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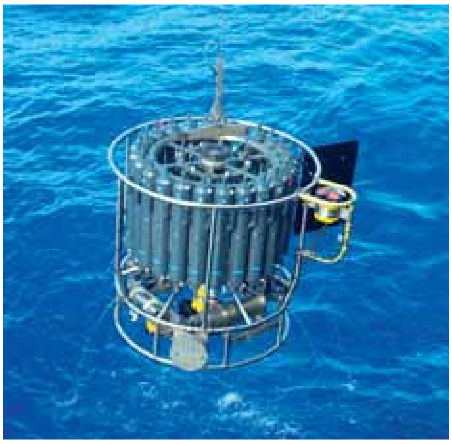
A stochastic model for options and strategies for the Spanish agricultural sector under climate change

Hyung Sik Choi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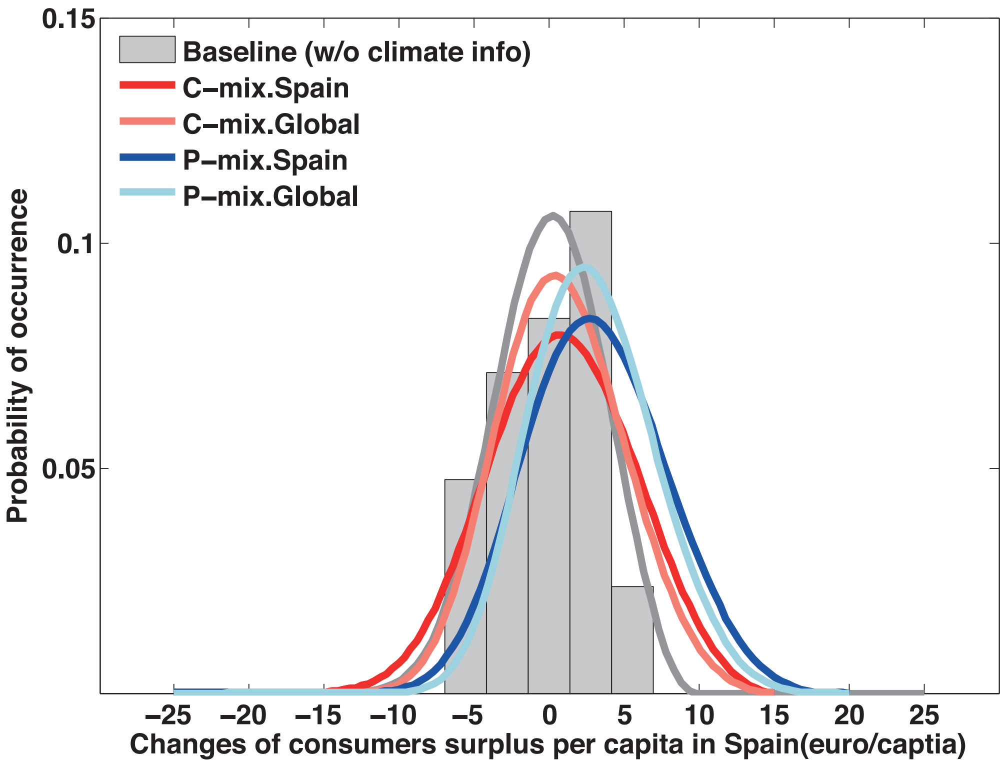

Hyung Sik Choi

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Abstract

Agriculture faces new challenges in the 21st century: climate changes and biofuel energy developments put pressures on agriculture. Climate change is expected to change not only weather means, but also frequency and intensity of weather extremes. Biofuel feedstock occupies cropland and causes conflicts within food production. The purpose of this thesis is to gain an integrated view of agriculture and land use in a stochastic framework, accounting for annual climate variability under climate change.

Spain is selected as a study region because it is one of the most vulnerable countries in the EU under climate change. The Spanish Stochastic Agricultural Sector Model (SSASM) is developed and applied to investigate climate change impacts, climate prediction effects, and land use change impacts. To provide the SSASM with climate change impacts on crop yields, a biophysical crop growth model (EPIC, Environmental Policy Integrated Climate) is driven with multiple regional climate model (RCM) outputs. The SSASM takes into account annual climate variability and makes management decisions to maximize the expected agricultural sector welfare.

In chapter 2, climate prediction effects on Spanish welfare, distributional effects and land use changes are investigated, using historical climate variability between 1961 and 1990. In line with the value of information theory, climate prediction enhances producer decisions and in general, increases consumer surplus and producer revenue. However, with adverse climate predictions, both consumers and producers lose in Spain and foreign producers' gain increases if Spanish farmers' reaction to climate information remains at a conservative level.

In addition, by sharing Spanish climate information with the rest of the world, the Spanish producers' gains always increase.

Chapter 3 simulates climate change impacts on Spain using three regional climate scenarios (REMO, RegCM, and Aladin). Between 2080 and 2099, consumer surplus will decrease by 2 – 3 percent in 2090s and producer revenue will decrease by 5 – 20 percent, and cultivated land in Spain will decline by 20 – 50 percent on average. A land retaining policy in Spain would benefit Spanish consumers by increasing production. Keeping marginal land in production, however, imposes a resource overuse. Thus, the overall costs of land retention are higher than those of abandonment by a factor of two. With a land abandonment policy under climate change, climate predictions increase consumer surplus but decrease agricultural GDP. However, climate predictions with a land retaining policy significantly reduce the overall value in comparison to using a land abandonment policy.

Chapter 4 analyzes cropland changes under climate change and crop transition towards renewable energy. Cropland in Spain will decrease by 5 to 20 percent in 2030s and by 10 to 70 percent in 2090s through productivity changes induced by climate change. The result shows that photovoltaic (PV) electricity potential on abandoned crop in 2030s with a land subsidy of 100 euro/ha is about 50 percent of total EU electricity consumption in 2010. Harnessing abundant PV electricity potential needs to be considered in the future, as biofuel feedstock productivity declines under climate change in Southern Europe.

Finally, climate prediction effects, land use change, and climate change impacts could be investigated and compared through the stochastic model framework. If climate prediction is available in the future, agricultural producers should be able to make strategic management decisions to cope with adverse climate conditions and the plan to share climate information should be prepared to increase the benefits from climate prediction. Furthermore, under climate change, the value of climate prediction is higher with the land abandonment scenario than with the land retention scenario. Agricultural land in Spain experiences considerable pressures due to productivity changes under climate change, and it becomes inefficient to retain this land. Land policy should consider transitions from agricultural land to other uses - solar energy, biofuel, and afforestation - accounting for rural economic viability and changing environmental conditions.

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Chapter 1. Introduction

1.1 Agriculture and climate change in the 21st century

Agricultural productivity has exponentially increased through the 20th century due to new cultivars and agronomic intensification achieved through nitrogen fertilization, enhanced irrigation, and weed control (Evans, 1997). As of today, global agriculture can feed a global population of 7 billion. Agriculture constitutes only 5 percent of the world's economic output, but occupies 40 percent of land area (Lotze-Campen and Schellnhuber, 2009). Yet, the annual growth in the global agricultural output is expected to slow down from the 2.6 percent of the current decade (led by growth in Brazil, China, India and the Russian Federation) to 1.7 percent in the next decade, due to soil degradation and water supply limits (OECD/FAO, 2012b). In addition, climate variations have played a major role in shaping the yield growth since 1980 (Lobell et al., 2011).

Despite growth in agricultural productivity, still 1 billion of humans suffer from hunger (Godfray et al., 2010). In developing countries, agriculture is vital to the local economy: 70 percent of the population lives in rural areas, agriculture is the largest supporter of livelihood, and people spend around 30 − 50 percent of their income on food (Willenbockel, 2011). Agriculture accounts for 40 percent of GDP in Africa and 28 percent in South Asia (Lotze-Campen and Schellnhuber, 2009). The national GDP of developing countries is vastly influenced by climate change and extreme events, such as prolonged droughts, heat waves, and flooding (Dercon, 2004).

The global agriculture will likely be confronted with manifold challenges in the 21st century. Global population is projected to rise to 9 billion by 2050 (Godfray et al., 2010). By that time, agricultural production needs to increase by 60 – 70 percent from its present-day value to be able to feed the rising population (OECD/FAO, 2012c). Agricultural land will get under increasing pressures from local human activities, soil erosion, water depletion, urbanization, and biofuel production. For instance, already in 2007, an estimated 1.6 percent of the global cultivated land, equal to 25.1 million ha, was devoted to the production of biofuel feedstock (FAO, 2008). Lastly, climate change is expected to impose risks on agricultural production and could therefore contribute to aggravating the expected agricultural production deficit. Of concern are not only changes in the mean climate, but also the increasing frequency and intensity of climate/weather extremes.

Recently, agricultural markets have already been under pressure from changes of climate, population increase and bio-energy, which are anticipated in the 21st century. The production deficit triggered by the concomitance of extreme weather events with the biofuel expansion, the latter is a consequence of a rise in oil price is among the main factors explaining the price shocks of food commodities in 2008 and 2011 (Trostle, 2008, 2011). There exists therefore the concern that impacts of future climate change on the agricultural sector will increase the threat to the system and consequently might lead to agricultural market instability. To address such a complex issue, it is necessary to integrate future climate change effects into agriculture, including land use and energy supply change.

1.2 Projections of climate change impacts on agriculture and their limitations and the need for stochastic models

Since the 1990s, numerous climate impact studies have assessed the potential of future climate-related risks for agriculture. In general, previous researches agree on the following: 1) in the early 21st century the global agricultural productivity has been benefitting from the global warming trends; 2) climate change impacts on the global agriculture in the late 21st century are expected to be manageable; 3) climate change is expected to impose damages mostly to developing countries at low latitudes whereas developed countries at high latitudes are expected to be less impacted (Reilly et al., 1994; Adams et al., 1995b; Parry et al., 1999; Fischer et al., 2005; Easterling et al., 2007).

