Modelling Climate Change Impact on European Agriculture:

Does the Choice of Global Circulation Model Matter?

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1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) predicts an average global temperature increase by nearly 3 °C and potentially increased frequency of extreme weather events, sea level rise, and changed precipitation patterns (IPCC, 2007). Given the vulnerability of the agricultural sector to variations in weather conditions, it will be one of the most vulnerable sectors to climate change and production will be substantially affected in most parts of the world. However, impacts vary upon regions and crops (Parry et al., 2004). Against this background, the main objective of this study is to simulate economic impacts of climate change on European agricultural markets at the member state, aggregated EU as well as global level under consideration of the uncertainty inherent in climate impact assessments.

Based on the predicted productivity changes from the joint application of a dynamic vegetation model (Müller et al., 2009), economic impacts of climate change are modelled with the European Simulation Model (ESIM[1]) (Banse, Grethe and Nolte, 2005).

In order to account for uncertainty, the mean value and standard deviation of five different ESIM outcomes which are based on five individual climate- and crop model results, is analyzed in order to account for uncertainty from a wide range of future climate assumptions. A closely connected purpose of this study is to consider climate change induced adaptation of farmers to changes in the relative profitability of crops.

Chapter 2 briefly describes the major methods of economic climate change assessments on agricultural markets, and further introduces into the major sources of inherent uncertainty. The following chapter describes the market and vegetation model used for this study and the methodological approach is described in chapter 4. Underlying scenario assumptions are given in Chapter 5 before results are interpreted in Chapter 6. Finally, conclusions are drawn in the last chapter.

2. Modelling Climate Change Impacts and Sources of Uncertainty

2.1 Methods of estimating economic effects of climate change

Over the past two decades, a variety of methods and modelling techniques have been developed to measure the impact of climate change on agriculture. Such studies focus either on the explicit productivity impacts of changing climatic conditions on crops and their growing conditions (Liu et al. 2007; Bondeau et al. 2007; Siebert and Döll 2008), while economically oriented studies instead analyze 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 analyze 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 simulation models (Parry et al. 2004; Adams et al. 1990). The Ricardian approach 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.

2.2 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.

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[1] ESIM is a partial equilibrium model which depicts the agricultural sector of the EU in substantial detail and the rest of the world in a highly aggregated form.

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 their major sources.

2.2.1 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 also influence plant photosynthesis and water use (Olesen et al., 2007).

2.2.2 Climate models

The outputs generated by General Circulation Models (GCMs) such as temperature, precipitation and radiation, are the most crucial climate variables in modeling impacts on crops and natural vegetation. However, the horizontal spatial scales of GCMs are often considerably bigger than scales of crop- or vegetation models (Easterling et al. 2001; Olesen et al., 2007). To account for variability in their outcomes, one common approach to represent uncertainty stemming from climate models is to implement output from different GCMs as input for crop models (Müller et al., 2009; Parry et al., 2004, Reilly et al., 2003; Fischer et al., 2001; Rosenzweig and Iglesias 2006).

2.2.3 Crop models

The outputs generated by General Circulation Models (GCMs) such as temperature, precipitation and radiation, are the most crucial climate variables in modeling impacts on crops and natural vegetation. Besides the above mentioned uncertainty in future emission pathways uncertainty in projected climate change may arise from uncertainty in modeled response to future emissions and uncertainty due to missing or misinterpreted physical processes in GCMs (Cubasch et al., 2001). To account for variability in GCM outcomes, one common approach is to implement outputs from different GCMs as input for crop models (Müller et al., 2009; Parry et al., 2004, Reilly et al., 2003; Fischer et al., 2001; Rosenzweig and Iglesias 2006).

2.2.4 Market models

Many factors also contribute to the uncertainty of market model results. 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 of data inputs and can vary greatly among chosen scenarios and model specification.

The briefly described sources of uncertainty and variability in climate impact modeling show the importance of implementing sensitivity analysis to climate impact studies. In this study, one approach of dealing with uncertainty is using productivity change outputs from the global vegetation model LPJmL (Bondeau et al., 2007) which are based on five individual GCM projections and the two emission scenario families A1B and B1.

3. ESIM and LPJmL – Description of the Models

3.1 General overview

ESIM is a comparative static, net trade, partial equilibrium model of the European agricultural sector (Banse, Grethe and Nolte, 2005). 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.

LPJmL is a process-based global vegetation model for natural and agricultural vegetation 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 in grid cells is described in terms of nine different plant functional types (PFTs) and 11 crop functional types (CFTs). Each CFT represents a group of crop and crop varieties and is parameterized using one representative crop[2]. PFTs are differentiated by physiological, morphological, phenological, and bioclimatic as well as 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)[3]. 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. (submitted).

