2.6	2.3	2.0	2.0	2.0	1.0	4.3	2.0
RAPSEED	1.4	1.9	0.4	3.1	1.9	2.6	1.1	0.4	2.7	2.4	-0.1	1.6	2.1	2.5	2.2
SUNSEED	1.2	1.2	1.2	1.9	3.4	0.8	2.4	2.3	3.4	1.2	1.2	1.6	0.7	2.2	1.2

Table 20: Rates of technical progress for different groups of agricultural products and regions A1B with CO2 effect (GCM-LPJmL, GFDL).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.1	0.9	0.4	0.2	0.8	0.3	2.1	1.3	0.2	0.8	0.2	0.1	1.4	0.3	2.0
BARLEY	1.4	0.9	0.5	1.0	0.1	0.4	0.4	0.3	1.2	0.7	0.5	0.6	0.8	0.5	0.5
RYE	0.1	2.3	1.2	1.1	1.6	0.5	2.7	0.8	1.1	0.3	0.6	1.1	1.3	0.6	2.6
OTHGRA	0.1	1.3	1.0	1.1	0.3	1.0	1.3	0.8	0.3	0.3	1.7	0.9	1.3	1.1	1.6
CORN	2.3	3.2	1.3	2.0	3.5	2.0	2.0	2.0	0.6	1.3	0.5	2.2	2.0	0.6	2.0
SMAIZE	2.2	2.7	1.1	1.8	2.8	1.8	1.8	1.8	0.7	1.8	1.8	2.2	1.8	1.9	1.8
RICE	1.2	1.2	2.6	1.2	1.2	1.2	1.2	1.2	1.2	0.3	0.0	2.9	1.2	0.9	1.2
SUGAR	1.4	2.1	2.3	2.0	2.6	2.0	2.0	3.6	1.1	1.4	0.3	1.6	2.3	0.5	3.0
POTATO	1.6	0.4	2.3	1.9	2.3	1.1	0.7	3.1	1.5	1.4	0.2	2.1	2.4	0.5	0.9
SOYBEAN	2.5	2.0	1.7	2.0	3.2	2.0	2.0	2.0	0.5	2.0	0.5	0.7	2.0	0.4	4.1
RAPSEED	1.2	1.9	2.3	1.9	1.8	2.5	2.9	0.5	0.4	2.3	1.9	2.2	-2.1	0.5	2.8
SUNSEED	0.4	2.3	1.3	1.2	1.2	1.2	1.2	1.2	0.8	0.6	0.3	2.3	1.2	-0.1	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	1.9	1.7	0.4	1.3	0.2	0.2	0.2	0.3	1.8	0.7	0.4	0.7	0.8	1.0	0.7
BARLEY	2.4	1.9	0.6	1.4	1.5	0.5	0.3	1.0	2.6	1.4	0.6	1.1	0.9	1.2	0.5
RYE	2.1	1.1	0.5	0.5	1.1	1.9	0.2	0.6	2.0	1.4	1.2	1.1	0.5	1.8	0.3
OTHGRA	0.5	1.1	1.3	0.6	1.1	1.0	1.0	2.0	2.1	1.7	0.3	1.0	1.3	0.3	0.0
CORN	2.0	2.0	2.5	1.9	2.4	0.6	1.0	2.1	2.6	2.0	2.0	1.8	1.1	2.4	1.8
SMAIZE	1.8	1.8	1.8	2.5	1.8	1.6	0.9	1.8	1.9	1.8	1.8	1.9	0.6	1.7	0.8
RICE	1.2	1.2	1.2	1.2	0.9	0.0	1.2	1.2	1.3	1.2	1.2	1.1	1.1	2.5	0.6
SUGAR	3.1	0.5	0.8	2.6	2.4	2.2	2.4	1.7	2.4	1.5	1.4	1.8	0.7	1.4	2.0
POTATO	0.9	0.3	0.3	1.2	0.2	0.6	0.9	2.3	2.4	0.8	0.7	1.2	0.5	1.1	1.3
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.1	1.6	1.9	1.9	2.0	2.0	1.8	0.0	2.9	1.2
RAPSEED	1.1	1.9	0.2	2.8	1.9	2.3	0.8	0.2	2.5	2.2	-0.2	1.4	1.8	2.5	1.9
SUNSEED	1.2	1.2	1.2	1.2	2.7	0.0	1.7	1.6	2.4	1.2	1.2	1.2	0.1	1.0	0.2

Table 21: Rates of technical progress for different groups of agricultural products and regions A1B without CO2 effect (GCM-LPJmL, GFDL).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.4	1.2	0.6	0.2	1.2	0.5	2.1	1.5	0.6	1.1	0.2	0.5	1.8	0.5	2.1
BARLEY	0.5	1.7	0.5	0.2	0.8	1.2	2.4	1.2	1.0	1.1	0.2	0.5	1.7	0.5	2.3
RYE	0.5	2.6	1.4	1.1	2.0	0.7	2.7	1.0	1.5	0.6	0.6	1.4	1.8	0.9	2.7
OTHGRA	0.5	1.6	1.3	1.1	0.6	1.2	1.3	1.0	0.7	0.6	1.7	1.3	1.7	1.4	1.7
CORN	2.6	3.4	2.7	2.0	3.5	2.0	2.0	2.0	1.0	1.3	0.5	3.0	2.0	0.7	2.0
SMAIZE	2.5	2.9	2.5	1.8	2.8	1.8	1.8	1.8	1.1	1.8	1.8	3.0	1.8	2.0	1.8
RICE	1.2	1.2	2.9	1.2	1.2	1.2	1.2	1.2	1.2	0.3	0.7	3.0	1.2	1.3	1.2
SUGAR	2.0	2.4	2.9	2.0	3.0	2.5	2.0	3.3	1.7	1.8	0.8	2.6	2.4	1.1	3.3
POTATO	2.2	0.7	2.9	1.9	2.7	1.6	0.7	2.8	2.1	1.8	0.6	3.1	2.5	1.1	1.2
SOYBEAN	2.7	2.0	3.1	2.0	3.6	2.0	2.0	2.0	1.2	2.0	0.5	1.9	2.0	1.0	3.8
RAPSEED	1.5	2.4	2.5	1.9	2.1	2.8	2.9	0.6	0.9	2.6	1.9	2.6	-1.3	0.8	2.8
SUNSEED	1.0	3.3	2.2	1.2	1.7	1.2	1.2	1.2	1.9	1.1	2.0	2.9	1.2	1.2	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.1	1.7	0.6	1.6	0.2	0.6	0.6	0.6	2.0	0.7	0.7	1.0	1.0	1.0	1.1
BARLEY	2.4	1.9	0.7	1.4	1.5	0.6	0.4	1.1	2.6	1.2	0.6	1.1	0.8	1.2	0.6
RYE	2.3	1.1	0.7	0.8	1.1	2.3	0.6	0.9	2.2	1.4	1.5	1.4	0.7	1.8	0.7
OTHGRA	0.7	1.1	1.5	0.9	1.1	1.4	1.4	2.3	2.4	1.7	0.6	1.2	1.5	0.3	0.4
CORN	2.0	2.0	2.5	1.9	2.4	1.4	1.0	2.3	2.7	2.0	2.0	2.0	2.1	2.7	2.1
SMAIZE	1.8	1.8	1.8	2.5	1.8	2.4	0.9	2.0	2.0	1.8	1.8	2.0	1.6	2.0	1.1
RICE	1.2	1.2	1.2	1.2	1.0	0.6	1.2	1.2	1.4	1.2	1.2	1.2	2.0	3.0	1.1
SUGAR	3.3	0.5	1.1	2.8	2.6	3.1	2.7	2.4	2.8	1.9	1.7	2.2	1.8	1.7	2.3
POTATO	1.2	0.3	0.6	1.4	0.4	1.5	1.2	2.9	2.8	1.2	0.9	1.6	1.6	1.4	1.6
SOYBEAN	2.0	2.0	2.0	2.0	2.0	3.0	1.5	3.2	2.3	2.0	2.0	2.1	1.3	3.3	2.2
RAPSEED	1.3	1.9	0.4	3.2	1.9	2.7	1.2	0.5	2.7	2.3	0.6	1.7	1.5	2.5	2.1
SUNSEED	1.2	1.2	1.2	1.7	3.5	1.1	2.4	2.5	3.2	1.2	1.2	1.7	0.8	2.3	1.4

Table 22: Rates of technical progress for different groups of agricultural products and regions B1 with CO2 effect (GCM-LPJmL, GFDL).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.2	1.1	0.4	0.2	0.9	0.3	2.0	1.3	0.4	0.8	0.2	0.2	1.7	0.3	1.9
BARLEY	0.3	1.6	0.3	0.2	0.5	1.0	2.2	1.0	0.8	0.8	0.2	0.3	1.6	0.3	2.1
RYE	0.3	2.4	1.2	1.1	1.7	0.5	2.5	0.8	1.3	0.3	0.6	1.2	1.6	0.7	2.5
OTHGRA	0.3	1.5	1.1	1.1	0.4	1.0	1.1	0.7	0.4	0.3	1.7	1.1	1.5	1.2	1.5
CORN	2.5	3.3	2.6	2.0	3.3	2.0	2.0	2.0	0.8	1.3	0.5	2.6	2.0	0.6	2.0
SMAIZE	2.4	2.8	2.4	1.8	2.7	1.8	1.8	1.8	0.9	1.8	1.8	2.6	1.8	1.9	1.8
RICE	1.2	1.2	2.5	1.2	1.2	1.2	1.2	1.2	0.9	0.3	0.2	2.7	1.2	1.0	1.2
SUGAR	1.7	2.0	2.6	2.0	2.7	2.2	2.0	3.1	1.2	1.5	0.5	2.0	2.1	0.7	3.0
POTATO	1.9	0.4	2.6	1.9	2.4	1.3	0.7	2.6	1.6	1.5	0.3	2.5	2.2	0.7	0.9
SOYBEAN	2.3	2.0	3.0	2.0	3.3	2.0	2.0	2.0	0.7	2.0	0.5	1.3	2.0	0.6	3.4
RAPSEED	1.4	2.2	2.4	1.9	1.9	2.6	2.7	0.4	0.7	2.4	1.9	2.4	-1.5	0.7	2.6
SUNSEED	0.6	3.0	1.8	1.2	1.4	1.2	1.2	1.2	1.0	0.8	0.8	2.4	1.2	0.4	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	1.9	1.7	0.5	1.4	0.2	0.3	0.3	0.5	1.8	0.6	0.5	0.8	0.8	1.0	0.9
BARLEY	2.1	1.9	0.5	1.2	1.5	0.3	0.2	1.0	2.4	1.1	0.4	1.0	0.6	1.2	0.4
RYE	2.1	1.1	0.6	0.6	1.1	2.1	0.4	0.8	2.0	1.3	1.3	1.2	0.5	1.8	0.5
OTHGRA	0.5	1.1	1.3	0.7	1.1	1.1	1.2	2.2	2.2	1.6	0.4	1.1	1.2	0.3	0.2
CORN	2.0	2.0	2.5	1.9	2.4	1.1	0.9	2.2	2.6	2.0	2.0	1.9	1.7	2.5	2.0
SMAIZE	1.8	1.8	1.8	2.5	1.8	2.1	0.9	1.9	1.9	1.8	1.8	2.0	1.2	1.8	1.0
RICE	1.2	1.2	1.2	1.2	0.7	0.3	1.2	1.2	1.0	1.2	1.2	1.1	1.4	2.6	0.9
SUGAR	3.1	0.5	0.8	2.6	2.4	2.6	2.5	2.1	2.5	1.6	1.3	1.9	1.4	1.4	2.0
POTATO	0.9	0.3	0.3	1.2	0.2	1.0	1.0	2.6	2.5	1.0	0.6	1.3	1.2	1.1	1.3
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.6	1.1	2.7	2.0	2.0	2.0	1.9	0.6	3.0	1.6
RAPSEED	1.1	1.9	0.3	3.0	1.9	2.5	1.0	0.4	2.5	2.1	0.4	1.5	1.3	2.5	1.9
SUNSEED	1.2	1.2	1.2	1.2	2.9	0.7	1.8	2.0	2.5	1.2	1.2	1.3	0.5	1.4	0.6