Counter-arguments exist to the above agreements that indicate economic damages and risks on agriculture to be likely underestimated (Cline, 2007; Ackerman et al., 2009; Ackerman and Munitz, 2012; Ackermann, 2013). The counter-arguments highlight the inherent limitations of previous approaches and their inadequacy to properly answer the question of how future climate change will impact agriculture and the associated economy.

In particular, assessments are based on outputs from numerical climate simulations (performed with so called General Circulation Models or GCMs). These simulations provide only representative pathways of future climate evolution. Historical climate simulations covering the last century demonstrate that GCMs are not yet able to reproduce satisfactorily fundamental aspects of the observed climate variability, for instance the El Niño–Southern Oscillation (ENSO) describing the interannual variability in the tropical Pacific (Randall et al., 2007). Furthermore, GCMs do not robustly represent the various climate feedbacks involving cloud, vegetation, and sea ice, which are known to modulate the amplitude of climate variations (Randall et al., 2007). Future extreme events from GCMs are hardly considered for impact analyses in agriculture. Climate downscaling techniques have been developed, but most of the previous researches used directly mean climate change information from GCM or simple ‘delta change’ methods for daily climate projections.

The effects of CO_2 fertilization are also controversially discussed. Initial studies reported substantial carbon fertilization effects: 30 percent grain yield gains in C_3 crops and 7 percent in C_4 crops from a doubling of CO_2 concentrations (Tubiello et al., 2007). However, recent Free-Air CO_2 Enrichment (FACE) experiments demonstrate approximately 50 percent lower estimates than previous results (Tubiello et al., 2007; Ackermann, 2011; Ackermann, 2013). Similarly, the role of temperature thresholds for crop yields is likely underestimated: the relationship between crop yield and temperature over threshold is non-linear, but has often been treated within a linear framework, i.e., based only on a mean climate response. In reality crop yield can decline sharply above the threshold temperature due to increasing frequency and intensity of extreme climate events (Schlenker and Roberts, 2009).

In this thesis, a stochastic agricultural model is developed which allows, for the first time, to account for annual climate variations in a comprehensive assessment of future climate impacts on agricultural market, land-use change, and adaptation. Future daily weather data for Spain obtained from a set of Regional Climate Models (RCMs) are used as input to a process-based crop model (EPIC, Environmental Policy Integrated and Climate) (Williams et al., 1989a). Explicit annual climate variability impacts on crop yields are transferred to the stochastic economic model. It is then used to make decisions by farmers about land management based on a probabilistic (i.e. distributional) description of the climate state as provided by EPIC. This model approach has several advantages: first, it allows assessing the impacts of extreme events which occur during a certain time period. Furthermore, a differentiation of decisions is produced by the stochastic optimization with respect to climate risk. The description of the stochastic model can be found in the chapter 2.10 appendix.

1.3 Study region – Spain

High temperature and low rainfall constrain crop productivities in Southern Europe. Under climate change, southern Europe is expected to face the largest temperature increase and the largest rainfall decrease in Europe (Bindi and Olesen, 2011). In Spain, agriculture constitutes about 3 percent of national GDP, which is $40 billion USD in 2010 (FAO). The land area under cereal production is around 6 million ha (FAO) with relatively low crop productivity and high solar irradiation (see Figure 4-1). Thus, Spain is a well-suited study region to investigate climate change impacts, land use change and its implications.

1.4 Objectives of this thesis

By coupling annual climate variability with the stochastic agricultural sector model, this thesis investigates the three topics outlined below.

Effects of seasonal climate forecasting on agricultural markets, welfare and land use: a case study for Spain (chapter 2)

Climate projections have emerged as an option to adapt to climate variability in agriculture. Within a comprehensive framework of the stochastic agricultural model, it is examined how much benefit can be obtained by both consumers and producers in Spain in terms of consumer surplus and producer revenue. Additionally, the effects of climate information sharing and its distribution in the rest of the world are also investigated.

Climate change impacts on cropland change and adaptation by climate prediction under a changing climate: case study in Spain with a stochastic model framework (chapter 3)

Climate impact research should account for not only long-term mean climate change but also for short-term climate variability and extreme events. We investigate the impacts of climate variability and climate extremes from three RCM climate change scenario outputs and their implication on the Spanish agricultural market, land change, and climate prediction values in the future. For this, three models are compared: the deterministic model, the stochastic model, and the stochastic model with perfect information. Two land use scenarios - land retention and land abandonment - are used.

Agricultural land abandonment under climate change and its potential use for renewable energy - A case study for Spain (chapter 4)

The competition of land either for food or energy is an important issue that concerns both mitigation and adaptation to climate change. Transition from cropland to other use in Spain is investigated under climate change. Spain has much higher solar irradiation potential but much lower crop productivity than other European countries. Thus, this chapter calculates the cropland transition to the renewable energy, which depends upon both climate change and land subsidy for renewable energy. The stochastic agricultural model estimates solar photovoltaic electricity and bioenergy on abandoned cropland with different land abandonment cost scenarios. A similar analysis is also performed in the deterministic model for comparison. The technical potential of photovoltaic and bioenergy is estimated and compared.

Chapter 2. Effects of seasonal climate forecasting on agricultural markets, welfare and land use: a case study for Spain[1]

Abstract

Climate forecasting has emerged as an adaptation option for agriculture to manage adverse impacts of increasing climate variability. We investigate the potential effects of climate forecasting for the Spanish agricultural sector because of its relatively high vulnerability to adverse climatic change. The results of our coupled climate-crop-economy modeling framework show the overall value of climate information (VOI) and diverse welfare consequences for producers and consumers in Spain and international agricultural markets. When farmers use forecasted climate information to choose profitable crop mixes outside historical bounds (proactive reaction) then the VOI is notably higher than otherwise (conservative reaction). The VOI under favorable climate conditions is greater than under adverse climate conditions. In particular, under adverse climate conditions, negative VOI could materialize for the Spanish agricultural sector because of production and welfare transfers from Spain to other countries. Information sharing of Spanish climate predictions with the rest of the world (ROW) increases not only global welfare but also Spanish producers' benefits. Through the competitive advantages of climate forecasts, Spanish producers' revenue increases between 1.9 - 7.4 percent for the examined cases. Finally, climate forecasting promotes a more efficient use of agricultural resources. On average, the agricultural production increase due to climate forecasts translates into welfare-neutral land

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[1] This chapter is submitted to Agricultural Systems as Hyung Sik Choi, Uwe A. Schneider, Livia Rasche, Junbo Cui, Erwin Schmid, Hermann Held, (2013) "Effects of seasonal climate forecasting on agricultural markets, welfare and land use: a case study for Spain".

gains of about 2 percent in Spain. This indicates that climate forecasting may create new opportunities to utilize agricultural land surplus for new economic activities.

2.1 Introduction

Climate change is altering the statistics of temperature and precipitation. More frequent and severer weather extreme events are anticipated to impose greater damages to ecosystems and agricultural systems (Katz and Brown, 1992; Easterling et al., 2007; Wigley, 2009). Recent analyses show that changes in climate partly contributed to stagnating crop yields in the EU since the 1990's (Brisson et al., 2010) and that extreme weather events can trigger rises of agricultural commodity prices (Spiertz and Ewert, 2009; Trostle, 2011). Potential impacts of climate change on the economy are of great concern to decision makers and early climate information could help to anticipate these impacts. Seasonal climate forecasting is emerging as a possible instrument for adaptation, and not only helps to cope with climatic constraints in crop production, but also to improve agricultural efficiency in general (Hansen, 2002; Smit and Skinner, 2002). Seasonal climate forecasting could be especially useful for agriculture, because year-to-year climate variability substantially affects crop yield and economic welfare (Adams et al., 1999; Dercon, 2004). Long-range seasonal climate forecasting with a lead time between three months and one year, enables farmers to tailor their choices regarding extent and management of crops to match anticipated climate and may help them to achieve higher outputs (Lu, 2007; WMO, 2007; Lim et al., 2011).

Since the launch of the Tropical Ocean and Global Atmosphere (TOGA) and the Global Climate Observing System (GCOS) program, seasonal climate forecasting has become more feasible by monitoring sea surface temperature and advancing climate modeling. Model-based seasonal climate predictions on the El Niño Southern Oscillation (ENSO) events have been valued ex-ante for agricultural sectors in pacific-oceanic regions where ENSO has caused high impacts in the past. Previous studies on ENSO forecasting have assessed the economic viability of investment into climate science research and climate prediction systems at farm, agricultural sector and global market level (Johnson, 1986; Adams et al., 1995a; Messina et al., 1999; Mjelde and Hill, 1999; Adams et al., 2003a). These studies show that climate forecasting systems could be beneficial to society by enhancing resource use efficiency and helping to improve management decisions. With an assumed perfect climate forecasting skill, Adams et al. (1995a) showed that ENSO forecasts could produce benefits as high as US$145 million in the southeastern U.S. regions, and Solow et al. (1998) estimated an overall benefit of US$323 million for the entire U.S. agriculture. With 70 percent forecasting skill, Mexico would benefit about US$10 million annually (Adams et al., 2003a). In some developing countries, seasonal climate forecasting has already been implemented, e.g. in Southern Africa (Patt et al., 2007; Hansen et al., 2011). These studies show that farmers' income increases when seasonal climate forecasts are provided. Even though seasonal climate predictability in Europe is limited (Palmer et al., 2004; Calanca et al., 2011; Doblas-Reyes et al., 2013), the DEMETER (development of a European multi-model ensemble system for seasonal to interannual predictions) project shows that wheat yield anomalies could be anticipated six months in advance through probabilities for some years and regions (Cantelaube and Terres, 2005). Integrated climate-crop modeling, which combines crop simulation models with dynamic seasonal forecast models, is suggested as a decision and policy support tool for the agricultural sector (Hansen, 2005).