3.2 Methodological approach to depict 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 global vegetation model LPJml (Bondeau et al., 2007, Müller et al., 2009).

The vegetation model LPJmL delivered yield changes for the period 1996-2005 to 2046-2055 based on climate data from five GCMs: 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), and the respective CO2-concentrations[4]. 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 of ESIM. Further, 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 function in ESIM was adjusted by a yield

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[2] Temperate cereals (wheat), tropical cereals (millet), temperate roots (sugar beet), tropical roots (cassava), pulses (field pea), rice, maize, groundnut, sunflower, soybean, rapeseed.

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

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

shifters to the power of the elasticities of area allocation with respect to own and cross yield shifters which are corrected for yield driven cost changes[5].

4. Dealing with Uncertainty in ESIM

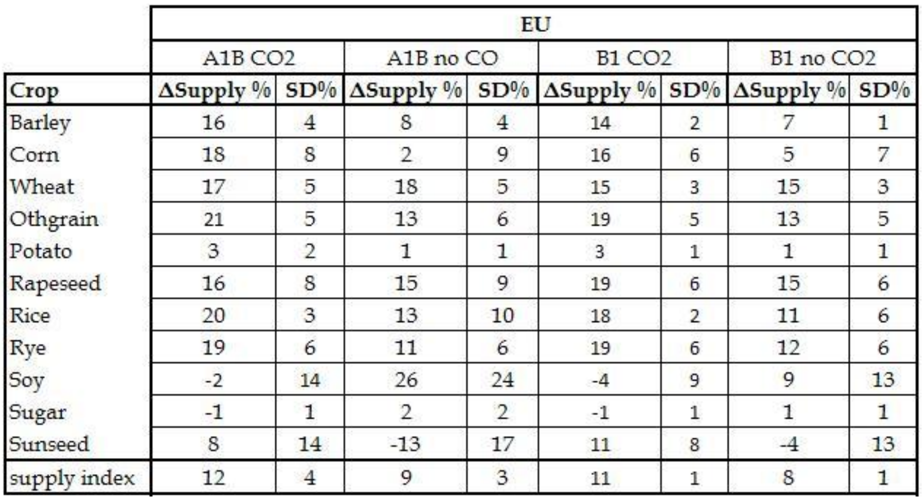
For this paper, the following method was applied to account for uncertainty. Five individual GCM- LPJmL outcomes served as basis for adjusting the yield function of ESIM. Further, the two SRES emission scenarios A1B and B1 were considered, which serves the purpose to a) account for different CO2 concentrations and b) take into account two potential socio-economic developments by adjusting the macro drivers, such as population and income growth in ESIM accordingly. This results in 20[6] scenario results, of which the mean and standard deviation have been generated for each SRES scenario in order to account for uncertainty.

5. Scenarios

For this paper, the underlying assumption of socio-economic developments from the A1B and B1 scenarios are used. The macro data in ESIM such as population and income growth are adjusted accordingly. The projection horizon is 45 years until the year 2050. For each of the SRES scenarios two scenarios were specified for this paper: one takes the CO2-fertilization effect into account and one 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. The overall trend of world market prices under the baseline is calibrated to meet projections published by IFPRI for 2050 (Nelson et al., 2009). Demand shifters in the aggregated non-European countries (NEU) are calibrated to approximate IFPRI 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[7].

6. Scenario Results

6.1 Crop supply changes for the EU, non European regions and the world



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

Table 1: Change of supply and standard deviation in % by 2050 vs. baseline scenario "no CC" for the aggregated EU
Source: own compilation

As a first step the mean and the standard deviation in percent are 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 the coefficients of variation (CV) as