Table 23: Rates of technical progress for different groups of agricultural products and regions B1 without CO2 effect (GCM-LPJmL, GFDL).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.5	1.1	0.7	0.1	1.3	0.9	2.4	1.3	0.4	1.1	0.5	0.4	1.3	0.4	2.5
BARLEY	0.5	1.6	0.5	0.1	0.9	1.6	2.6	1.0	0.8	1.1	0.6	0.5	1.2	0.4	2.7
RYE	0.5	2.5	1.5	1.0	2.1	1.1	2.9	0.8	1.3	0.6	0.9	1.4	1.2	0.8	3.0
OTHGRA	0.5	1.5	1.4	0.9	0.7	1.7	1.6	0.7	0.5	0.6	2.0	1.3	1.2	1.3	2.1
CORN	2.6	2.6	1.9	2.0	4.0	2.0	2.0	2.0	0.4	2.5	0.4	1.9	2.0	0.5	2.0
SMAIZE	2.5	2.1	1.7	1.8	3.3	1.8	1.8	1.8	0.5	3.0	1.7	1.9	1.8	1.8	1.8
RICE	1.2	1.2	2.9	1.2	1.2	1.2	1.2	1.2	1.6	0.3	0.3	3.1	1.2	1.2	1.2
SUGAR	1.5	1.8	2.5	2.0	2.8	2.3	2.0	4.8	0.8	1.6	0.7	1.4	2.5	0.8	3.5
POTATO	1.7	0.2	2.5	1.9	2.5	1.4	0.7	4.3	1.2	1.6	0.5	1.9	2.6	0.8	1.4
SOYBEAN	3.0	2.0	2.2	2.0	4.0	2.0	2.0	2.0	0.9	2.0	0.5	0.8	2.0	0.8	5.1
RAPSEED	1.3	2.2	2.5	1.9	2.2	3.0	3.0	0.4	0.7	2.7	1.9	2.5	1.9	0.7	3.3
SUNSEED	0.6	3.1	1.6	1.2	1.8	1.2	1.2	1.2	1.0	1.0	0.9	2.3	1.2	1.3	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.5	1.7	0.5	1.6	0.3	0.5	0.6	0.6	2.0	1.2	0.8	1.0	1.0	1.2	0.9
BARLEY	2.7	1.9	0.5	1.4	1.6	0.5	0.5	1.1	2.5	1.7	0.7	1.2	0.8	1.4	0.4
RYE	2.7	1.1	0.5	0.8	1.2	2.3	0.7	0.9	2.2	1.9	1.6	1.4	0.7	2.0	0.5
OTHGRA	1.1	1.1	1.3	0.9	1.1	1.3	1.5	2.3	2.3	2.2	0.7	1.3	1.4	0.5	0.2
CORN	5.3	2.0	4.1	4.1	2.4	0.4	1.1	2.0	2.6	2.0	2.0	2.1	1.5	2.6	2.0
SMAIZE	5.1	1.8	3.4	4.7	1.8	1.4	1.0	1.7	1.9	1.8	1.8	2.2	1.0	1.9	1.0
RICE	1.2	1.2	1.2	1.2	1.4	0.2	1.2	1.2	1.8	1.2	1.2	1.6	1.7	2.9	1.2
SUGAR	3.0	0.5	0.8	2.8	2.6	1.7	2.5	1.7	2.7	2.1	1.5	2.0	1.5	1.5	1.9
POTATO	0.9	0.3	0.3	1.4	0.5	0.1	1.0	2.2	2.7	1.4	0.7	1.4	1.3	1.2	1.2
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.4	2.2	2.2	2.2	2.0	2.0	2.4	0.7	3.3	2.0
RAPSEED	1.9	1.9	0.1	3.3	1.9	2.6	1.0	0.5	2.8	2.5	1.0	1.8	1.9	2.5	2.1
SUNSEED	1.2	1.2	1.2	1.4	2.9	0.2	1.9	1.8	3.2	1.2	1.2	1.4	0.8	1.5	0.9

Table 24: Rates of technical progress for different groups of agricultural products and regions A1B with CO2 effect (GCM-LPJmL, HadCM).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.2	0.8	0.4	-0.1	1.0	0.6	2.1	0.9	0.1	0.8	0.3	0.1	1.0	0.2	2.2
BARLEY	0.2	1.3	0.2	-0.1	0.6	1.3	2.3	0.6	0.5	0.8	0.3	0.2	0.9	0.2	2.4
RYE	0.2	2.2	1.2	0.8	1.8	0.8	2.7	0.4	1.0	0.3	0.7	1.1	1.0	0.5	2.7
OTHGRA	0.2	1.2	1.1	0.7	0.5	1.4	1.3	0.4	0.2	0.3	1.8	1.0	0.9	1.0	1.7
CORN	2.1	2.0	0.8	2.0	3.6	2.0	2.0	2.0	0.0	2.1	0.3	1.0	2.0	0.3	2.0
SMAIZE	2.0	1.5	0.7	1.8	2.9	1.8	1.8	1.8	0.1	2.6	1.6	1.0	1.8	1.6	1.8
RICE	1.2	1.2	2.3	1.2	1.2	1.2	1.2	1.2	1.1	0.3	-0.4	2.6	1.2	0.6	1.2
SUGAR	0.9	1.1	2.0	2.0	2.2	1.8	2.0	4.4	0.0	1.0	0.3	0.2	2.1	0.2	3.0
POTATO	1.1	-0.5	2.0	1.9	1.9	0.9	0.7	3.9	0.4	1.0	0.1	0.7	2.2	0.2	0.9
SOYBEAN	2.3	2.0	1.6	2.0	3.3	2.0	2.0	2.0	0.2	2.0	0.5	-0.1	2.0	0.2	4.4
RAPSEED	1.1	2.0	2.3	1.9	2.0	2.6	2.7	0.1	0.4	2.4	1.9	2.3	1.7	0.5	3.0
SUNSEED	-0.2	2.6	0.8	1.2	1.2	1.2	1.2	1.2	-1.0	0.4	-0.1	1.6	1.2	0.0	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.2	1.7	0.3	1.3	0.0	0.1	0.3	0.3	1.7	0.9	0.5	0.7	0.7	0.9	0.6
BARLEY	2.4	1.9	0.3	1.1	1.3	0.2	0.2	0.8	2.2	1.4	0.4	0.9	0.5	1.1	0.1
RYE	2.4	1.1	0.3	0.5	0.9	1.9	0.4	0.6	1.9	1.6	1.3	1.1	0.4	1.7	0.2
OTHGRA	0.8	1.1	1.1	0.6	0.9	1.0	1.2	2.0	2.1	1.9	0.4	1.0	1.2	0.1	-0.1
CORN	4.9	2.0	3.9	4.0	2.4	-0.4	1.0	1.7	2.4	2.0	2.0	1.9	1.0	2.2	1.8
SMAIZE	4.8	1.8	3.2	4.6	1.8	0.6	0.9	1.4	1.7	1.8	1.8	1.9	0.5	1.6	0.8
RICE	1.2	1.2	1.2	1.2	1.0	-0.4	1.2	1.2	1.2	1.2	1.2	1.0	0.5	2.2	0.9
SUGAR	2.5	0.5	0.2	2.5	2.3	0.4	2.1	1.1	2.3	1.7	1.0	1.5	0.9	1.2	1.4
POTATO	0.3	0.3	-0.3	1.1	0.2	-1.2	0.6	1.6	2.3	1.0	0.2	0.9	0.7	0.9	0.7
SOYBEAN	2.0	2.0	2.0	2.0	2.0	1.7	1.5	1.2	1.9	2.0	2.0	1.7	-0.2	2.5	1.2
RAPSEED	1.6	1.9	-0.1	3.1	1.9	2.3	0.8	0.2	2.5	2.2	0.8	1.6	1.6	2.5	1.8
SUNSEED	1.2	1.2	1.2	0.6	1.8	-1.0	1.0	0.9	2.3	1.2	1.2	0.9	0.3	0.7	0.4