Despite these developments, employing climate forecasting for adaptation measures in the agricultural sector still lags behind, mostly due to substantial technical deficiencies and an uncertainty about its value. The gap between its goal - reducing vulnerability to climate variability - and its feasibility hinders policy makers from promoting climate forecasting systems (IRI, 2006).

Comprehensive economic assessments can help to narrow this gap. In this study, we approach the value of climate information from various perspectives: different farmers' reactions to climate forecasts, sharing of climate information, and cultivated land changes. We aim to examine the adaptability of Spanish farmers to perfect climate forecasts under adverse, normal and favorable climate conditions. We analyze their effects on crop management in Spain and on international agricultural market adjustments within the framework of a probabilistic global partial equilibrium model, which is linked to climate driven crop productivity simulations. Another objective is to quantify how much cropland can be spared through the use of climate information without affecting the overall welfare in the agricultural sector. In the present study, both the skill of the seasonal climate forecast and farmers' uptake of this forecast are assumed to be 100 percent. This study is the first to analyze the effects of climate forecasts on an EU country, Spain, which is anticipated to be adversely impacted by climate change. The modelling framework is unique in that a high resolution Spanish agricultural sector model is nested in a global partial equilibrium model.

2.2 Material and methods

We establish an integrated modeling framework which links climate information through bio-geophysical crop simulations to an economic partial equilibrium model, to analyze the interactions of climate, crop management choices, and international agricultural markets. The impact of climate on crop growth is analyzed with the Environmental Policy Integrated Climate model (EPIC, Williams et al. (1989b)), using 30 years of weather data (1961 - 1990).

The climate impacts on crop productivity are integrated in an agricultural sector model, which depicts the aggregate response of producers and markets for each single year. The sector model also assesses the effects of seasonal climate forecasting on welfare measures, i.e. changes in consumer surplus and producer revenue both for Spain and the rest of the world (ROW). The main adaptation options include the choice of crop mix and irrigation regime. Farmers can change their crop mix choices if they are provided with information about upcoming seasonal climate approximately five to twelve months before harvesting (Meinke and Stone, 2005). We use scenarios containing different combinations of assumptions about crop mix adaptation, dissemination of climate information, and cropland availability.

2.3 Study area

We chose Spain for this case study as agricultural production has been annually varying by 20 percent, mainly due to highly variable weather conditions (Iglesias et al., 2000), and because it is one of the most vulnerable countries to climate change in Europe (Christensen et al., 2007b). Europe's climate is driven by different modes of climate variability than ENSO. At annual time scale, the North Atlantic Oscillation (NAO) and Arctic Oscillation (AO) have a strong influence on Europe's summer and winter temperatures. At decadal time scale, the Atlantic Multidecadal Oscillation (AMO) and Atlantic Meridional Overturning Circulation (AMOC) affect large scale climate patterns in Europe (Marshall et al., 2001). Cantelaube et al. (2004) show that the NAO has a significant impact on winter wheat yield variability in Europe.

2.3.1 Conceptual decision model with climate information

We introduce a simple mathematical model to describe the decision behavior of agricultural producers who face uncertain climate/weather conditions, resource limitations, and internationally linked commodity markets. Here, uncertainty is represented as a discrete set of alternative climate states (index s) with an associated probability vector ρ_s. The model's objective function denoted by $\nu\left(\boldsymbol{X}_{(s)},\boldsymbol{Y}_s,\xi_s\right)$ maximizes the sum of consumer and producer surplus in agricultural commodity markets and is a function of i) control variable vector $\boldsymbol{X}$ representing agricultural decisions before the uncertain climate state is revealed (e.g. choice of crops planted), ii) control variable vector $\boldsymbol{Y}_s$ representing agricultural decisions after the climate state is revealed (e.g. trade and domestic sales of produced crops), and iii) a climate state dependent crop yield parameter ξ_s. Both ξ_s and ρ_s are given exogenously and remain unchanged during the analysis. The optimal decision for the control variable vector $\boldsymbol{X}$ is either independent (no climate forecast available) or dependent (climate forecast available) on alternative climate states. The following subsections explain in more detail the differences between the two forecast availability modes and how the value of information (VOI) is determined.

2.3.2 Probabilistic decision model without climate forecast

The decision model in this section depicts a situation where farmers make management choices in an uncertain environment and only possess knowledge of historical crop yield variability (Lambert et al., 1995). Thus, the optimal values for the control variables $\boldsymbol{X}$ and $\boldsymbol{Y}$ are determined by maximizing economic surplus in agricultural markets:

$$\max_{\boldsymbol{X},\boldsymbol{Y}}\left[\sum_s\left(\rho_s\cdot\nu\left(\boldsymbol{X},\boldsymbol{Y}_s,\xi_s\right)\right)\right],\ \boldsymbol{Y}=(\boldsymbol{Y}_1,..,\boldsymbol{Y}_S) \tag{1}$$

As mentioned above, the state of climate is observed after the decisions on $\boldsymbol{X}$ but before the decisions on $\boldsymbol{Y}_s$. Particularly, the decision vector $\boldsymbol{X}$ includes the area allocation choice to different crops at planting time. Without the availability of a seasonal climate forecast, farmers' optimal decision on $\boldsymbol{X}$ is independent of the later realized state of climate. Farmers chose a crop distribution, which maximizes the probability weighted net returns across all climate states. Thus, the decision vector $\boldsymbol{X}$ is not indexed by climate state. On the other hand, the decision vector $\boldsymbol{Y}_s$ includes aggregate levels of production, consumption, and trade, all of which are influenced by the specific climate realized during the growing season. The solution of the probabilistic maximization problem shown above implicitly includes a cost of climate uncertainty because farmers are likely to utilize a different level of resources than they would with climate forecasts (Kall, 1994; Meza et al., 2008).

2.3.3 Probabilistic decision model with seasonal climate forecasts and the value of information

In this setting, we assume i) perfectly accurate seasonal climate forecast, ii) perfect knowledge about the consequences of the predicted climate state on crop productivity, and iii) perfect integration of the crop productivity response to particular climate states in agricultural decision making. In contrast to the previous setting without climate forecasts, the optimal decision levels for variable vector $\boldsymbol{X}$ are now dependent on the climate state and thus include index s. Farmers will choose a specific optimal crop mix for a specific forecasted climate. Thus, with perfect seasonal climate forecast skill, the optimal values for $\boldsymbol{X}_s$ and $\boldsymbol{Y}_s$ are determined by a specific objective function for each climate state:

$$\max_{\boldsymbol{X}_s,\boldsymbol{Y}_s}\left[\nu\left(\boldsymbol{X}_s,\boldsymbol{Y}_s,\xi_s\right)\right] \qquad \forall s \tag{2}$$

The VOI can now be computed as the difference between the economic surplus attained without climate information and the probability weighted average of agricultural surplus across all climate states attained with perfect climate forecasting:

$$\text{VOI} = \sum_s \left(\rho_s \cdot \max_{\boldsymbol{X}_s, \boldsymbol{Y}_s} \left[\nu\left(\boldsymbol{X}_s, \boldsymbol{Y}_s, \xi_s \right) \right] \right) - \max_{\boldsymbol{X}, \boldsymbol{Y}} \left[\sum_s \left(\rho_s \cdot \nu\left(\boldsymbol{X}, \boldsymbol{Y}_s, \xi_s \right) \right) \right] \tag{3}$$

Note that we consider in this study only the gross VOI which does not include the cost of information. As the cost of generating the information increases, the net VOI becomes smaller (Macauley, 2005). The gross value of correct additional information can never be negative (Gollier, 2001). Furthermore, a higher degree of uncertainty, i.e. a higher variability of climate related crop yields, generally implies a larger VOI.

2.4 Simulation of crop yield variability

We selected six major crops (barley, winter wheat, rice, corn, potato, cotton) in Spain and analyzed their yield variability with the EPIC model. This bio-geophysical model simulates the daily development of crops under specific environmental and land management conditions. The model has been applied to different climate regions, e.g. tropical west Africa, Europe, and Asia (Tan and Shibasaki, 2003; Wriedt et al., 2009; Gaiser et al., 2010; Jia et al., 2012; Balkovic et al., 2013), and in climate change impact studies (Izaurralde et al., 2003; Eitzinger et al., 2012; Strauss et al., 2012). Furthermore, the crop growth module of EPIC has been validated under different regional climate and environmental conditions (Gassman et al., 2005). A previous study showed that the current version of EPIC adequately simulates crop yield responses to heat waves and dry conditions in Europe, but achieves a relatively poor quality in simulating heavy rainfall impacts (van der Velde et al., 2012).

For the EPIC simulations, we used different datasets on physical characteristics (topography, soil, and climate), land cover, and crop management: Topographical information such as altitude and slope was derived from digital elevation models (GTOPO30 and SRTM90). Soil data, i.e. soil texture class, soil depth to rock, and stone content were taken from the European soil database (ESDB v.2). The MARS (Monitoring of Agriculture by Remote

Sensing) project provides crop calendar data. The regional fertilizer inputs were estimated by linking national fertilizer use data from New CRONOS-EUROSTAT with average crop yields by NUTS-2 region, nutrient removal coefficients for harvested crops, and a multiplier that accounts for surplus fertilization.

The Homogeneous Response Units (HRU) and the simulation unit approach developed by Schmid et al. (2006) for the European Union were adopted. HRUs are delineated by altitude, slope, and soil information at a 1km pixel resolution. Individual simulation unit is a spatial intersection of HRU, land cover data, irrigation and NUTS-2 regions (Balkovič et al., 2010) (Table 2-1) and are the basis of crop management activities at aggregated farm level which link the economic model with the biophysical model EPIC. The final simulation unit areas for harvested crops are assigned to be consistent with EUROSTAT at NUTS2 level in terms of crop area and crop yields.