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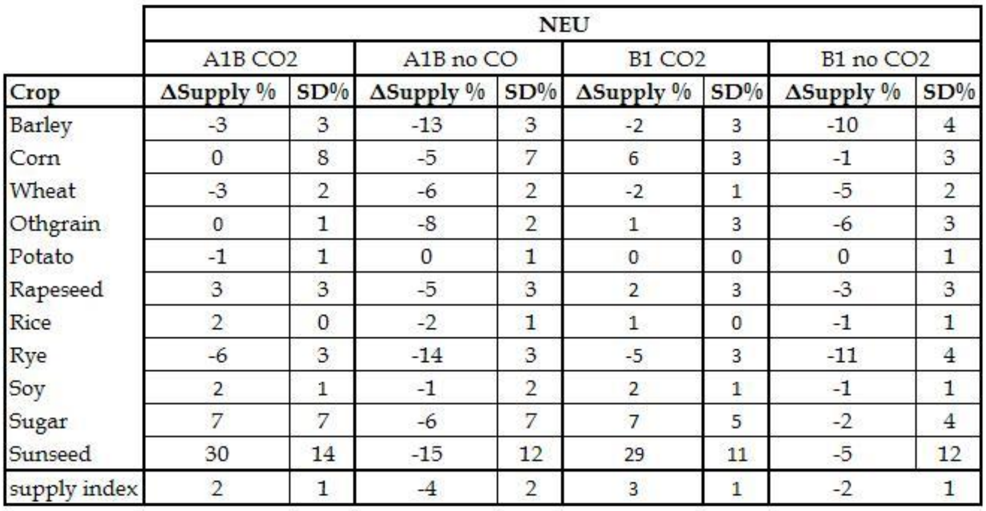
[5] For a detailed description of deriving those elasticities see Moeller and Grethe (2010).

[6] Climate input from five GCMs and the two SRES scenarios A1B and B1 are used. CO2 concentrations were kept constant ("without CO2") or increased over time, allowing for CO2 fertilization (“with CO2”), resulting in 20 scenarios.

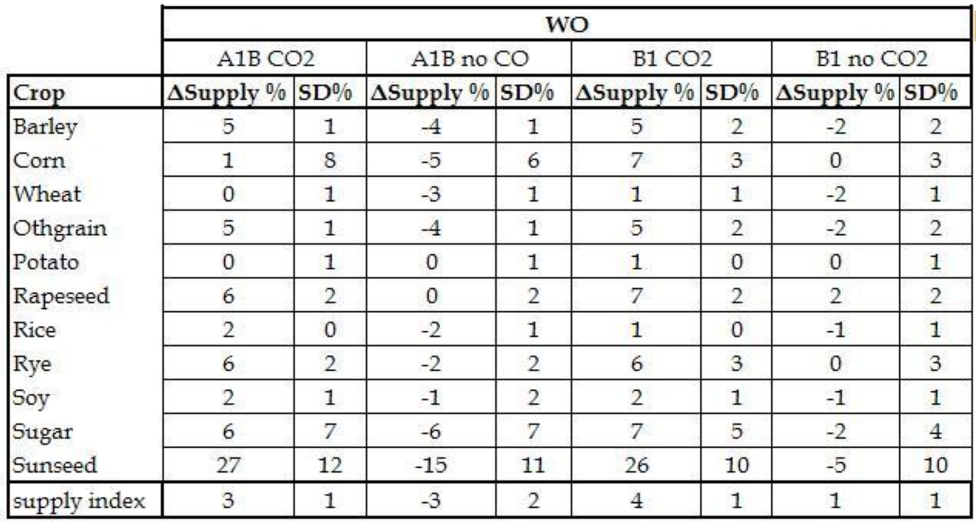
[7] Assumption about consumption of transport fuels in 2050 are from the World Energy Outlook 2008, as cited in Fischer (2009).

standard deviation in percentage change of the mean value, is depicted. Table 1 to 3 show supply differences and CVs by 2050 for selected crops for the EU, non European regions (NEU) and the world (WO). Under the A1B "with CO2" scenario in EU supply increases for most crops range between 3% for potato and 21% for the category other grains (Othgrain). Only for sugar and soy, supply declines can be observed for EU (1% and 2% respectively). The comparatively high CVs of 8% for corn and 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%). The CVs are particularly high for the A1B and B1 "without CO2" scenario ranging from 1% for potato to as much as 24% for soybean. Within EU, the only supply decline is estimated for sunflower seed with 13%. Increases for other crops in contrast range between 1% (potato) and 26% (soybean) (Table 1). By contrast, in NEU supply declines are between 6% for rye, 4% for barley and 1% for potatoes as compared to the baseline scenario. Also in NEU, CVs are highest for corn (8% under A1B “with CO2"), and for sunflower seed (14% 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 (30% and 29%, respectively). In contrast, declines are most pronounced for barley (13%), rye (14%) and sunflower seed (15%) for the A1B "without CO2" scenario (Table 2). The aggregated global supply effects under A1B and B1 "with CO2" scenarios are all positive by as much as 27% for sunflower seed and 1% for corn. Only exception is a marginal change for the crops wheat and potatoes.