Table 25: Rates of technical progress for different groups of agricultural products and regions A1B without CO2 effect (GCM-LPJmL, HadCM).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.5	1.2	0.7	0.1	1.2	1.0	2.2	1.3	0.4	1.2	0.5	0.5	1.3	0.4	2.5
BARLEY	0.5	1.7	0.5	0.1	0.8	1.7	2.4	1.0	0.8	1.2	0.5	0.6	1.2	0.4	2.7
RYE	0.5	2.5	1.5	1.0	2.0	1.2	2.8	0.8	1.3	0.7	0.9	1.5	1.2	0.8	3.1
OTHGRA	0.5	1.6	1.3	1.0	0.7	1.7	1.4	0.8	0.5	0.7	2.0	1.3	1.1	1.2	2.1
CORN	2.4	2.3	2.1	2.0	3.5	2.0	2.0	2.0	0.4	2.1	0.5	2.5	2.0	0.5	2.0
SMAIZE	2.3	1.8	1.9	1.8	2.9	1.8	1.8	1.8	0.5	2.6	1.8	2.5	1.8	1.8	1.8
RICE	1.2	1.2	2.7	1.2	1.2	1.2	1.2	1.2	1.4	0.3	0.5	2.8	1.2	1.1	1.2
SUGAR	1.8	2.0	2.6	2.0	2.9	2.1	2.0	4.7	1.0	1.7	0.7	2.2	2.0	0.7	3.4
POTATO	2.0	0.3	2.6	1.9	2.6	1.2	0.7	4.2	1.4	1.7	0.6	2.7	2.1	0.7	1.3
SOYBEAN	2.5	2.0	2.0	2.0	3.3	2.0	2.0	2.0	0.8	2.0	0.5	1.1	2.0	0.7	6.0
RAPSEED	1.3	2.5	2.6	1.9	2.1	2.9	2.9	0.4	0.8	2.8	1.9	2.5	2.0	0.6	3.2
SUNSEED	0.7	2.4	1.6	1.2	1.4	1.2	1.2	1.2	0.7	0.7	1.3	2.5	1.2	0.4	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.6	1.7	0.6	1.7	0.3	0.5	0.6	0.6	1.9	1.0	0.8	1.0	1.0	1.2	0.9
BARLEY	2.8	1.9	0.7	1.5	1.6	0.6	0.5	1.1	2.5	1.5	0.7	1.2	0.8	1.4	0.4
RYE	2.8	1.1	0.7	0.9	1.2	2.3	0.6	0.9	2.1	1.7	1.6	1.4	0.7	2.0	0.5
OTHGRA	1.1	1.1	1.5	1.0	1.2	1.4	1.4	2.3	2.3	2.0	0.7	1.3	1.5	0.5	0.2
CORN	3.6	2.0	3.7	3.0	2.4	0.7	0.8	2.1	2.5	2.0	2.0	2.0	1.9	2.6	2.0
SMAIZE	3.5	1.8	3.0	3.6	1.8	1.7	0.7	1.8	1.8	1.8	1.8	2.1	1.4	1.9	1.0
RICE	1.2	1.2	1.2	1.2	1.2	0.3	1.2	1.2	1.5	1.2	1.2	1.5	1.9	2.9	1.1
SUGAR	3.3	0.5	0.8	2.8	2.6	2.5	2.6	2.1	2.7	1.8	1.4	2.0	1.8	1.6	2.2
POTATO	1.1	0.3	0.3	1.4	0.4	0.9	1.1	2.6	2.7	1.1	0.6	1.4	1.6	1.3	1.5
SOYBEAN	2.0	2.0	2.0	2.0	2.0	2.5	1.4	2.6	2.2	2.0	2.0	2.3	1.1	3.5	2.0
RAPSEED	1.4	1.9	0.6	3.3	1.9	2.7	1.0	0.5	2.7	2.2	1.1	1.8	1.9	2.5	2.0
SUNSEED	1.2	1.2	1.2	1.5	2.6	0.4	2.1	2.2	2.6	1.2	1.2	1.3	0.9	1.9	0.9

Table 26: Rates of technical progress for different groups of agricultural products and regions B1 with CO2 effect (GCM-LPJmL, HadCM).

	AT	BE	BG	CY	CZ	DK	EE	FI	FR	GE	GR	HU	IE	IT	LV
WHEAT	0.2	0.9	0.4	-0.1	1.0	0.7	2.0	1.1	0.2	1.0	0.3	0.2	1.0	0.2	2.3
BARLEY	0.3	1.4	0.3	0.0	0.6	1.4	2.2	0.8	0.6	1.0	0.3	0.3	0.9	0.2	2.5
RYE	0.3	2.3	1.2	0.9	1.8	0.9	2.6	0.5	1.1	0.5	0.6	1.2	1.0	0.6	2.8
OTHGRA	0.3	1.3	1.1	0.8	0.5	1.5	1.2	0.5	0.2	0.5	1.7	1.1	0.9	1.0	1.8
CORN	2.0	2.0	1.6	2.0	3.3	2.0	2.0	2.0	0.1	1.9	0.4	1.7	2.0	0.4	2.0
SMAIZE	1.9	1.6	1.4	1.8	2.6	1.8	1.8	1.8	0.2	2.4	1.7	1.7	1.8	1.7	1.8
RICE	1.2	1.2	2.2	1.2	1.2	1.2	1.2	1.2	1.0	0.3	-0.1	2.5	1.2	0.6	1.2
SUGAR	1.3	1.5	2.2	2.0	2.5	1.8	2.0	4.4	0.5	1.3	0.4	1.3	1.7	0.3	3.0
POTATO	1.5	-0.1	2.2	1.9	2.2	0.9	0.7	3.9	0.9	1.3	0.2	1.8	1.8	0.3	0.9
SOYBEAN	2.0	2.0	1.6	2.0	2.8	2.0	2.0	2.0	0.4	2.0	0.5	0.1	2.0	0.2	5.7
RAPSEED	1.1	2.3	2.4	1.9	1.9	2.7	2.7	0.2	0.6	2.6	1.9	2.3	1.8	0.5	3.0
SUNSEED	0.2	1.9	1.0	1.2	0.9	1.2	1.2	1.2	-0.4	0.3	0.6	2.0	1.2	-0.4	1.2

	LT	MT	NL	PL	PT	RO	SK	SI	ES	SW	UK	EU	US	TU	ROW
WHEAT	2.4	1.7	0.5	1.5	0.1	0.2	0.3	0.4	1.7	0.9	0.6	0.8	0.8	0.9	0.7
BARLEY	2.6	1.9	0.5	1.3	1.4	0.3	0.2	0.9	2.3	1.4	0.5	1.0	0.6	1.1	0.2
RYE	2.6	1.1	0.5	0.7	1.0	2.0	0.4	0.7	1.9	1.6	1.4	1.2	0.4	1.7	0.3
OTHGRA	0.9	1.1	1.3	0.8	0.9	1.1	1.2	2.1	2.1	1.9	0.5	1.1	1.2	0.2	0.0
CORN	3.4	2.0	3.6	2.9	2.4	0.1	0.7	1.9	2.4	2.0	2.0	1.8	1.5	2.4	1.9
SMAIZE	3.3	1.8	2.9	3.5	1.8	1.1	0.7	1.6	1.7	1.8	1.8	1.9	1.0	1.7	0.9
RICE	1.2	1.2	1.2	1.2	0.9	-0.2	1.2	1.2	1.1	1.2	1.2	1.1	1.0	2.4	0.9
SUGAR	3.0	0.5	0.5	2.6	2.3	1.6	2.4	1.6	2.4	1.5	1.0	1.7	1.4	1.3	1.8
POTATO	0.8	0.3	0.0	1.2	0.2	0.0	0.9	2.1	2.4	0.8	0.2	1.1	1.2	1.0	1.1
SOYBEAN	2.0	2.0	2.0	2.0	2.0	1.9	0.9	1.8	1.9	2.0	2.0	1.8	0.4	3.0	1.4
RAPSEED	1.2	1.9	0.5	3.2	1.9	2.4	0.8	0.3	2.5	2.0	0.9	1.7	1.6	2.5	1.8
SUNSEED	1.2	1.2	1.2	1.0	1.8	-0.5	1.4	1.5	2.1	1.2	1.2	1.0	0.5	1.1	0.5

Table 27: Rates of technical progress for different groups of agricultural products and regions B1 without CO2 effect (GCM-LPJmL, HadCM).

Appendix C

Crop yield changes in European countries in % by 2050 as compared to the no climate change scenario for all GCM-LPJmL-scenarios

	Barley		Corn		Wheat		Othgrain		Potato		Rapseed		Rice		Rye		Soybean		Sugar		Sunseed	
	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo
Austria	10	-1	32	15	11	1	9	-1	7	-10	11	5			7	2	59	38	9	-12	20	-6
Belgium	12	1	50	30	11	2	12	2	10	-8	11	5			12	2			14	-11		
Bulgaria	9	0	-7	-27	5	-1	8	0	1	-12	-4	-7	15	7	5	-3	-17	0	4	-15	7	-12
Cyprus	-35	-38					-35	-37	-2	1												
CzechRep.	20	11	68	49	20	13	23	13	16	1	29	26			19	10	54	73	23	0	38	23
Denmark	32	20			32	21	35	23	34	12	21	10			31	20			40	13		
Estonia	17	14			18	16	21	11	-3	1	13	10			16	12						
Spain	7	1	3	1	10	1	11	1	11	-3	7	1	48	21	9	-1	5	17	13	-4	36	-2
Finland	27	10			27	11	23	12	149	117	16	10			22	11			181	138		
France	12	1	7	-3	12	2	13	3	3	-20	2	-3	42	21	11	1	9	17	4	-22	31	-24
Germany	17	5	64	48	16	7	17	6	15	-4	21	14			16	6			18	-4	43	16
Greece	10	-1	-1	-2	11	1	12	2	6	-8			6	-14	11	1	-3	3	9	-8	31	-18
Hungary	10	1	2	-24	9	3	8	0	-2	-25	-4	-7	30	26	9	2	3	-19	0	-30	11	-8
Ireland	17	10			16	11	19	8	24	8	-21	-25							28	9		
Italy	10	-1	3	2	11	1	9	4	11	-10	9	2	15	-2	6	1	15	-5	13	-12	37	-14
Lithuania	33	24	110	101	34	26	34	23	26	15	14	11			35	25			32	13		
Latvia	28	19			23	21	26	16	34	20	13	10			26	16			46	23		
Malta	-4	0							-3	0												
Netherlands	15	8	100	97	15	10	19	13	20	0	-4	-6			17	11			23	0		
Poland	25	16	91	91	25	17	26	17	17	5	30	25			24	16	2	2	18	4	25	0
Portugal	3	-7	-1	1	6	-3	4	-5	6	-4			42	26	2	-7			4	-4	51	5
Romania	13	0	-3	-21	14	3	13	0	-2	-26	0	-7	-7	-10	9	2	-1	23	0	-31	12	-19
Slovenia	5	2	7	-2	5	4	6	1	6	-13	-3	-9			5	1	-7	5	9	-15	16	-16
Slovakia	15	6	21	21	14	7	13	9	5	-5	24	15			16	7	69	48	8	-8	21	-8
Sweden	27	20			27	21	27	21	38	24	21	10			26	20			45	23		
UK	17	5			16	7	17	6	23	3	-10	-11			15	5	-2	5	28	4	-2	3