Table 2-1 Data source and resolution for the simulation unit delineation

Data				**Data source**	**Resolution (pixel)**
Simulation Unit	HRU	Topography	Height, Slope	SRTM90,GTOPO30	1km
		Soil	Texture, Depth to rock, Stone content	European Soil Database (ESDB v.2)	1km
	Land cover			CORNIE-PELCOM	1km
	Irrigation			LUCAS (Land Use/Cover Area frame Statistical Survey)	1km
	NUTS-2 boundaries			Geographic Information System of European Commission (AGISCO)	

To capture the variability in climate, we used weather data from the regional climate model REMO (Jacob and Podzun, 1997) as input to EPIC, which were bias corrected using ERA-40 data. Thus, the mean and the variance of the adopted REMO data are consistent with ERA-40 data. The employed data include daily maximum and minimum temperature, solar radiation, precipitation and relative humidity over the period from 1961 to 1990 with a spatial resolution of 25 km × 25 km. We assume that the climate variability between 1961 and 1990 covers the range of possible climate events for agricultural producers in Spain.

For each year, we calculated regional crop yields at NUTS-2 level as bias corrected weighted average over individual simulation unit:

$$Y_{t,n,c} = \frac{\sum_m \left(\hat{Y}_{t,n,c,m} \cdot A_{n,m}\right)}{\sum_m A_{n,m}} \cdot \frac{\sum_{\tilde{t}} \tilde{Y}_{\tilde{t},n} \Big/ \sum_{\tilde{t}} 1}{\sum_t \left(\frac{\sum_m \left(\hat{Y}_{t,n,c,m} \cdot A_{n,m}\right)}{\sum_m A_{n,m}} \right) \Bigg/ \sum_t 1}$$

where $Y_{t,n,c}$ is the bias corrected yield of crop *c* in NUTS-2 region *n* and year *t*, $\hat{Y}_{t,n,c,m}$ is the crop yield simulated with EPIC for each spatial simulation unit *m*, and $A_{n,m}$ is the arable area of a simulation unit *m* in NUTS-2 region *n*. Yields simulated with default crop parameters in EPIC show deviations to observed yield data $\left(\tilde{Y}_{\tilde{t},n}\right)$ in the EU (Balkovic et al., 2013). As shown above, we calibrated EPIC yields through linear scaling. The scaling factor (second multiplicative term on the right hand side of the equation below) is derived by dividing the average NUTS-2 crop yields from EUROSTAT over the period from 1995 to 2004 by the mean values of simulated EPIC yields for the 30-year period from 1961 to 1990.

2.5 Probabilistic agricultural sector model

For the economic analysis, we used a probabilistic partial equilibrium model for the Spanish agricultural sector. The general concept and structure are analogous to the US Agricultural Sector and Mitigation of Greenhouse Gas (ASMGHG) model (Schneider et al., 2007). The livestock sector is represented in a reduced form as used in earlier versions of the Global Biomass Optimization Model (Sauer et al. (2010)). Demand functions are explicitly defined using a price-quantity observation with constant own-price elasticities of demand estimated from the United States Department of Agriculture.

Commodity supply functions exist only implicitly as endogenous aggregation over many Leontief production functions. While both agricultural land and water use in Spanish producer regions are physically limited, water use faces an explicit constant-elasticity supply function. Market prices are internally determined and equilibrate supply and demand. International agricultural production is aggregated to 28 regions according to political and climatic conditions. The probabilistic model concepts are similar to Discrete Stochastic Programming with Recourse (DSPR) (Lambert et al., 1995) in that the agricultural market equilibrium is computed by maximizing the expected sum of producer and consumer surplus subject to resource and technological constraints. The model includes the six agricultural commodities mentioned above. We used agricultural market data from FAOSTAT to calibrate the base model to year 2000 conditions (Table 2-2). The model equations can be found in the appendix.

The model depicts farming activities in Spain for around 2,000 different sites. Cropping activities are restricted by maximum crop share rules for crop rotations. Decisions to expand or abandon crop land and to install irrigation incur additional costs. A two-stage decision process is implemented: Crop management decisions are made during the first stage, i.e. before the seasonal climate is revealed, all other decisions are determined during the second stage, i.e. after the climate has influenced agricultural production. These decisions relate to total production, commodity trade, and resource usage. Crop mix restrictions are often used in agricultural sector models to properly aggregate farm level activities to sectoral level (McCarl, 1982; Chen and Onal, 2012). Here, we use two types of crop mix constraints – proactive and conservative – to represent alternative reactions of farmers to climate forecasts.

Table 2-2 Observed data and baseline economic model output. Area (EUROSTAT) and price (FAO) observed data are averaged over the period of 1995 – 2004.

Crop	Area (1000 ha)			Price (€/Tonne)		
	Observed	Model	Gap (%)	Observed	Model	Gap (%)
Barley	3313.47	3285.80	-0.83	126.99	141.74	11.62
Corn	449.76	449.66	-0.02	149.35	147.93	-0.95
Cotton	94.59	96.46	+1.98	210.64	199.73	-5.18
Potato	128.86	116.74	-9.41	184.73	169.44	-8.28
Rice	108.06	108.31	+0.23	300.07	298.63	-0.48
Wheat	2191.48	2183.16	-0.38	147.73	157.10	6.34
Total	6286.22	6240.13	-0.73			

The details on the crop mix concept are explained in the next section. Agricultural commodities are traded among Spain and 28 aggregated international regions covering the entire globe. The market activities of the regions outside Spain are portrayed with demand and supply functions. The reference supply quantity for all international regions was computed from the average crop yields over the period of year 1999 ~ 2001. Spain is the only country to experience climate variability impacts, and thus also the only country to employ climate forecasting for adaptation.

2.6 Different scenarios of employing climate forecasts

Figure 2-1 shows how different scenarios are used in the model analysis. Of the many factors that can affect the VOI, we consider three: i) farmers' willingness to deviate from conventional crop choice decisions, ii) the dissemination level of a detailed Spanish climate forecast, and iii) the total area of cultivated cropland in Spain.

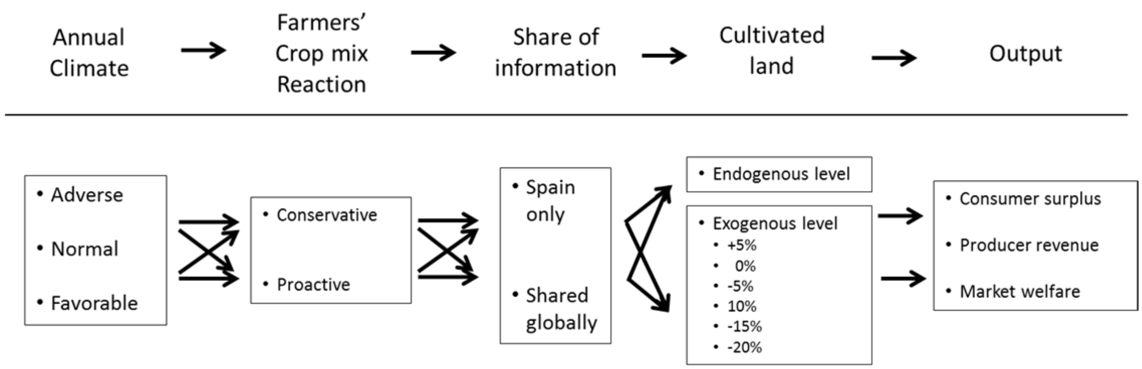

Figure 2-1 Schematic diagram of climate forecasts use scenarios and model outputs

We consider two crop mix adaptation strategies (conservative and proactive) to distinguish different degrees of responsiveness to climate forecasts. Under the conservative crop mix assumption, farmers' crop mix decisions are restricted to fall within historical crop shares. The proactive crop mix setting, however, allows deviations from observed crop mix choices to combinations which better incorporate the climate forecasts. In this option, farmers are more flexible than in the conservative crop mix setting to avoid negative outcomes, utilizing positive outcomes when they use climate forecasts. The proactive crop mix values are generated by sampling area values from normal distributions of downscaled historical crop area at simulation unit levels. These normal distributions take mean and standard deviation values from a statistical analysis of historical choices. We use normal distributions to create possible crop mix choices other than the historical values. This has the advantage of generating unknown crop mix values for each simulation unit. Farmers' proactive crop mix decisions are made within combinations of higher or lower boundary ranges than the conservative mix.

The dissemination level of climate forecasts distinguishes two alternative scenario settings. In the 'Spain' scenario, the climate forecast is only available to Spanish farmers. One can interpret this scenario in two ways: On the one hand, the Spanish government may want to protect domestic farmers by providing them a small advantage. On the other hand, ROW farmers may simply not have the capacity to take Spanish climate forecasting into account. The second dissemination scenario 'Global' assumes that climate forecasts generated for Spain are shared globally and ROW farmers adapt their decisions as well.

Finally, we distinguish different cropland availability scenarios in Spain. First, farmers could decide to increase or decrease the cultivated land according to the provided seasonal climate forecasts. Hill et al. (1999) also showed that climate information could affect the planted acreage at different market price levels. Secondly, the available cropland could be decreased by increased land demands for other purposes, e.g. renewable energy installations. To reflect these differences, we first simulate an autonomous response of Spanish farmers' to climate forecasts. Here, farmers decide on optimal crop land use by comparing climate information, predicted yields, and crop land expansion or abandonment costs. In addition, we force the model exogenously to use a certain level of cropland in Spain ranging from a 20 percent reduction to a 5 percent expansion of the observed cropland in 2010. This represents possible changes in governmental policy and socio-economic states.