	NEU							
	A1B CO2		A1B no CO		B1 CO2		B1 no CO2	
Crop	ΔSupply %	SD%	ΔSupply %	SD%	ΔSupply %	SD%	ΔSupply %	SD%
Barley	-3	3	-13	3	-2	3	-10	4
Corn	0	8	-5	7	6	3	-1	3
Wheat	-3	2	-6	2	-2	1	-5	2
Othgrain	0	1	-8	2	1	3	-6	3
Potato	-1	1	0	1	0	0	0	1
Rapeseed	3	3	-5	3	2	3	-3	3
Rice	2	0	-2	1	1	0	-1	1
Rye	-6	3	-14	3	-5	3	-11	4
Soy	2	1	-1	2	2	1	-1	1
Sugar	7	7	-6	7	7	5	-2	4
Sunseed	30	14	-15	12	29	11	-5	12
supply index	2	1	-4	2	3	1	-2	1

Table 2: Change of supply and standard deviation in % by 2050 vs. baseline scenario “no CC” for the aggregated non European regions
Source: own compilation



	WO							
	A1B CO2		A1B no CO		B1 CO2		B1 no CO2	
Crop	ΔSupply %	SD%	ΔSupply %	SD%	ΔSupply %	SD%	ΔSupply %	SD%
Barley	5	1	-4	1	5	2	-2	2
Corn	1	8	-5	6	7	3	0	3
Wheat	0	1	-3	1	1	1	-2	1
Othgrain	5	1	-4	1	5	2	-2	2
Potato	0	1	0	1	1	0	0	1
Rapeseed	6	2	0	2	7	2	2	2
Rice	2	0	-2	1	1	0	-1	1
Rye	6	2	-2	2	6	3	0	3
Soy	2	1	-1	2	2	1	-1	1
Sugar	6	7	-6	7	7	5	-2	4
Sunseed	27	12	-15	11	26	10	-5	10
supply index	3	1	-3	2	4	1	1	1

Table 3: Change of supply and standard deviation in % by 2050 vs. baseline scenario "no CC" for the aggregated world
Source: own compilation

Declines on a global level for the A1B "without CO2" scenario are as high as 15% for sunflower seed. Marginal changes are estimated for potato, rapeseed (A1B) and corn (B1). The CVs are similar to the once in NEU with sunflower seed and sugar being the most amplified (Table 3).

Aggregated crop supply indices in Table 1 to 3 indicate that the variance is most pronounced for the A1B “without CO2” scenario, with a CV of 4% for the EU and 3% for NEU.

6.2 Comparing coefficient of variation between individual GCM-LPJmL outputs

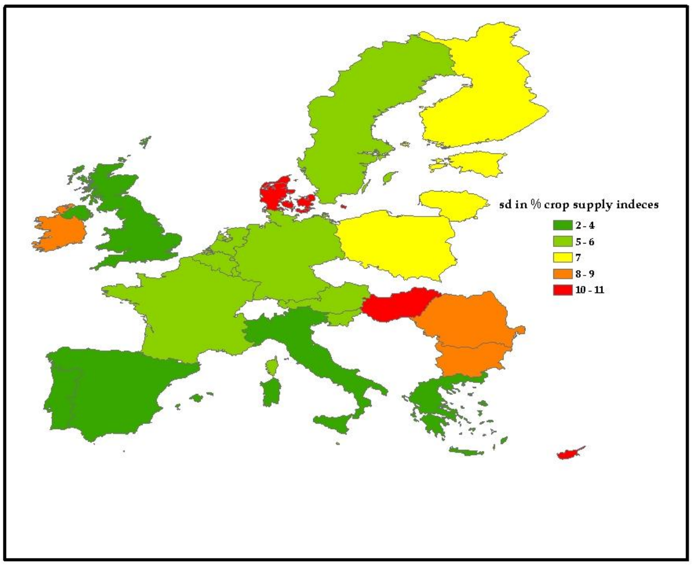


Figure1: Standard deviation of crop supply index in % by 2050 vs. baseline scenario "no CC" for European countries
Source: own compilation

Taking a closer look to the results by country level, the strong regional differences of yield results projections between the five GCMs can be observed. In Portugal, for example, wheat yields are projected to decline in two out of five GCMs. Results for the CCSM3, ECHAM5 and HadCM3 model, however, indicate a yield increase of 11%, 2% and 3%, respectively. This offsets the projected declines of the ECHO_G and GFDL model (both about 2%), and results in a change in the multi-GCM mean of 2%. These different projections highlight the source of uncertainty from different climate predictions and underline the necessity to consider several potential climate developments.

In a second step, it is exemplarily analyzed for the emission scenario A1B “with CO2”, 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 the variance between the shifter rates is more pronounced than that of the crop supply results. 46% of the shifter rates‘CVs are above 5%. By contrast, only 39% of the crop supplies’ CVs are greater than 5 %. By subtracting the values of the crop supply CVs from values of the shifter rates’ CVs shows that 56% are equal or smaller than that of the shifter rates. This indicates that the impact of input shifters is smoothed by various equilibrium processes in the model, which is within expectations.