	Barley		Corn		Wheat		Othghrain		Potato		Rapseed		Rice		Rye		Soybean		Sugar		Sunseed	
	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo
Austria	10	3	27	19	11	0	8	2	11	-4	11	9			7	1	45	26	13	-4	26	5
Belgium	12	5	32	24	12	6	12	5	6	-8	21	13			12	2			9	-8		
Bulgaria	5	-1	10	-3	6	2	8	-1	5	-6	0	-4	14	8	5	0	-3	-9	8	-8	17	-3
Cyprus	-12	-13					-13	-13	-2	0												
CzechRep.	20	15	42	35	20	16	23	12	13	4	29	24			20	14	34	27	18	4	32	20
Denmark	22	14			22	15	24	17	29	12	16	9			21	14			34	14		
Estonia	13	8			14	10	16	10	-2	0	9	4			12	6						
Spain	7	0	3	1	6	0	6	0	7	-3	7	0	38	20	4	-1	4	-2	8	-4	30	1
Finland	22	9			22	10	18	11	149	124	16	9			22	10		0	181	148		
France	12	0	7	-4	12	1	8	2	3	-14	7	4	32	15	11	0	8	-2	4	-15	10	-22
Germany	12	5	50	41	12	6	12	5	15	0	26	18			11	5			18	0	32	15
Greece	6	-1	3	-3	6	0	7	1	6	-5			11	-7	6	0	-4	2	9	-4	25	-8
Hungary	6	1	14	-3	10	1	8	-1	12	-9	-4	-4	24	17	5	0	15	-6	18	-11	16	1
Ireland	8	0			7	1	9	3	15	4	-17	-19							18	4		
Italy	6	-1	3	1	6	0	9	3	11	-3	9	2	11	-3	6	0	13	-2	13	-4	37	1
Lithuania	40	33	70	61	40	35	45	33	28	18	9	4			42	35			33	18		
Latvia	29	17			24	19	26	20	35	23	9	9			26	20			46	29		
Malta	-4	-1																				
Netherlands	15	12	76	73	16	9	13	12	15	0	4	-3			12	10			18	0		
Poland	26	20	55	53	26	21	26	20	17	9	35	29			25	19	2	2	18	9	15	-2
Portugal	3	-4	-2	1	2	-4	0	-6	2	-5			32	20	2	-4			4	-4	39	3
Romania	9	-1	10	-3	10	1	8	-1	9	-12	0	-4	1	-5	10	0	6	-6	13	-15	23	-2
Slovenia	6	1	6	5	6	2	5	0	10	-3	-3	-7			6	0	13	-1	14	-4	26	6
Slovakia	15	5	11	15	14	10	13	7	5	1	24	19			16	6	41	34	8	0	32	10
Sweden	22	14			22	15	21	15	38	24	11	4			21	14			39	23		
UK	12	5			12	6	12	5	14	3	-2	-4			11	5	-3	4	18	4	-2	2

Table 28: Yield changes in % under A1B and B1 "with" and "without" CO_2 vs. baseline scenario "no CC" (GCM-LPJmL mean)

	Barley		Corn		Wheat		Othghrain		Potato		Rapseed		Rice		Rye		Soybean		Sugar		Sunseed	
	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo
Austria	15	3	55	35	16	6	13	3	16	9			16	1	51	31	44	16	13	-12	36	-3
Belgium	16	10	62	35	16	11	16	10	21	14			16	6	57	31			14	-11		
Bulgaria	-1	-9	18	-3	1	-9	-1	-9	-5	-11	14	4	-1	-12	16	-3	-19	-26	4	-15	11	-17
Cyprus	-54	-56					-54	-56							-2	-1						
CzechRep.	41	31	88	66	42	34	39	33	45	41			40	29	79	57	38	18	28	4	55	28
Denmark	57	41			57	44	59	45	36	24			55	41	-2	0			45	18		
Estonia	17	8			18	11	15	11	13	9			15	11	-5	0						
Spain	16	5	6	5	15	10	15	5	11	4	32	5	13	7	6	4	3	-6	13	0	35	2
Finland	22	14			21	16	23	12	16	9			21	10					218	170		
France	22	10	21	9	22	11	18	12	11	0	32	10	20	9	20	9	7	-10	13	-19	90	6
Germany	27	14	77	53	27	16	27	15	31	24			25	14	70	47			18	0	55	16
Greece	5	-5	3	-3	2	-7	2	-7			7	-18	1	-8	3	-4	-5	3	9	-8	54	6
Hungary	5	-3	23	-11	5	-1	7	-5	-5	-8	29	18	4	-4	21	-9	19	-9	4	-27	20	-13
Ireland	21	10			21	11	18	12	-6	-12					-1	0			23	5		
Italy	10	-1	7	5	6	1	8	-1	4	-2	11	-7	5	0	11	4	28	7	23	-4	92	26
Lithuania	33	23	68	48	34	26	33	22	13	5			29	19	49	40			32	8		
Latvia	22	18			23	21	26	15	13	5			25	15	-4	0			46	18		
Malta	-5	-1																				
Netherlands	20	17	144	130	21	15	23	17	4	-2			21	15	129	115			23	0		
Poland	48	36	89	81	49	39	48	37	40	34			46	35	75	68	2	2	23	9	47	13
Portugal	12	1	-2	0	11	1	8	-1			27	10	10	0	-1	0			9	-4	51	-4
Romania	-1	-13	0	-15	0	-10	-1	-13	-9	-15	-7	-20	-5	-15	-3	-13	-8	-23	-8	-37	16	-16
Slovenia	5	1	15	5	6	4	5	1	-3	-10			5	0	14	4	12	-12	19	-12	61	-1
Slovakia	19	10	25	19	19	12	17	8	34	30			20	6	24	19	45	24	8	-8	20	-13
Sweden	32	24			32	26	32	25	21	14			30	24					51	28		
UK	22	14			22	16	21	15	-10	-12			20	14	-1	0	-4	4	23	0	-2	3

	Barley		Corn		Wheat		Othghrain		Potato		Rapseed		Rice		Rye		Soybean		Sugar		Sunseed	
	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo
Austria	5	-2	20	8	6	-4	8	-3	7	-7	15	8			6	-4	19	7	44	24	9	-8
Belgium	12	4	15	0	11	5	11	5	-2	-18	25	17			11	5	15	0			0	-18
Bulgaria	9	3	23	4	10	1	11	2	1	-7	2	-2	9	1	8	-1	20	3	9	-3	3	-8
Cyprus	-12	-13					-10	-14	-3	0							-2	-1				
CzechRep.	36	24	35	18	36	25	32	26	13	1	37	32			34	22	31	16	32	15	18	0
Denmark	44	29			44	30	39	32	25	8	25	17			42	28	-2	-1			28	9
Estonia	22	17			18	18	20	14	-2	0	11	7			20	14	-3	-1				
Spain	3	-4	6	4	5	-5	1	-5	6	-4	1	-5	43	24	4	-2	6	3	-1	-7	8	-4
Finland	22	14			21	14	22	11	131	108	26	18			21	14					159	129
France	7	-4	-2	-9	7	-4	3	-3	-8	-23	15	8	38	19	5	-5	-1	-8	-5	-19	-8	-25
Germany	17	9	55	34	16	10	16	9	11	-4	30	22			15	8	51	36			13	-4
Greece	10	-2	-2	-4	6	0	6	0	6	-8			7	-12	5	-1	2	-1	-5	1	4	-8
Hungary	1	-8	17	-5	0	-8	2	-6	5	-15	-2	-6	14	5	-1	-9	16	-4	19	-3	9	-18
Ireland	7	0			7	1	8	-2	20	4	-11	-13					-1	-1			23	4
Italy	5	-2	2	-4	1	-4	4	-2	7	-11	8	1	11	-4	1	-5	2	-1	-1	-15	8	-12
Lithuania	57	44	30	19	58	46	57	49	15	3	11	7			59	45	31	20			22	4
Latvia	39	32			39	29	36	29	26	11	11	7			36	29	-2	0			34	13
Malta	-4	-2							-3	-1												
Netherlands	25	17	115	102	20	18	23	16	11	-4	3	1			21	14	105	92			13	-4
Poland	48	41	59	51	48	42	48	41	12	4	51	43			46	39	51	44	2	2	13	4
Portugal	-6	-12	2	4	-7	-12	-5	-10	2	-8			44	29	-7	-13	2	4			0	-8
Romania	9	-2	8	-5	9	0	7	-2	-5	-24	-2	-10	0	-8	8	-5	8	-4	1	-11	-5	-29
Slovenia	5	0	5	-5	5	1	5	-1	5	-10	-4	-8			5	-1	5	-4	17	-7	9	-12
Slovakia	15	4	1	4	14	5	17	6	5	-3	32	27			15	4	4	2	33	20	8	-4
Sweden	27	19			27	19	26	19	32	19	10	3			25	18					39	23
UK	17	4			16	5	16	5	14	3	-3	-9			15	4	-1	0	-4	3	18	0

Table 29: Yield changes in % under A1B and B1 "with" and "without" CO2 vs. baseline scenario "no CC" (CCSM)