2.7 Results

2.7.1 Climate variability impacts on Spanish agriculture

We firstly examine the 30 years historical climate variability impacts on the Spanish agricultural market without employing climate forecasting (probabilistic decision mode) and calculate market impacts on the basis of consumer surplus per capita and producer revenue. We take these outputs as the baseline.

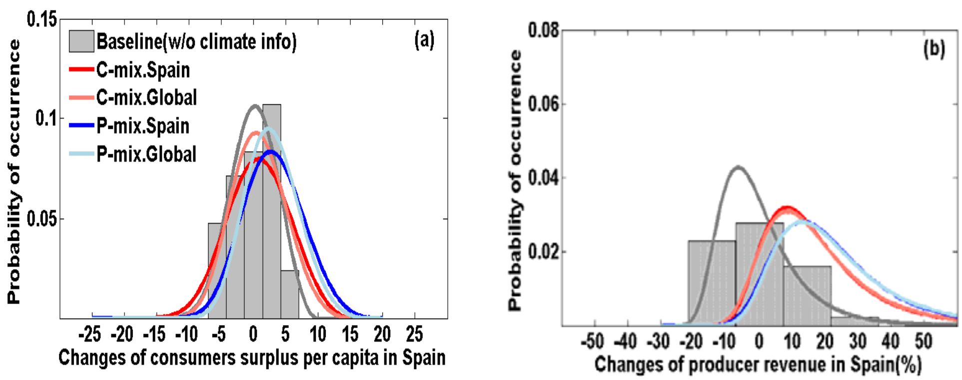

Figure 2-2 Climate variability impacts on consumer surplus per capita and producer revenue in Spain. Grey bars & line: output anomaly values by climate variability compared with baseline values at year 2000 level. Distributions are fitted with the generalized extreme value distribution. Lines: climate information scenarios: Proactive crop mix (P-mix), Conservative mix (C-mix), Climate forecasting only in Spain (Spain), Climate forecasts shared globally (Global).

Without climate forecasting and compared to the baseline year 2000 economic levels, total agricultural consumer surplus in Spain decreases by €250 million under adverse conditions and increases by €234 million under favorable conditions. These values correspond to a per capita loss of €6.22 and a per capita gain of €5.86 in Spain (Figure 2-2), respectively. Likewise, total producer revenue from six crops and one aggregate livestock commodity ranges from a €2.30 billion loss to a gain of €3.49 billion. These changes correspond to a 14.5 percent decrease and a 22.0 percent increase relative to the revenue of the reference period.

Producers incur greater impacts than consumers because climate variability directly affects the agricultural production and producer revenue. Consumers face smaller impacts because production deficits can be compensated by international commodity trade.

Barley and winter wheat account for 87 percent of the represented area with cotton, rice, potato, and corn being grown on the rest (

Table 2-2). Table 2-3 shows that crop yields substantially differ across climate conditions. The climate sensitivity of barley yield is highest. Barley and winter wheat also require more water than the other crops. These results indicate that it is important for Spanish farmers to choose a suitable crop management – i.e. area and technology (rainfed and irrigated) – for winter wheat and barley corresponding to seasonal climate forecasts, saving natural resources (land, water).

2.7.2 Value and impact of climate forecasts on Spanish agriculture

We group 30 years of climate data into three categories based on the effect climate has on consumer surplus in Spain. Particularly, we compare the VOI under different climate states: adverse (lower 10th percentile), normal (10th ~ 90th percentile), favorable (upper 90th percentile) climate states for communicating our results. We consider adverse climate as extreme climate, e.g. drought and heat waves, favorable climate as optimal weather conditions for the growing season and the rest as normal climate. We use economic metrics, e.g. consumer surplus, to classify climate states because they are easily comparable, unlike temperature and rainfall, which are heterogeneous in each region.

The results (Figure 2-3) show that both agricultural consumers and producers in Spain can benefit from climate forecasts. On average, the consumer surplus increases between €0.82/capita and €3.10/capita and the producer revenue increases between 1.94 percent and 7.04 percent with irrigation water savings of 2.01 percent to 4.36 percent. Spanish welfare in agriculture increases between €30 million and €118 million (Table 2-4). Proactive crop mix decisions create higher surplus values than conservative crop mix decisions both for consumers and producers in Spain under all scenarios, as farmers have a wider range of options and thus are able to fully take advantage of the climate information.

Table 2-3 Measured (FAO) and simulated (EPIC) Spanish crop yields at national level in three categorized climate states: adverse, normal, and favorable (lower 10th percentile, 10th – 90th percentile, upper 90th percentile of baseline outputs), and simulated irrigation water use (total irrigation water consumption at national level in categorized climate states).

Crop		FAO (ton/ha)	EPIC yield (ton/ha)					EPIC irrigated water (10^{-3} km3)				
		AVG	AVG	SD/ CV	Adverse	Normal	Favorable	AVG	SD/ CV	Adverse	Normal	Favorable
Barley		2.60	2.64	0.50/0.19	2.00	2.62	3.47	1253.13	141.84/0.11	1315.30	1253.09	1191.22
	(%)				(-24.48)	(-0.86)	(+31.35)			(+4.96)	(0.00)	(-4.94)
Corn		9.14	9.16	1.02/0.11	8.19	9.08	10.79	243.67	18.03/0.07	266.88	242.10	233.04
	(%)				(-10.56)	(-0.90)	(+17.72)			(+9.52)	(-0.64)	(-4.37)
Cotton		3.44	3.47	0.47/0.14	2.91	3.48	3.89	78.79	3.61/0.05	82.53	78.39	78.24
	(%)				(-16.19)	(+0.49)	(+12.26)			(+4.75)	(-0.51)	(-0.70)
Potato		24.34	25.34	3.65/0.14	19.94	25.31	30.97	59.17	4.12/0.07	61.90	58.69	60.25
	(%)				(-21.30)	(-0.11)	(+22.20)			(+4.62)	(-0.81)	(+1.84)
Rice		7.08	7.50	0.87/0.12	6.84	7.41	8.90	83.72	4.14/0.05	88.11	83.64	79.98
	(%)				(-8.79)	(-1.24)	(+18.71)			(+5.24)	(-0.10)	(-4.47)
Wheat		2.64	2.60	0.31/0.12	2.29	2.58	3.04	1281.53	137.82/0.11	1372.06	1278.66	1213.92
	(%)				(-11.84)	(-0.65)	(+17.08)			(+7.06)	(-0.22)	(-5.28)

*AVG: Average, SD : Standard deviation, CV : Coefficient of Variation

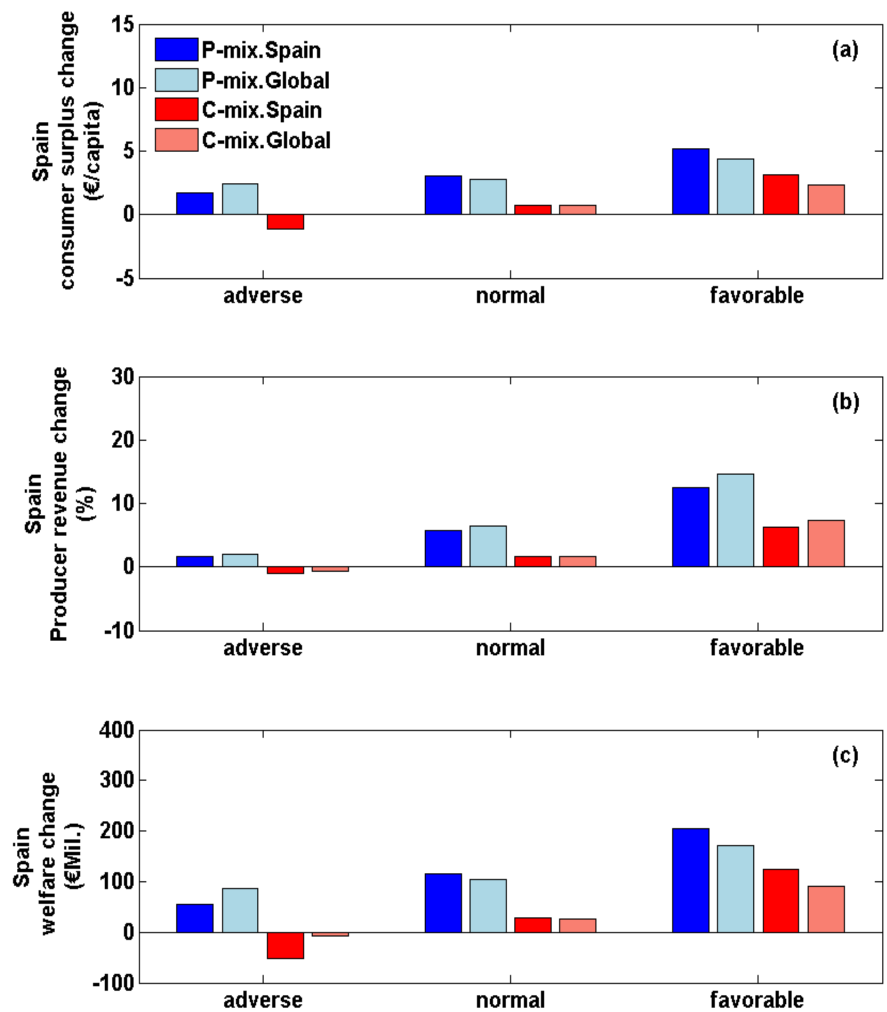

Figure 2-3 Effects of climate forecast information on (a) consumers, (b) producers and (c) welfare in Spain under different climate conditions: adverse, normal, and favorable (lower 10th percentile, 10th ~ 90th percentile, upper 90th percentile of baseline outputs). Bars: four scenarios of different climate information use: Proactive crop mix (P-mix), Conservative crop mix (C-mix), Climate forecasting only in Spain (Spain), Climate forecasts shared globally (Global).