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 last row in Figure 1 illustrates the CVs of aggregated crop supply indices for the EU. The European average is about 6%, whereas by contrast on country level, the highest CVs are estimated for Cyprus, Denmark and Hungary with around 10% to 11%. In Cyprus, the high deviation from the mean stems from the high variance of supply results for the categories barley and other grains (around 30%). 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, barley and other grains. By contrast, in Hungary, the CV of 11% results from the crop categories corn and soy, which both show a standard deviation of 22% between the individual model results.

6.3 Change in supply and crop price indices

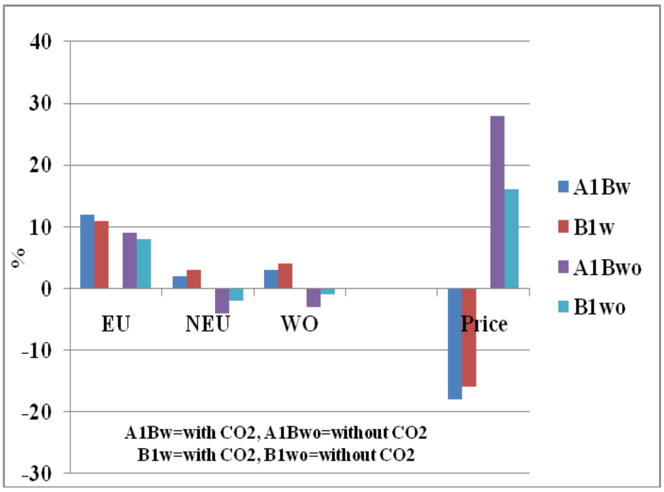


Figure 2: Supply and price indices by 2050 vs. baseline scenario "no CC"

Source: own compilation

The climate change induced supply changes will also have effects on global food prices, and therefore, the aggregated crop supply and price changes, based on mean values of the five individual GCM-LPJmL results for all emission scenarios, as compared to the reference scenario without climate change were analyzed. In order to present aggregated regional and global effects, Figure 2 shows crop supply and price index changes for the EU, NEU and the WO, for both SRES and CO2 concentration-scenarios compared to the baseline scenario “no climate change” (no CC). Crop supply indices are positive in the A1B and B1 "with CO2" for all regions. For the EU, crop supply changes are positive for all scenarios showing a more pronounced supply increase for both “with CO2” scenarios (12% for A1B and 11% for B1, respectively). The aggregated global crop supply increase in WO of about 3% and 4% for the “with CO2” scenario, results in a price decline of 18% and 16%. For the “without CO2” scenarios, in NEU, however, the estimates for the scenarios are negative with a relative production decline of 4% and 2% under A1B and B1. This results in an aggregated relative global supply decline of 3% and 1% respectively. Production declines on world markets lead to a price increase of 28% and 16% under the A1B and B1 scenario, respectively. The relatively large price increase/decline compared to the small supply changes can be explained by the relatively low demand and supply elasticities incorporated in the model. Because of the increasing income level, it is assumed that demand elasticities are about 50% below the level assumed for simulations until 2020[8]. Here, for example, the own price elasticities of demand in the aggregated ROW are 0.077 for wheat and 0.028 for sunflower oil. Under the A1B scenario aggregated crop supply is higher in EU as compared to the B1 scenario. Especially countries in higher latitudes experience crop productivity increases. In contrast, for the aggregated global crop supply productivity is higher under the B1 scenario.

7. Concluding Remarks

In this paper we examine potential effects of climate change on European agricultural markets based on scenario simulation up to the year 2050 based on inputs from five individual GCMs.

The variability in development of crop supply mainly results from the underlying simulated crop yield changes from LPJmL. Effects of changing temperature and precipitation patterns as

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[8] 2020 is the original projection period of ESIM.

well as rising CO2 concentrations on crop growth are considered in a process-based way. The main plant responses to elevated CO2 concentrations implemented in the model are an increase in the rate of photosynthesis and an increase in the water use efficiency (Farquar et al. 1990). C4 plants (e.g. maize, millet) are less influenced by rising CO2 concentrations like C3 (e.g. wheat, rice, sunflower) plants (Tubiello et al., 2002). We showed that results from different GCMs can vary substantially for some crops and regions. Those variances, however, are mostly smoothed on aggregate levels. The shifter rate variability which is reflecting climate change impacts in the market model, are of greater variance as compared to the resulting crop supply outcomes. This indicates that the impact of input shifters is smoothed by various equilibrium processes in the model, which is within expectations.

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