	Barley		Corn		Wheat		Othghrain		Potato		Rapseed		Rice		Rye		Soybean		Sugar		Sunseed	
	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo
Austria	16	4	10	-7	16	6	14	3	0	-13	17	10			13	6	0	-7	34	9	4	-15
Belgium	17	5	15	15	17	7	17	6	-1	-8	22	15			18	7	-1	13			14	-8
Bulgaria	15	0	-46	-63	11	4	13	4	-1	-15	1	-2	18	11	11	2	-1	-57	-36	-44	0	-18
Cyprus	-25	-29					-26	-29	-1	1							-1	1				
CzechRep.	21	16	48	26	21	18	23	18	0	-1	42	37			21	15	-1	22	24	12	18	-4
Denmark	33	20			33	21	35	17	0	21	22	1			32	20	-1	0			52	23
Estonia	10	5			10	7	12	7	-1	1	10	2			8	3	-1	1				
Spain	3	-7	5	-3	2	-7	2	-7	0	-6	3	-7	62	31	1	-9	-1	-3	4	-4	9	-8
Finland	18	1			17	2	19	3	0	117	12	1			18	2					181	138
France	13	1	1	-11	12	2	14	3	0	-23	7	1	43	15	12	1	0	-11	0	-16	0	-25
Germany	18	6	48	31	17	7	17	6	0	0	32	25			17	6	-1	26			23	0
Greece	16	4	2	-2	16	6	17	6	-1	-8			11	-11	16	6	0	-4	-4	5	9	-8
Hungary	17	6	-17	-43	15	8	13	4	-1	-37	1	-2	33	31	15	6	-1	-39	-21	-44	-11	-43
Ireland	3	-3			3	-2	5	-1	0	12	-1	-7					-1	0			34	14
Italy	11	-1	2	-6	11	1	9	3	0	-19	9	3	-2	2	12	1	0	-4	4	-12	0	-22
Lithuania	35	24	84	64	35	27	40	28	-1	23	10	2			37	25	-1	51			50	28
Latvia	24	14			24	17	21	16	0	28	10	2			22	12	-1	0			58	34
Malta	-3	0							-2	0.5												
Netherlands	21	13	105	98	21	15	19	13	0	4	0	-6			18	11	-1	85			29	4
Poland	27	21	68	63	26	23	27	22	0	9	42	36			26	21	-1	51	2	2	23	9
Portugal	3	-7	1	2	2	-7	0	-9	-1	-4			63	43	2	-7	0	0			9	-4
Romania	25	9	-17	-38	20	12	23	9	0	-30	10	2	0	-7	20	6	0	-34	-10	-21	-4	-37
Slovenia	11	7	6	-6	11	9	11	6	0	-16	7	0			11	6	0	-7	-22	-32	0	-19
Slovakia	16	7	16	12	15	12	19	8	-1	-2	31	27			17	7	1	11	35	17	8	-4
Sweden	23	15			22	16	22	15	-2	29	12	5			21	15					58	34
UK	13	1			12	2	12	2	-1	3	-1	-7			12	1	-1	0	-3	6	34	4

	Barley		Corn		Wheat		Othghrain		Potato		Rapseed		Rice		Rye		Soybean		Sugar		Sunseed	
	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo
Austria	15	8	37	24	16	9	13	6	11	0	16	9			16	5	35	21	38	24	13	0
Belgium	12	0	11	14	12	1	11	1	14	-1	21	13			7	1	11	12			19	0
Bulgaria	5	-1	-15	-22	2	2	3	3	1	-10	-5	-9	23	18	0	0	-12	-17	-16	-22	4	-12
Cyprus	-12	-17					-13	-17	-2	0							-2	0				
CzechRep.	26	19	54	40	26	21	28	21	16	4	28	28			24	18	46	34	26	14	23	4
Denmark	22	9			22	10	18	11	35	16	11	0			20	9	-2	-1			40	18
Estonia	9	3			9	5	11	5	-2	0	4	-1			6	5	-3	0				
Spain	7	0	2	0	6	0	6	0	11	0	6	0	39	21	4	-2	2	0	2	0	13	0
Finland	12	0			12	1	13	2	221	190	6	0			11	1					274	231
France	8	0	12	5	7	1	8	2	11	-4	2	-4	28	16	6	0	11	4	12	-4	13	-4
Germany	17	9	56	47	17	10	16	10	15	4	26	18			15	9	51	41			18	4
Greece	1	-9	-1	-4	2	-8	-2	-8	6	-5			12	-6	-3	-8	-1	-4	-5	1	9	-8
Hungary	16	5	24	5	14	10	17	7	12	-9	-1	-5	28	28	14	4	21	4	24	5	18	-11
Ireland	-9	-15			-10	-15	-12	-17	20	12	-2	-8					-1	0			23	13
Italy	10	-1	7	5	6	0	9	2	15	0	4	1	-1	2	6	0	7	4	22	5	18	0
Lithuania	65	51	76	74	66	54	65	50	33	23	4	-1			60	52	70	62			44	28
Latvia	28	22			29	25	31	19	54	41	4	-1			26	19	-3	-1			72	52
Malta	-4	-1							-2	0												
Netherlands	10	3	76	72	6	5	9	2	20	8	13	6			7	1	69	64			23	9
Poland	43	36	48	53	43	37	43	36	17	9	40	33			41	34	41	45	2	2	18	9
Portugal	12	0	-2	0	11	0	9	2	6	-1			28	21	10	0	-1	0			4	-4
Romania	14	3	25	9	14	6	17	7	17	-3	4	-5	9	8	13	4	21	7	9	-4	23	-4
Slovenia	10	5	15	14	11	7	10	4	18	8	1	5			10	4	14	11	26	14	24	9
Slovakia	20	14	11	14	19	15	23	12	5	0	28	23			21	9	12	10	44	36	8	0
Sweden	22	14			22	15	21	14	43	28	6	4			20	13					45	34
UK	8	0			7	1	7	1	19	3	6	0			6	0	-1	0	-4	2	23	4

Table 30: Yield changes in % under A1B and B1 "with" and "without" CO2 vs. baseline scenario "no CC" (ECHAM)

	Barley		Corn		Wheat		Othghrain		Potato		Rapseed		Rice		Rye		Soybean		Sugar		Sunseed	
	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo
Austria	10	-1	38	29	11	1	9	-2	15	-4	7	0			8	-2	73	72	18	-4	24	0
Belgium	7	-3	84	73	7	-3	7	-3	10	-5	11	0			8	-2			14	-4		
Bulgaria	14	4	20	-7	11	3	13	4	9	-6	-8	-8	10	5	10	1	-2	107	13	-8	24	5
Cyprus	-29	-32					-29	-32	-2	0												
CzechRep.	6	1	55	46	6	3	8	-1	16	4	13	5			6	1	67	208	23	4	34	19
Denmark	38	25			39	26	41	22	16	0	26	14			38	25			18	0		
Estonia	13	9			14	11	11	6	-3	1	8	0			12	7						
Spain	7	-3	7	0	6	-4	6	-4	7	-3	2	-4	55	31	5	-5	4	87	9	-4	23	-4
Finland	22	10			22	11	24	12	79	61	16	9			22	11			94	71		
France	12	1	17	5	12	2	9	3	7	-14	2	-4	42	20	11	1	14	114	9	-15	19	-26
Germany	12	1	78	74	12	2	12	1	15	0	16	9			11	1			18	0	41	25
Greece	15	3	-1	-8	11	5	12	6	10	-5			10	-15	11	5	-4	-4	9	-8	47	-8
Hungary	16	1	15	-7	15	7	13	4	12	-12	-8	-8	30	25	15	1	16	-10	18	-15	18	-4
Ireland	38	24			38	26	35	27	24	12	-10	-15							28	14		
Italy	10	-1	8	1	11	1	9	3	11	-10	4	-2	20	1	7	1	19	-8	13	-12	35	-19
Lithuania	52	40	56	61	53	42	52	39	18	11	4	0			48	42			27	8		
Latvia	28	18			29	20	32	20	21	11	4	0			27	21			29	13		
Malta	-4	0							-2	0												
Netherlands	15	8	100	95	16	10	14	8	16	0	4	-2			17	11			18	0		
Poland	20	10	55	53	21	12	21	11	12	4	19	14			20	10	2	2	13	4	18	2
Portugal	-1	-11	-1	0	-2	-7	0	-9	6	-5			42	26	-2	-11			4	-4	49	7
Romania	19	8	15	-4	20	7	23	8	16	-10	4	-4	-3	-7	20	6	7	155	23	-12	30	1
Slovenia	6	1	11	5	6	3	6	1	14	-3	-7	-10			6	1	1	96	19	-4	13	-8
Slovakia	15	6	16	19	15	7	13	8	8	1	13	9			17	7	100	61	13	0	23	-4
Sweden	33	25			33	26	32	25	19	7	16	9			32	25			23	4		
UK	12	1			12	2	12	1	19	3	-2	-4			11	1	-2	-3	23	4	-3	2

	Barley		Corn		Wheat		Othghrain		Potato		Rapseed		Rice		Rye		Soybean		Sugar		Sunseed	
	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo
Austria	11	4	33	25	12	2	10	3	16	0	12	5			13	3	54	40	18	0	21	6
Belgium	8	1	57	47	8	3	8	2	6	-8	16	9			9	3			5	-8		
Bulgaria	1	-4	-2	-17	3	-4	1	-4	6	-2	-8	-8	16	11	2	-6	-5	-7	8	-4	14	3
Cyprus	-28	-32					-28	-32	-1	1												
CzechRep.	12	7	32	25	12	9	14	9	17	9	14	9			12	7	43	38	23	9	29	22
Denmark	23	15			23	17	25	13	20	4	21	9			22	16			23	4		
Estonia	1	-3			2	-1	3	-2	-2	1	0	-4			0	-1						
Spain	4	-3	3	6	7	1	7	1	11	1	2	-4	38	21	6	0	5	4	13	0	21	1
Finland	13	1			13	3	14	-1	93	81	7	0			13	-2			111	94		
France	13	6	13	6	13	7	14	8	0	-17	12	5	27	16	12	6	15	4	0	-19	16	-15
Germany	13	1	58	48	13	3	13	2	15	0	21	14			12	2			18	0	33	16
Greece	6	0	4	2	7	2	8	-2	10	-4			12	-7	8	-2	-3	5	9	-4	21	-7
Hungary	8	-2	16	2	7	0	10	1	17	-2	-4	-8	43	37	7	-1	18	-3	23	-3	13	3
Ireland	18	15			18	17	20	13	20	8	2	0							23	9		
Italy	6	0	8	6	7	2	5	0	15	0	9	2	12	2	8	2	20	9	18	0	71	32
Lithuania	30	25	86	84	31	28	30	23	25	15	0	-4			32	26			33	18		
Latvia	15	10			16	13	13	7	40	24	0	-4			13	8			52	29		
Malta	-3	1							-2	1												
Netherlands	11	4	93	89	7	6	10	4	11	-4	0	-2			9	7			13	-4		
Poland	12	7	38	42	12	9	13	8	12	5	15	14			12	7	2	2	13	4	16	-1
Portugal	-1	-7	-1	1	-2	-7	-3	-9	6	-1			33	21	-1	-6			9	-4	29	0
Romania	1	-8	7	-6	2	-5	1	-8	10	-9	-8	-15	2	-2	2	-5	4	-7	13	-12	14	-5
Slovenia	3	3	12	11	3	5	3	2	19	5	-6	-10			3	2	16	7	19	5	18	12
Slovakia	12	7	12	16	11	8	15	4	6	2	19	14			13	8	64	51	8	0	23	3
Sweden	18	15			18	17	18	16	28	15	11	5			17	16			34	18		
UK	13	6			13	7	13	7	10	-1	-2	-8			12	6	-2	6	13	-4	-1	3