Table 2-4 Effects of climate forecasts on Spanish consumers and producers (30 years average values) under baseline and four climate information use scenarios: Proactive crop mix (Proactive), Conservative crop mix (Conservative), Climate forecasting only in Spain (Spain), Climate forecast shared globally (Global).

			No climate forecasts	Perfect climate forecasts			
			Baseline	Conservative		Proactive	
				Spain	Global	Spain	Global
Consumer surplus	Change	(€ Mil)		+32.84	+33.11	+124.16	+115.33
		(€/capita)		+0.82	+0.83	+3.10	+2.88
Producer revenue	Absolute	(€ Mil.)	15,834.68	16,149.31	16,184.11	16,812.86	16,956.98
	Change	(€ Mil.)		+314.63	+349.43	+978.18	+1,122.30
		(%)		+1.94	+2.16	+6.13	+7.04
Irrigation water	Absolute	(km^3)	2.98	2.92	2.92	2.85	2.85
	Change	(km^3)		-0.06	-0.06	-0.13	-0.13
		(%)		-2.01	-2.01	-4.36	-4.36
Welfare	Change	(€ Mil.)		+29.68	+29.96	+118.03	+109.00

Furthermore, the VOI depends substantially on the forecasted climate state. In adverse climate conditions, the VOI is not as high as in the other two conditions. Figure 2-3 shows that under favorable climate conditions, consumer surplus per capita in Spain increases up to €5/capita and producer revenue up to 14 percent. Under adverse climate conditions in Spain, consumer surplus per capita changes between -€1.1 and +€2.1 and producer revenue changes between -1.1 percent and 2.0 percent. Interestingly, we can see that seasonal climate forecasts on adverse conditions may not benefit Spanish consumers and producers regardless of informing ROW or not: If farmers change their crop mixes only within historical limits (conservative reaction), total cultivated area declines up to -10 percent and crop production in Spain declines (Table 2-5, Table 2-6) and crop prices increase (Table 2-7) in response to climate forecasts and international agricultural market production (Table 2-8). Disseminating climate information lowers the market damage, but still Spanish consumers and farmers lose compared with the scenario of no climate forecasting. Thus, a conservative use of climate forecasts may reduce their economic benefits in Spain (Figure 2-3, Table 2-5).

Table 2-5 Negative changes in Spain's producer revenue in the adverse climate condition (10th percentile of baseline climate output) with various climate information use scenarios: Proactive crop mix (Proactive), Conservative crop mix (Conservative), Climate forecasting only in Spain (Spain), Climate forecasts shared globally (Global). Unit: € 1 mil.

	Conservative		Proactive	
	Spain	Global	Spain	Global
Total revenue change	-152.6	-108.8	+195.46	+254.6
Production change effect on revenue	-201.4	-82.50	+224.5	+396.7
Price change effect on revenue	+48.7	-26.3	-89.0	-142.4
Total cropland change (%)	-9.6	-9.9	-7.6	-7.8

Table 2-6 Production changes (%) in the Spanish agricultural market with climate forecasts compared to the baseline output without climate forecasts under different categorized climate conditions: adverse, normal, favorable (lower 10th percentile, 10th – 90th percentile, upper 90th percentile of baseline outputs). Four climate forecast use scenarios: Proactive crop mix (Proactive), Conservative crop mix (Conservative), Climate forecasting only in Spain (Spain), Climate forecasts shared globally (Global).

	Adverse				Normal				Favorable			
	Conservative		Proactive		Conservative		Proactive		Conservative		Proactive	
	Spain	Global	Spain	Global	Spain	Global	Spain	Global	Spain	Global	Spain	Global
Barley	-1.10	-1.76	+3.52	+1.71	+1.74	+1.74	+4.08	+4.19	+4.31	+4.78	+6.64	+8.49
Corn	-7.56	-8.12	+1.31	+1.35	+5.47	+5.66	+28.28	+30.15	+36.05	+38.24	+75.89	+79.46
Cotton	-1.66	-1.37	+12.29	+12.21	-3.37	-3.26	+1.32	+1.46	-0.78	+-0.79	-4.02	-3.28
Potato	-3.20	-6.17	+15.9	+14.15	+5.71	+6.04	+16.56	+18.77	+12.71	+16.9	+20.92	+21.33
Rice	+0.18	-0.84	+26.37	+27.78	+9.06	+9.91	+43.77	+52.43	+36.79	+46.41	+78.92	+100.02
Wheat	-7.21	-7.28	-2.21	-0.08	+0.16	+0.22	+4.14	+4.28	+2.5	+2.11	+6.27	+3.33
Animal calorie	-0.61	+0.76	+1.34	+2.48	+1.56	+1.53	+4.74	+5.13	+5.27	+5.27	+10.36	+11.36

The global dissemination of climate forecasts (scenario 'Global') shows consistent benefits for Spanish producers (Figure 2-3). Climate forecast information helps ROW producers to adjust their production with respect to Spanish climate conditions. Global food supply decreases under favorable climate conditions (Table 2-8). This keeps prices stable and Spanish producer revenues at higher levels (Table 2-7). Under adverse climate conditions, global dissemination may also benefit Spanish producers, because ROW producers may increase cultivation of those crops which suffer worst from climate damage in Spain, but decrease the cultivated area of crops which suffer relatively little (Table 2-8). As a consequence, Spanish producers may receive better prices. However, the effect of global climate forecast dissemination on Spanish consumers is ambiguous. Under favorable climate conditions, Spanish consumers are better off without climate forecast dissemination because overall crop supply is higher. Under adverse climate conditions, consumers benefit from information sharing because the expected supply shortage in Spain is partially compensated by ROW producers who can then increase exports to Spain and slow down commodity price increases.

Finally, climate forecasts serve to lessen irrigation water use in Spain: In all scenarios, the amount of irrigation water used decreases because famers can choose suitable crops according to climate forecasts. This could be beneficial in the future where water resource depletion is anticipated to become aggravated in Spain (Table 2-4).

Table 2-7 Domestic market price changes (%) in the Spanish agricultural market with climate forecasts compared to the baseline output without climate forecasts under different categorized climate conditions: adverse, normal, favorable (lower 10th percentile, 10th – 90th percentile, upper 90th percentile of baseline outputs). Four climate forecast use scenarios: Proactive crop mix (Proactive), Conservative crop mix (Conservative), Climate forecasting only in Spain (Spain), Climate forecasts shared globally (Global).

		Adverse				Normal				Favorable			
		Conservative		Proactive		Conservative		Proactive		Conservative		Proactive	
		Spain	Global	Spain	Global	Spain	Global	Spain	Global	Spain	Global	Spain	Global
Food	Barley	+0.17	-3.41	-1.94	-4.54	-0.36	-0.39	+1.03	+1.37	+3.55	+6.92	+12.55	+15.54
	Corn	+1.25	+1.12	-0.01	-0.16	-0.65	-0.57	-5.02	-4.89	-6.94	-6.32	-18.85	-18.47
	Cotton	-1.3	-1.21	-12.17	-12.18	+3.69	+3.73	-1.15	-1.09	+2.93	+2.95	+6.58	+6.37
	Potato	+0.74	-0.60	-5.57	-5.75	-3.49	-3.55	-9.91	-9.79	-15.05	-14.00	-21.62	-21.86
	Rice	0	-0.38	-5.98	-6.01	-2.11	-1.84	-9.11	-8.22	-8.71	-6.21	-16.86	-15.05
	Wheat	+2.12	+3.06	+1.13	+1.65	+0.26	+0.30	-0.47	-0.22	+0.62	-0.61	+0.44	+0.36
Animal calorie		+0.23	-0.15	-0.21	-0.50	-0.09	-0.08	-0.36	-0.30	-0.28	-0.02	-0.51	-0.24

Table 2-8 Production changes (%) in the global agricultural market with climate forecasts compared to the baseline output without climate forecasts under different categorized climate conditions: adverse, normal, favorable (lower 10th percentile, 10th – 90th percentile, upper 90th percentile of baseline outputs). Four climate forecast use scenarios: Proactive crop mix (Proactive), Conservative crop mix (Conservative), Climate forecasting only in Spain (Spain), Climate forecasts shared globally (Global).

	Adverse				Normal				Favorable			
	Conservative		Proactive		Conservative		Proactive		Conservative		Proactive	
	Spain	Global	Spain	Global	Spain	Global	Spain	Global	Spain	Global	Spain	Global
Barley	-0.054	+0.507	+0.171	+0.619	+0.111	-0.219	+0.262	-0.086	+0.357	-0.914	+0.55	-0.606
Corn	-0.045	+0.091	+0.008	+0.13	+0.037	-0.027	+0.189	-0.045	+0.301	-0.214	+0.634	-0.293
Cotton	-0.012	-0.088	+0.092	+0.037	-0.032	-0.066	+0.013	-0.053	-0.009	-0.271	-0.046	-0.313
Potato	-0.024	+0.093	+0.122	+0.103	+0.054	-0.153	+0.157	-0.154	+0.151	-0.674	+0.248	-0.662
Rice	0	-0.075	+0.029	-0.064	+0.012	-0.055	+0.056	-0.076	+0.061	-0.105	+0.13	-0.087
Wheat	-0.064	-0.068	-0.02	-0.032	+0.002	-0.042	+0.04	-0.031	+0.027	-0.094	+0.067	-0.066
Animal calorie	0	+0.039	+0.016	+0.049	+0.004	-0.007	+0.019	-0.004	+0.013	-0.043	+0.026	-0.043

2.7.3 **Impacts of Spanish climate forecasting on international agriculture**

With the implementation of climate forecasting only in Spain, ROW consumer surplus increases, and ROW producer revenue decreases by around 0.2 percent on average due to declining market prices (Figure 2-4). This reflects that Spanish producers with climate information become more competitive: They can make more cost-efficient management decisions and reduce their vulnerability to climate events, whereas ROW producers are not able to change their decisions. However, when crop production declines in Spain due to adverse climate forecasts, ROW producers benefit (Fig. 2-4b, 'C-mix.Spain'). Their revenue increases because they can export more to Spain due to a production deficit there.