Table 31: Yield changes in % under A1B and B1 "with" and "without" CO2 vs. baseline scenario "no CC" (ECHO)

	Barley		Corn		Wheat		Othghrain		Potato		Rapseed		Rice		Rye		Soybean		Sugar		Sunseed	
	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo
Austria	6	-5	33	22	6	-2	4	-5	11	-7	11	5			3	-6	68	50	13	-8	25	2
Belgium	12	1	57	50	12	3	12	2	23	3	7	-3			8	3			24	5		
Bulgaria	9	1	-9	-22	6	5	8	0	5	-5	-4	-6	20	21	6	3	-8	-21	8	-8	7	-5
Cyprus	-4	1					0	5	-1	2												
CzechRep.	11	3	63	58	10	5	8	4	17	5	18	16			11	2	64	51	23	4	38	23
Denmark	8	1			7	3	9	-1	35	17	11	1			7	2			40	18		
Estonia	29	20			24	22	27	21	-3	2	28	20			27	23						
Spain	12	1	8	7	10	6	11	1	11	-3	7	1	48	27	9	5	6	-1	13	-4	54	6
Finland	45	25			44	27	41	28	123	103	32	25			39	27			148	120		
France	12	1	18	3	12	3	14	3	16	-7	-2	-7	48	27	11	2	11	-2	18	-8	48	-2
Germany	12	1	-1	3	12	3	12	2	20	0	11	5			12	2			23	0	37	16
Greece	-3	0	0	3	-2	2	-1	2	10	-4			10	-10	-2	2	-2	8	13	-8	42	-14
Hungary	6	-2	12	-7	5	0	4	-4	13	-11	-8	-10	35	42	6	-1	9	-7	18	-14	16	4
Ireland	17	10			17	12	19	13	29	16	-81	-82							34	19		
Italy	10	4	9	8	11	6	9	4	15	-6	9	3	20	3	11	2	21	3	18	-8	26	-14
Lithuania	18	10	0	5	19	13	23	13	30	24	13	6			20	11			44	28		
Latvia	23	15			24	17	21	16	29	20	18	16			22	18			40	23		
Malta	-4	1							-3	1												
Netherlands	15	13	-1	3	16	11	14	13	26	8	-5	-10			17	12			28	9		
Poland	16	7	-1	4	16	9	16	7	17	9	24	15			15	7	2	2	18	9	30	4
Portugal	-1	1	-1	3	-2	2	0	4	6	-4			31	22	-2	2			9	-4	51	18
Romania	9	1	12	-3	10	4	8	0	17	-8	0	-6	-3	-3	10	-1	5	-7	23	-11	17	-8
Slovenia	2	-1	3	4	2	0	2	-3	7	-5	-7	-9			2	-2	0	-12	9	-12	11	-9
Slovakia	6	3	23	29	10	4	9	0	5	-1	18	11			7	-1	88	80	8	-4	32	8
Sweden	22	15			22	17	22	16	38	19	21	14			21	16			39	23		
UK	12	1			12	3	12	2	33	15	-36	-37			11	2	-1	9	39	13	-2	3

	Barley		Corn		Wheat		Othghrain		Potato		Rapseed		Rice		Rye		Soybean		Sugar		Sunseed	
	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo
Austria	10	3	31	29	6	0	8	1	15	4	16	13			7	1	45	31	18	4	25	9
Belgium	12	9	55	52	11	9	11	9	14	2	16	9			12	6			19	0		
Bulgaria	9	3	28	29	5	1	7	2	13	4	-5	-4	15	7	5	0	20	26	18	4	25	13
Cyprus	-4	-2					-2	2	-2	0												
CzechRep.	15	4	47	40	14	5	12	6	16	7	23	18			15	4	45	44	23	8	36	29
Denmark	7	0			7	0	4	-2	40	26	11	4			6	0			46	29		
Estonia	17	12			12	13	15	9	-2	0	13	8			16	10						
Spain	12	4	6	4	10	3	10	4	11	0	6	0	27	10	9	3	4	-2	13	0	41	9
Finland	33	24			32	24	33	20	79	67	27	19			33	25			94	79		
France	17	9	16	9	16	9	17	6	15	-4	11	4	22	10	16	9	18	2	18	-4	47	4
Germany	12	0	-2	0	11	0	11	0	15	4	16	9			11	0			18	4	36	24
Greece	-3	-2	-2	0	-3	0	-2	0	10	-1			17	-3	-3	0	-4	2	13	0	67	4
Hungary	6	0	18	4	8	0	7	2	20	0	0	-4	25	22	5	0	31	12	28	0	20	4
Ireland	27	24			26	24	28	21	20	8	-75	-77							23	9		
Italy	10	3	7	5	10	4	13	6	15	0	13	11	16	5	11	4	18	7	18	0	42	5
Lithuania	17	7	-2	1	12	8	17	11	32	21	8	4			15	9			38	27		
Latvia	13	7			12	8	15	9	30	19	8	4			16	10			40	23		
Malta	-4	-2							-3	-1												
Netherlands	20	12	-2	0	15	13	18	11	20	8	-5	-7			17	15			23	9		
Poland	15	9	-3	0	15	10	15	9	17	8	29	23			14	9	2	2	18	9	19	1
Portugal	-2	0	-2	0	-3	0	-1	2	2	-5			22	10	-3	0			4	-4	57	26
Romania	13	3	24	14	13	4	11	2	20	4	4	0	6	3	9	4	15	7	28	4	32	19
Slovenia	5	4	5	4	5	5	5	4	13	4	-3	-3			5	4	23	12	19	5	20	4
Slovakia	10	4	20	19	13	4	12	6	4	0	23	18			11	5	41	33	8	0	30	9
Sweden	12	9			11	9	11	9	38	28	16	9			11	9			45	28		
UK	12	4			11	5	11	4	23	11	-14	-19			11	4	-3	3	28	9	-2	1

Table 32: Yield changes in % under A1B and B1 "with" and "without" CO2 vs. baseline scenario "no CC" (GFDL)

	Barley		Corn		Wheat		Othghrain		Potato		Rapseed		Rice		Rye		Soybean		Sugar		Sunseed	
	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo
Austria	11	0	34	13	12	2	9	0	-4	-22	7	1			8	-1	70	39	-4	-25	7	-21
Belgium	8	-2	13	-9	8	-1	8	-2	-5	-26	7	1			9	-1			-8	-31		
Bulgaria	10	1	-4	-36	12	6	14	6	-1	-15	-3	-6	13	1	11	4	-14	-24	0	-17	1	-23
Cyprus	-7	-11					-8	-11	-1	2												
CzechRep.	21	13	87	66	22	15	19	14	10	-7	30	27			21	12	82	60	13	-11	48	23
Denmark	28	16			28	18	30	19	30	9	21	5			27	16			34	9		
Estonia	30	21			31	24	33	22	-2	3	19	11			28	23						
Spain	8	-2	4	-1	11	2	7	2	7	-6	12	1	49	20	10	1	3	-1	9	-7	43	2
Finland	23	6			23	8	19	9	210	172	17	6			23	8			259	205		
France	8	-2	-8	-20	8	-1	9	0	-17	-38	3	-7	43	20	7	-2	7	-13	-19	-42	3	-55
Germany	13	2	66	45	13	3	13	3	7	-14	22	10			12	2			9	-15	33	7
Greece	16	4	-4	-5	12	7	13	7	6	-8			-2	-25	12	7	-1	8	9	-6	7	-28
Hungary	7	-1	-22	-43	7	1	9	1	-19	-44	-3	-6	28	20	6	-1	-14	-33	-21	-51	-3	-23
Ireland	3	-7			3	-5	5	-4	24	8	-1	-7							29	10		
Italy	6	0	0	-5	7	2	10	0	4	-16	9	3	11	-11	7	-2	13	-5	4	-18	51	-10
Lithuania	35	26	296	254	36	29	41	30	18	1	42	32			37	27			22	0		
Latvia	35	26			36	29	39	22	39	21	35	26			33	23			52	23		
Malta	-3	1							-2	1												
Netherlands	11	4	95	85	12	7	10	4	7	-14	-16	-20			8	3			9	-15		
Poland	17	8	150	153	17	10	17	9	17	5	36	31			16	8	2	2	18	4	7	-19
Portugal	3	-7	0	3	3	-6	1	-4	6	-4			43	26	3	-6			4	-8	24	-19
Romania	10	1	-16	-36	11	1	9	1	-25	-50	1	-6	-12	-22	11	-1	-6	-20	-29	-57	-7	-40
Slovenia	7	-1	-4	-11	7	1	7	-2	-11	-26	-1	-8			7	-1	-14	-34	-12	-31	-7	-32
Slovakia	16	8	29	30	16	10	19	10	-1	-10	15	12			17	8	101	75	0	-15	10	-19
Sweden	39	26			40	28	39	27	48	29	27	15			38	27			58	34		
UK	18	6			18	8	18	7	15	-4	3	-3			17	7	0	10	18	-4	0	3

	Barley		Corn		Wheat		Othghrain		Potato		Rapseed		Rice		Rye		Soybean		Sugar		Sunseed	
	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo	B1w	B1wo
Austria	11	3	22	6	12	1	9	3	7	-10	7	0			8	2	36	18	9	-12	12	-7
Belgium	13	1	-1	-11	13	2	12	1	-1	-15	22	14			8	2			0	-18		
Bulgaria	10	4	2	-13	12	3	9	4	2	-9	1	-3	9	-4	11	1	-22	-28	4	-11	1	-18
Cyprus	-7	-9					-4	-9	-1	1												
CzechRep.	16	11	49	43	17	13	18	12	13	1	25	20			16	10	33	21	18	0	25	6
Denmark	33	19			34	21	30	22	20	8	17	9			32	20			23	9		
Estonia	19	13			20	16	22	16	-1	1	15	10			22	16						
Spain	8	1	-1	-3	7	1	7	1	7	-3	7	0	33	15	5	-1	1	-4	9	-4	12	-7
Finland	23	15			23	16	24	12	199	170	17	9			23	11			245	205		
France	8	1	-9	-18	8	2	9	-2	-11	-25	7	0	33	15	7	1	1	-9	-12	-28	-10	-42
Germany	18	10	39	31	18	11	17	10	11	-4	27	19			17	10			13	-4	17	1
Greece	11	3	-1	-2	12	5	12	1	10	-4			8	-15	12	1	-2	4	9	-4	27	-3
Hungary	12	1	-2	-27	11	3	9	4	6	-20	-3	-7	18	13	11	1	-4	-31	9	-24	5	-10
Ireland	3	-7			3	-6	1	-5	3	-7	3	-4							4	-8		
Italy	6	-1	-1	-2	7	1	5	-1	0	-13	5	2	8	-11	7	1	6	-8	0	-15	3	-25
Lithuania	41	34	94	85	42	37	40	33	29	19	15	10			43	36			38	23		
Latvia	35	29			36	31	38	26	36	20	30	24			39	26			46	23		
Malta	-3	0							-2	0												
Netherlands	21	13	63	60	17	15	19	12	7	-4	5	2			18	11			9	-4		
Poland	22	15	56	55	22	17	22	16	17	9	36	35			21	15	2	2	18	9	12	-6
Portugal	3	-3	-1	1	3	-3	5	-5	2	-4			33	20	3	-3			4	-8	10	-20
Romania	15	4	-6	-24	11	3	14	4	-1	-26	6	-3	-4	-16	11	1	-4	-18	0	-31	2	-27
Slovenia	7	2	-2	-6	7	3	6	1	3	-13	-1	-6			7	1	-1	-20	5	-15	10	-14
Slovakia	16	6	12	11	16	7	14	8	2	-2	15	10			12	6	40	27	4	-4	19	-6
Sweden	28	25			28	26	27	25	33	19	12	5			27	25			39	23		
UK	18	10			18	11	17	10	10	-5	7	0			16	10	-1	6	13	-4	0	2

Table 33: Yield changes in % under A1B and B1 "with" and "without" CO2 vs. baseline scenario "no CC" (HadCM)

Appendix D

Crop supply changes in European countries in % by 2050 as compared to the no climate change scenario for all GCM-LPJmL-scenarios

	Barley		Corn		Wheat		Othgrain		Potato		Rapseed		Rice		Rye		Soybean		Sugar		Sunseed	
	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo
Austria	6	1	35	21	7	9	7	2	0	0	5	8			2	3	50	67	0	0	13	-1
Belgium	8	3	56	39	8	13	11	5	2	0	5	11			7	4			0	0		
Bulgaria	12	-2	-2	-30	8	3	13	1	3	-7	-8	-11	-3	35	6	-4	-27	9	-1	-4	-1	-11
Cyprus	-37	-38																				
CzechRep.	19	8	78	47	21	18	26	12	5	1	34	32			18	7	52	108	0	0	37	41
Denmark	32	27			34	37	38	32	8	5	23	19			29	25			0	0		
Estonia	24	14			26	22	31	12	3	0	22	13			21	10						
Spain	6	0	5	1	10	5	14	1	3	-1	4	-2	51	25	8	-3	-6	31	-26	66	35	0
Finland	26	16			26	22	24	19	8	6	19	20			18	13			0	0		
France	8	3	7	-1	8	11	12	6	0	-2	-4	-5	39	28	6	2	-4	35	0	0	24	-23
Germany	13	8	73	62	14	17	16	11	2	1	22	23			11	7			0	0	40	29
Greece	6	1	-4	0	8	7	11	5	-1	1			-1	-13	6	2	-20	19	-70	125	24	-15
Hungary	12	0	5	-27	10	7	11	1	0	-7	-9	-12	18	79	9	0	-6	-17	0	0	3	-7
Ireland	13	15			14	22	18	14	1	1	-31	-28										
Italy	6	2	2	5	7	8	8	8	0	1	3	3	9	1	1	2	1	6	-12	31	32	-11
Lithuania	47	23	149	106	51	33	50	23	12	2	33	14			49	23			0	0		
Latvia	35	21			30	31	36	19	6	3	14	16			31	17						
Malta	-8	1																				
Netherlands	12	12	118	123	15	23	19	19	9	3	-8	0			13	14			0	0		
Poland	26	14	105	95	27	20	29	18	5	2	36	30			23	13	4	-4	0	0	24	1
Portugal	-2	-7	-4	4	3	1	3	-3	0	0			39	35	-3	-8			-16	0	46	12
Romania	14	2	-1	-22	15	11	15	5	1	-5	-5	-10	-35	2	7	4	-13	40	-5	-23	3	-26
Slovenia	0	4	5	-1	0	13	3	6	0	-6	-13	-10			0	3	-21	18			3	-11
Slovakia	16	4	28	19	16	12	17	9	1	-1	30	17			17	4	73	70	0	0	18	-4
Sweden	25	26			25	35	27	28	3	3	19	18			22	24			0	0		
UK	14	8			14	17	16	10	3	2	-16	-14			11	8	-16	22	0	0	-10	13
EU total	14	8	17	4	15	15	22	14	3	1	17	16	23	11	18	10	-1	30	-1	3	14	-11
Non EU	-2	-10	3	-4	-2	-5	-1	-9	0	0	4	-5	1	-1	-5	-12	2	-1	7	-7	23	-18
World	5	-2	4	-3	1	-2	4	-4	0	0	7	0	1	-1	6	-1	2	-1	7	-6	22	-16

	Barley		Corn		Wheat		Othgrain		Potato		Rapseed		Rice		Rye		Soybean		Sugar		Sunseed	
	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo	A1Bw	A1Bwo
Austria	8	4	27	24	9	5	6	5	1	0	5	10			3	1	28	44	0	0	20	8
Belgium	9	6	33	29	9	13	9	8	1	-1	15	16			8	1			0	0		
Bulgaria	7	-2	14	-4	9	5	10	0	5	-3	-4	-9	5	26	5	-1	-17	-5	2	-5	10	-3
Cyprus	-12	-13					-13	-12	-3	2												
CzechRep.	22	13	48	34	23	20	25	11	4	1	33	27			20	11	23	42	0	0	31	29
Denmark	21	18			22	24	24	23	7	4	14	13			18	16			12	18		
Estonia	17	9			17	14	20	12	1	0	7	4			13	5						
Spain	8	0	3	0	6	3	7	1	2	-1	3	-3	41	23	3	-4	-12	4	-58	20	28	1
Finland	22	14			22	18	18	17	8	7	19	17			19	12			0	0		
France	10	1	5	-4	10	6	6	4	0	-2	0	2	31	19	7	0	-10	6	0	0	2	-24
Germany	10	7	55	51	10	12	10	8	2	1	27	24			7	5			0	0	28	22
Greece	3	-1	0	-3	3	3	4	3	-1	0			8	-6	2	-1	-24	13	-100	97	19	-7
Hungary	8	-1	18	-4	12	4	9	-1	4	-3	-10	-9	21	44	4	-2	2	-1	0	0	10	2
Ireland	4	2			4	6	6	6	0	1	-28	-23										
Italy	3	0	1	2	3	4	7	5	0	0	3	0	8	-2	2	0	-5	7	-24	9	33	3
Lithuania	45	34	79	62	47	42	51	34	7	3	9	3			44	33			0	0		
Latvia	33	18			27	24	30	22	6	3	2	8			28	19						
Malta	-7	0							0	0												
Netherlands	14	16	87	88	16	18	12	16	5	2	1	0			9	11			0	0		
Poland	28	19	61	55	29	23	28	22	5	3	42	34			24	17	4	-3	0	0	13	-3
Portugal	-1	-4	-5	1	-1	-2	-3	-5	0	0			31	25	-2	-5			-71	24	33	5
Romania	9	-1	12	-3	10	6	7	1	3	-3	-6	-8	-16	1	7	1	-9	0	7	-13	19	-5
Slovenia	2	2	4	7	3	8	3	3	4	0	-12	-9			1	1	-3	8			18	13
Slovakia	17	3	13	13	16	14	15	7	1	0	26	20			16	3	30	49	0	0	29	15
Sweden	21	18			21	23	20	19	3	3	6	6			17	15			0	0		
UK	10	6			10	12	10	8	2	1	-9	-8			7	5	-22	16	0	0	-10	6
EU total	13	6	16	7	13	12	18	13	3	1	20	18	19	8	16	11	-4	7	-2	1	15	-4
Non EU	-2	-7	4	-1	-2	-4	1	-7	0	0	4	-3	1	-1	-5	-9	2	-1	11	-3	24	-8
World	5	-1	5	-1	1	-1	5	-3	1	0	8	2	1	-1	5	0	2	-1	10	-3	22	-7

Table 34: Supply changes in % under A1B and B1 "with" and "without" CO2 vs. baseline scenario "no CC" (GCM-LPJmL mean)

Appendix E

Change of farm production value of crops in % under A1B and B1 by 2050 as compared to the no climate change scenario for all GCM-LPJmL-scenarios

	A1B w	A1B w/o	B1 w	B1w/o
Austria	0	29	-4	20
Belgium	-4	25	-6	16
Luxembourg	-4	25	-4	25
Bulgaria	-17	7	-10	8
Cyprus	-33	-12	-20	-2
CzechRep.	5	38	3	26
Denmark	2	41	-2	24
Estonia	-4	28	-6	14
Spain	-10	20	-10	10
Finland	-4	26	-5	16
France	-11	20	-10	9
Germany	-3	30	-5	18
Greece	-17	23	-16	10
Hungary	-12	1	-7	5
Ireland	-11	27	-13	8
Italy	-16	24	-16	11
Lithuania	5	37	10	34
Latvia	-5	27	-3	17
Malta	-21	19	-17	10
Netherlands	-10	16	-12	8
Poland	6	38	5	27
Portugal	-15	22	-16	11
Romania	-22	13	-13	6
Slovenia	-12	18	-14	12
Slovakia	-5	22	-4	16
Sweden	-2	39	-4	21
UK	-11	25	-10	14
EU total	-8	24	-7	14
Non EU	-17	18	-18	9
World	-17	18	-17	9

Table 35: Change of farm production value of crops in % under A1B and B1 "with" and "without" CO2 vs. baseline scenario "no CC" (GCM-LPJmL mean).