The effects of global dissemination of climate information are ambiguous for consumers and producers of ROW. For example, in adverse climate conditions, sharing of climate information can lead to a production increase in the ROW regions and both consumers in Spain and ROW can benefit (Table 2-8). But in favorable climate conditions, it results in production decreases (Table 2-8) and ROW consumer surplus decreases. However, the global dissemination of climate information consistently benefits producer revenue in Spain, as global production surplus is reduced by employing climate information. These results show that the economic outputs of the ROW are uncertain in extreme climate conditions (adverse and favorable) and that they are determined by specific scenario combinations of climate conditions, crop mix, and the sharing of climate forecast information (Figure 2-4, Table 2-9).

Despite the foregoing distributional impacts, total global welfare increases by US$61 - US$189 million by employing climate forecasts only in Spain. However, these benefits are distributed largely to Spain (Figure 2-4, Table 2-9, Table 2-10).

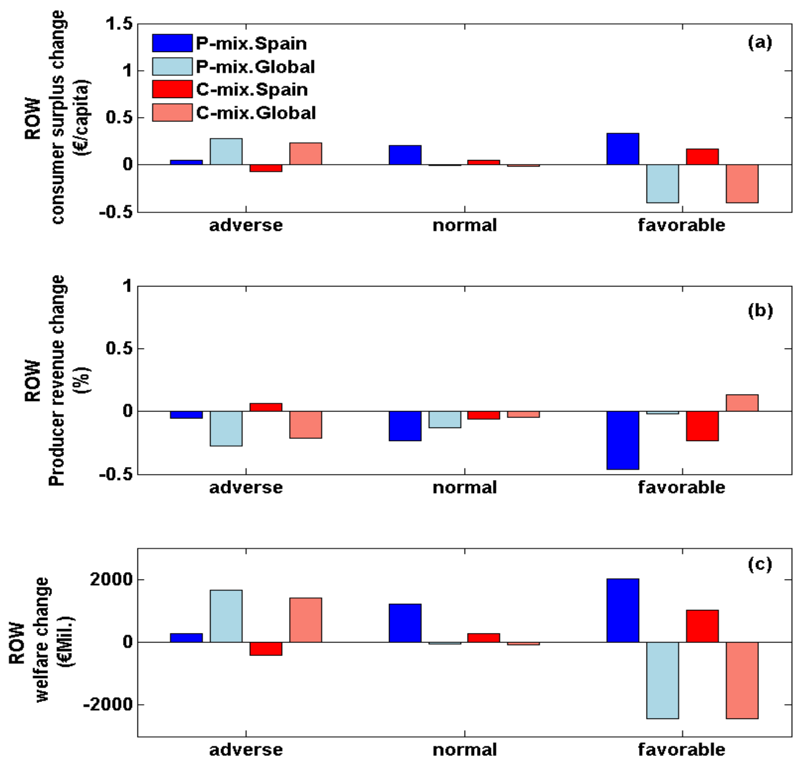

Figure 2-4 Effect of the use of climate forecasts in Spain on (a) consumers, (b) producers and (c) welfare in the 'Rest of the World' (ROW). Values are shown in categorized climate conditions; adverse, normal, and favorable (lower 10th percentile, 10th ~ 90th percentile, upper 90th percentile of baseline outputs). Bars: four different scenarios of employing climate information: Proactive crop mix (P-mix), Conservative crop mix (C-mix), Climate forecasting only in Spain (Spain), Climate forecasts shared globally (Global).

Table 2-9 Distributional impacts on the Rest of the World (ROW) caused by employing climate forecasting in Spain (30 years average) under baseline and four climate information use scenarios: Proactive crop mix (Proactive), Conservative crop mix (Conservative), Climate forecasting only in Spain (Spain), Climate forecasts shared globally (Global).

			No climate forecasts	Perfect climate forecasts			
			Baseline	Conservative		Proactive	
				Spain	Global	Spain	Global
ROW consumer surplus	Change	(€ Mil.)		+274.91	-171.75	+1210.06	-113.81
		(€/capita)		+0.05	-0.03	+0.20	-0.02
ROW producer revenue	Abs	(€ Mil.)	906,191	905,605	905,789	904,020	904,964
	Change	(€ Mil.)		-586	-4012	-2,170	-1,227
		%		-0.06%	-0.04%	-0.24%	-0.14%
ROW welfare	Abs	(€ Mil.)		+274.63	-171.94	+1,209.79	-113.94

Table 2-10 Global welfare (model objective value) change caused by employing climate forecasting adaptation in Spain (US$ million 2000) under baseline and four climate information use scenarios: Proactive crop mix (Proactive), Conservative crop mix (Conservative), Climate forecasting only in Spain (Spain), Climate forecasts shared globally (Global).

		No climate forecasts	Perfect climate forecasts			
		Baseline	Conservative		Proactive	
			Spain	Global	Spain	Global
Global welfare	Base ($ Mil.)	30,694,937	30,694,997	30,694,587	30,695,938	30,694,713
	Change ($ Mil.)		+ 61.05	+66.54	+180.38	+189.46
	(%)		0.02%	0.02%	0.06%	0.07%

Table 2-11 Changes of rainfed (Rain) and irrigated (Irr) cultivated area (%) in Spain under different categorized climate conditions: adverse, normal, and favorable (lower 10th percentile, 10th – 90th percentile, upper 90th percentile of baseline outputs). Values are compared with average crop area data at year 2000 in two crop mix scenarios; conservative crop mix (Conservative), proactive crop mix (Proactive).

Crop	Adverse				Normal				Favorable			
	Conservative		Proactive		Conservative		Proactive		Conservative		Proactive	
	Rain	Irr	Rain	Irr	Rain	Irr	Rain	Irr	Rain	Irr	Rain	Irr
Barley	-9.2	+2.2	-8.3	+6.3	-1.0	+2.0	0	+1.4	+2.3	+2.2	+8	-6.8
Corn	-23.5	-6.3	-36.5	-0.2	-9.9	-4.4	-13.3	-1.6	+8.4	+5.3	+16	+2.7
Cotton	-29.7	-3.7	-36.7	+12	-12.6	-3.5	-12.8	-3.6	-12.4	-3.3	-19	-13.7
Potato	-38.1	-5.1	-36	+1.2	-18	-7.8	-24.2	-26.7	-9.7	-20.2	-16.1	-50.5
Rice	-33.6	-11	-45.6	+2.1	-10.8	-11.3	-6.3	-20.8	+4.9	+5.6	+28.2	-15.9
Wheat	-11.5	-1.8	-4.1	-5.5	-1.2	-1.2	-0.5	+2.6	+0.9	+1	-6.1	+18.1
Total Area		-9.4		-7.6		-1.8		-1.2		+1.8		+3.0

2.7.4 Changes in cultivated area and their impacts on the agricultural market

With seasonal climate forecasts, Spanish farmers can manage agricultural land more efficiently. On average, total cropland area decreases by around 2 percent in Spain (Table 2-11). Depending on climate conditions, cropland changes range from -9 percent to +3 percent. Climate forecasts drive the least fertile fraction of the land out of production. The cultivated land area can decrease because of enhanced agricultural productivity or abandonment of farming due to predicted poor growing conditions.

Figure 2-5 shows how agricultural welfare of Spain and ROW change in response to different cropland endowments in Spain. Without climate forecasts, an increase of cropland in Spain enhances economic surplus and a decrease lowers it. Under the climate forecast scenarios, both Spanish and global welfare peaks at 2 percent cultivated land reduction level in Spain (asterisk marks on Figure 2-5) on 30 years average. The surplus of ROW slightly increases or decreases, depending on scenario. Dissemination of climate forecasts yields higher benefits for Spain and losses for ROW. From the viewpoint of welfare changes in Spain, cultivated land in Spain could decrease up to 5 percent in conservative crop mix scenarios and more than 20 percent in proactive crop mix scenarios. However, cultivated land reductions beyond 5 percent result in losses to consumers and producers in the ‘conservative crop mix’ scenarios. From consumers’ and producers’ views, forced arable land reductions between 0 percent and -5 percent due to governmental policy changes would be justifiable in climate forecast scenarios (Figure 2-6, Figure 2-7). This implies that in conservative crop mix scenarios 5 percent, and in proactive crop mix scenarios 15 percent of cultivated land reduction is a feasible level in this analysis, protecting domestic farmers and consumers.