	CCSM3	ECHAM5	ECHO-G	GFDL	HadCm3
Austria	2	10	3	6	16
Belgium	-4	6	2	0	1
Bulgaria	-15	-19	-8	-15	-6
Cyprus	-44	-19	-29	-15	-12
CzechRep.	17	15	-3	3	20
Denmark	19	14	12	-12	11
Estonia	-6	-4	-5	7	14
Spain	-9	0	-10	-3	2
Finland	-10	0	-3	13	3
France	-4	-1	-8	-5	-5
Germany	2	9	-3	-8	6
Greece	-20	3	-15	-17	-5
Hungary	-7	-6	-7	-2	-16
Ireland	-9	-9	8	-7	-10
Italy	-16	-3	-13	-8	-4
Lithuania	4	14	22	-2	19
Latvia	-7	3	-1	-3	12
Malta	-21	-10	-18	-18	-11
Netherlands	-9	8	-8	-12	0
Poland	14	17	2	-3	18
Portugal	-20	11	-15	-10	-2
Romania	-28	-7	-15	-13	-17
Slovenia	-13	12	-9	-7	-4
Slovakia	-6	4	-6	-3	5
Sweden	-1	4	6	-1	19
UK	-8	-4	-9	-13	2
EU total	-4	3	-5	-6	2
Non EU	-21	-13	-17	-15	-9
World	-20	-12	-16	-14	-9

Table 36: Change of farm production value of crops in % under A1B "with" CO2 vs. baseline scenario "no CC" for five individual GCM-LPJmL outputs.

	CCSM3	ECHAM5	ECHO-G	GFDL	HadCm3
Austria	31	22	22	53	61
Belgium	27	28	23	40	41
Bulgaria	3	-6	9	21	11
Cyprus	-27	-4	-12	21	19
CzechRep.	51	41	20	42	61
Denmark	62	43	40	28	55
Estonia	20	22	17	41	47
Spain	19	16	9	34	35
Finland	25	19	22	49	36
France	27	20	13	32	32
Germany	35	34	20	29	45
Greece	13	30	12	40	54
Hungary	-1	-8	1	23	-4
Ireland	25	16	37	36	26
Italy	20	24	10	49	48
Lithuania	35	39	46	30	59
Latvia	24	25	22	32	48
Malta	17	21	14	25	34
Netherlands	16	17	10	13	38
Poland	46	42	23	28	58
Portugal	11	28	10	42	47
Romania	2	5	11	29	30
Slovenia	13	20	11	37	33
Slovakia	20	22	13	34	39
Sweden	40	35	38	42	66
UK	34	24	15	25	46
EU total	27	24	16	32	40
Non EU	12	21	3	37	34
World	13	21	4	37	35

Table 37: Change of farm production value of crops in % under A1B "without" CO2 vs. baseline scenario "no CC" for five individual GCM-LPJmL outputs.

	CCSM3	ECHAM5	ECHO-G	GFDL	HadCm3
Austria	-13	0	8	-9	2
Belgium	-10	-10	4	-8	-3
Bulgaria	-6	-22	-7	-9	-6
Cyprus	-23	-20	-23	-20	-13
CzechRep.	8	6	4	-4	9
Denmark	11	-2	10	-17	16
Estonia	-4	-10	-8	-7	5
Spain	-14	-10	-4	-12	-5
Finland	-9	-12	-1	-2	3
France	-17	-12	0	-11	-7
Germany	-5	-3	4	-14	5
Greece	-22	-18	-8	-25	-8
Hungary	-9	-3	0	-10	-9
Ireland	-16	-24	3	-5	-9
Italy	-22	-15	-5	-17	-10
Lithuania	18	25	12	-11	18
Latvia	1	-3	-3	-13	11
Malta	-20	-17	-9	-22	-11
Netherlands	-10	-14	-6	-17	-5
Poland	13	12	2	-9	9
Portugal	-20	-16	-10	-22	-9
Romania	-16	-10	-9	-12	-12
Slovenia	-20	-9	-4	-20	-11
Slovakia	-3	-3	0	-9	1
Sweden	-4	-4	4	-15	8
UK	-10	-13	0	-17	2
EU total	-8	-6	0	-12	-1
Non EU	-19	-18	-11	-18	-12
World	-18	-17	-11	-18	-11

Table 38: Change of farm production value of crops in % under B1 "with" CO2 vs. baseline scenario "no CC" for five individual GCM-LPJmL outputs.

	CCSM3	ECHAM5	ECHO-G	GFDL	HadCm3
Austria	5	20	39	17	23
Belgium	9	10	32	15	17
Bulgaria	7	-2	15	15	5
Cyprus	-6	-5	-5	0	6
CzechRep.	26	29	32	14	32
Denmark	34	18	45	2	39
Estonia	16	9	16	11	25
Spain	3	8	22	6	16
Finland	13	5	23	20	26
France	-1	9	32	10	14
Germany	16	20	31	3	30
Greece	3	5	29	2	23
Hungary	-1	7	17	4	-4
Ireland	3	-7	42	21	9
Italy	0	14	33	9	19
Lithuania	40	49	45	6	44
Latvia	21	18	24	5	34
Malta	6	10	26	2	17
Netherlands	10	2	17	-1	15
Poland	36	35	28	9	32
Portugal	5	9	20	4	20
Romania	1	6	13	9	6
Slovenia	-3	15	27	5	14
Slovakia	13	15	26	8	18
Sweden	19	19	41	8	40
UK	9	11	34	4	29
EU total	10	15	29	7	21
Non EU	2	11	20	6	16
World	3	11	20	6	16

Table 39: Change of farm production value of crops in % under B1 "without" CO2 vs. baseline scenario "no CC" for five individual GCM-LPJmL outputs.

Appendix F

Coefficients of variation of shifter rates and crop supply for the A1B "with CO_2" scenario for selected crops and all regions depicted in ESIM

	Barley	Corn	Wheat	OthGrain	Potato	Rapseed	Rice	Rye	Soybean	Sugar	Sunseed
Austria	4	4	4	12	8	17		4	14	2	4
Belgium	4	4	4	22	11	11		4		7	
Bulgaria	4	27	4	14	5	9		4	18	12	1
Cyprus	27			11	0						
CzechRep	11	14	11	17	5	10		11	6	8	11
Denmark	13		13	14	9	10		13		21	
Estonia	7		7	5	0	5		7		0	
Spain	5	6	5	3	3	2	22	5	3	15	4
Finland	8		8	8	23	6		8		60	
France	4	7	4	12	14	4	16	4	14	15	11
Germany	6	13	6	25	5	15		6		10	7
Greece	7	7	7	8	1		7	7	4	4	2
Hungary	4	14	4	18	19	14	22	4	20	20	5
Ireland	12		12	3	4	1					
Italy	1	4	1	5	9	7	5	1	6	9	9
Lithuania	9	15	9	60	9	5		9		22	
Latvia	4		4	11	8	37		4			
Malta	0				0						
Netherlands	4	30	4	37	7	1		4		12	
Poland	11	17	11	35	3	20		11	8	11	7
Portugal	4	5	4	1	1		25	4		12	27
Romania	8	15	8	14	22	8	12	8	22	7	5
Slovenia	3	2	3	8	11	12		3	15		5
Slovakia	4	4	4	4	4	19		4	16	4	8
Sweden	6		6	11	10	6		6			9
UK	5		5	7	6	0	0	5	12	14	18
EU	1	3	1	6	4	9	9	1	6	7	4
ROW	2	3	2	2	8	7	19	2	11	18	4

Table 40: Coefficients of variation of shifter rates under A1B "with CO2".

	Barley	Corn	Wheat	OthGrain	Potato	Rapseed	Rice	Rye	Soybean	Sugar	Sunseed
Austria	4	11	4	3	1	5		4	20	0	10
Belgium	5	22	4	4	3	8		4		0	
Bulgaria	7	28	5	7	3	5	8	6	23	5	9
Cyprus	29			30	2						
CzechRep	11	10	12	10	2	13		10		0	12
Denmark	14		16	14	3	9		13		0	
Estonia	9		9	10		11		10			
Spain	4	3	6	5	1	5	8	4	8	22	15
Finland	10		10	8	4	9		8		0	
France	4	11	5	3	2	6	4	3	11	0	38
Germany	5	23	6	5	1			4		0	7
Greece	9	4	9	8	0		6	8	11	77	22
Hungary	6	21	5	4	4	5	5	6	22	0	10
Ireland	13		15	12	1	46					
Italy	2	3	3	2	0	3	9	4	12	9	32
Lithuania	10	63	12	8	5	21		9		0	
Latvia	5		7	8	3	16		6			
Malta	2				0						
Netherlands	4	30	3	4	4	10		3			
Poland	11	34	12	11	3	9		9			13
Portugal	5	5	6	3	0		11	4			
Romania	10	17	8	10	5	9	7	11	17	21	18
Slovenia	5	7	4	3	6	8		4	17		30
Slovakia	4	5	4	3	1	10		4	28	0	8
Sweden	6		8	7	2	7		7		0	
UK	3		5	4	2	21		3	11	0	9
EU	4	7	5	5	2	8	4	6	14	1	14
NEU	3	7	2	1	0	3	0	4	7	1	11
WO	1	7	1	1	1	2	0	2	1	7	10

Table 41: Coefficients of variation of crop supply by 2050 under A1B "with CO2".

Author's declaration

I hereby declare that I have completed the dissertation independently, and this research is original. I have not been supported by a commercial agent in writing this dissertation. Additionally, no aids other than the indicated sources and resources have been used. Furthermore, I assure that all quotations and statements that have been inferred literally or in a general manner from published or unpublished writings are marked as such. This work has not been previously used neither completely nor in parts to achieve any other academic degree.

Berlin, June 2011

Thordis Möller