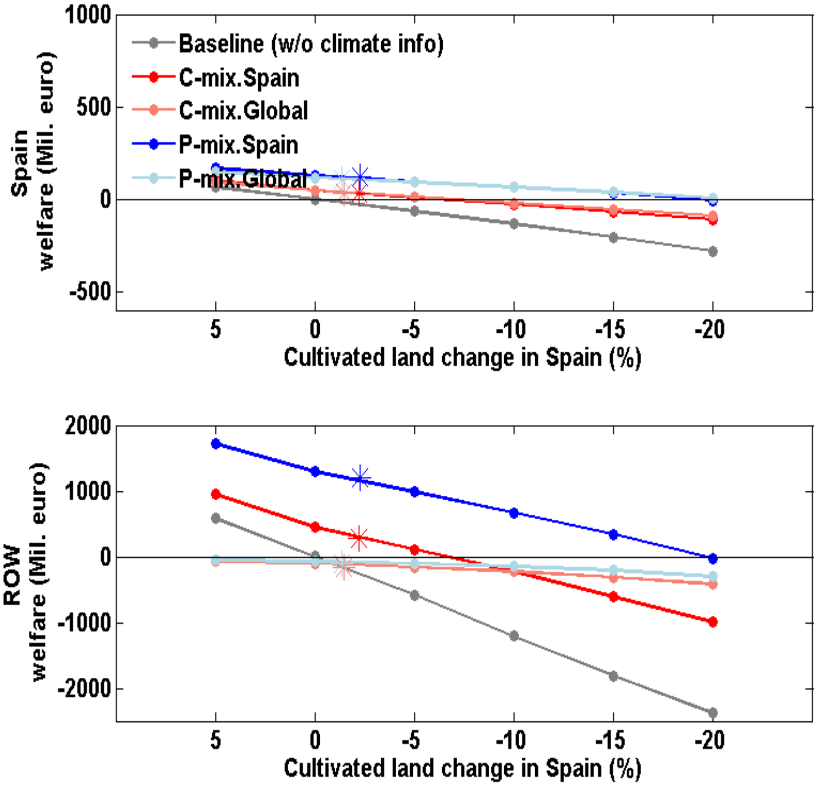

Figure 2-5 Welfare changes in Spain, Rest of the World (ROW) due to cultivated land area changes in Spain, and baseline welfare value without climate information. Four other scenarios are in employing climate information; Proactive crop mix (P-mix), Conservative crop mix (C-mix), Climate forecasting only in Spain (Spain), Climate forecasts shared globally (Global).

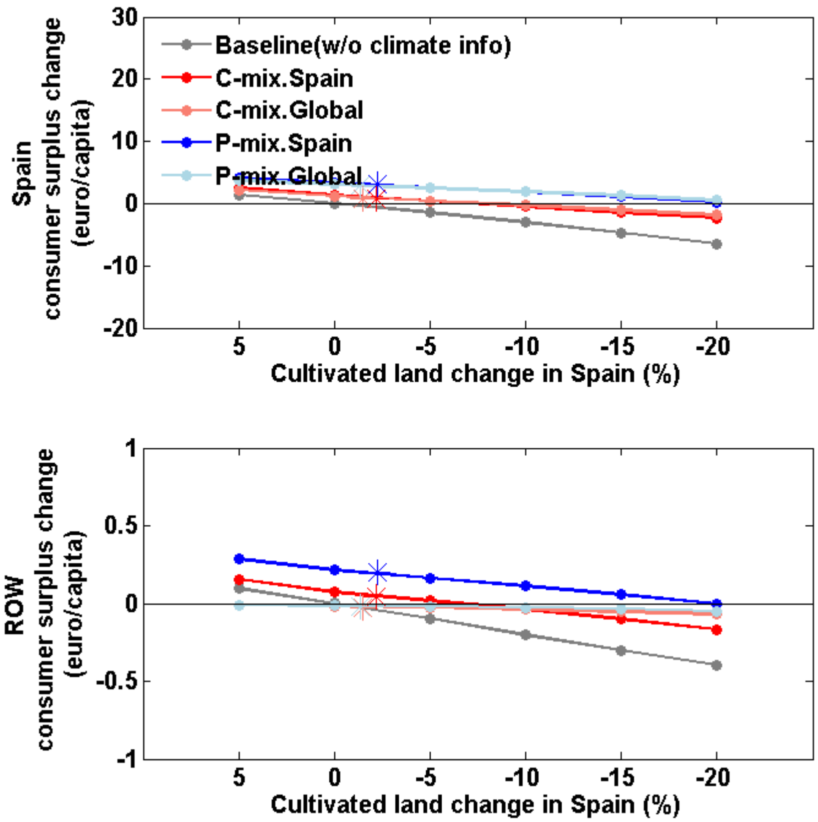

Figure 2-6 Consumer surplus (€/capita) changes in Spain and the Rest of the World (ROW) due to changes in cultivated land area and the baseline welfare value without climate information. Four other scenarios are in employing climate information; Proactive crop mix (P-mix), Conservative crop mix (C-mix), Climate forecasting only in Spain (Spain), Climate forecasts shared globally (Global).

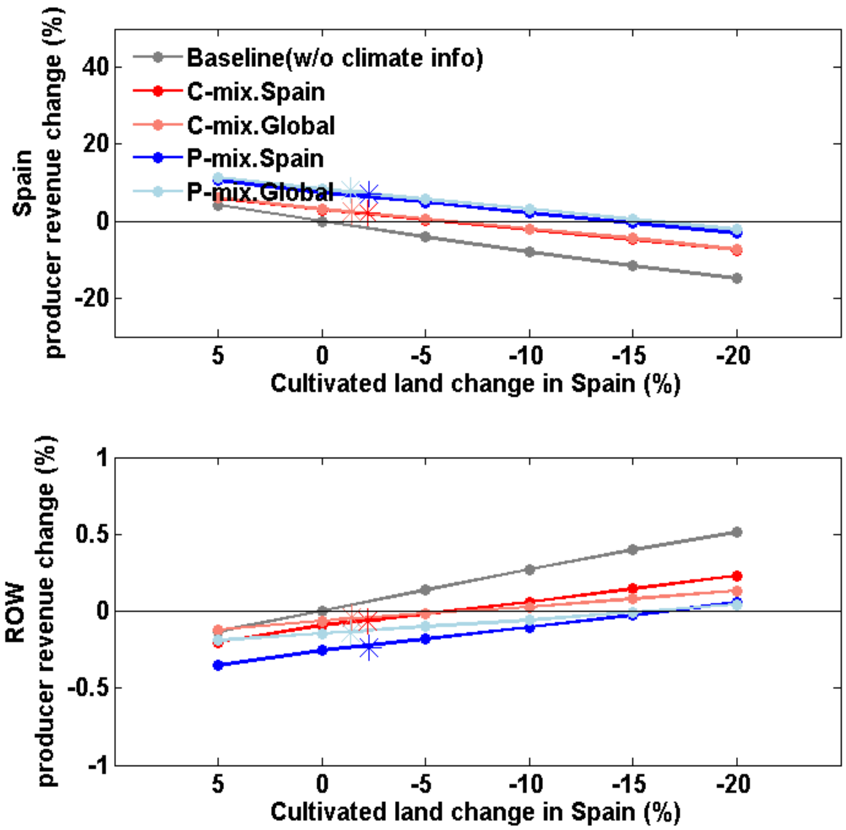

Figure 2-7 Producer revenue changes (%) in Spain and the Rest of the World (ROW) due to changes in cultivated land area and baseline welfare value without climate information. Four other scenarios are in employing climate information; Proactive crop mix (P-mix), Conservative crop mix (C-mix), Climate forecasting only in Spain (Spain), Climate forecasts shared globally (Global).

2.8 Discussion

Using climate forecasting in Spain increases both the economic surplus of domestic agricultural consumers and the overall revenue of domestic agricultural producers in Spain. The value of climate predictions to society depends on farmers' willingness to deviate from historical decisions, the nature of the predicted climate states, and the possible sharing of climate information with other countries. Proactive producer adaptation and global dissemination of climate information show higher benefits for the agricultural market in Spain. However, the proactive crop mix is feasible only when farmers actively work to optimize their benefits with higher flexibility (Hansen, 2002; Letson et al., 2005) and fully trust the climate information given to them. Farmers' responsiveness to climate prediction is jointly influenced by the forecasting skill and by farmers' ability to use this information (Hansen, 2002; Rubas et al., 2006). The level of farmers' trust is determined by the level of forecasting skill and the farmers' experiences working with forecasts (Ziervogel et al., 2005). It is thus important that forecasting skills and forecast user education should be enhanced together for the successful implementation of climate forecasting as a management tool. In this study, perfect climate forecasting skill is assumed, as well as the full adoption of climate forecasts by farmers. The reported VOI should therefore be interpreted cautiously, as they are limited to the model framework used in this study.

It is notable that a negative VOI may materialize in Spain under adverse climate conditions. Here, Spanish producers lose revenue by abandoning cultivation due to forecasted poor growing conditions, considering only historical crop mix options (conservative reaction), and ROW producers' revenue increases. Letson et al. (2005) also reported negative VOI in a whole farm model from the interactions between extreme prices, unusual weather and historical decision options in 3.8% out of all possible weather and price realizations. In decision theory, based on expected utility maximization in which our framework operates, VOI should be non-negative (Gollier, 2001), but it can become negative in a multi-person non-cooperative game (Baiman, 1975; Pfeifer et al., 2009). Additional information produced by new information systems, e.g. seasonal climate forecasting, may not always benefit information users because it is affected by other persons' decisions. In our model, Spanish farmers' decisions could impair their market surplus by using the information in a conservative way as it results in a production decline. This implies that the prediction of extreme climate events may not be sufficient to adequately deal with them. To take advantage of climate information, coordinated plans and actions are needed for climate information users and they should be able to employ all possible adaptation options. Otherwise, conservative responses to climate forecasts could impair the market, which proves the fact that climate forecasting should not be considered as a panacea to solve agricultural sector vulnerability to climate variability (Broad and Agrawala, 2000). A long-term investment into the agricultural sector is needed as well.

The adoption of climate prediction systems in one country can affect producers and consumers in other countries. Improved information for some producers increases their efficiency and decreases the marginal cost of production. This will affect the market and trade equilibrium with benefits for foreign consumers and losses to ROW producers. This shows that agricultural producers without climate information incur higher losses and an asymmetric distribution of climate information between the rich and the poor farmers can exacerbate the disparity of agricultural competitiveness at national or international level (Hill et al., 2004). Additionally, distributional impacts are also dependent on the country's willingness to disseminate forecasting information to other countries and on ROW countries' capability to employ this information. If regional climate predictions are shared and used by agricultural decision makers globally under adverse climate conditions, ROW producers' reactions contribute to the increase of global welfare, as global commodity production becomes more balanced with concerted reactions to climate variability. However, this study does not account for climate variability and climate prediction in regions outside Spain. As more regions install climate prediction systems, the individual value of predictions in a particular region could decrease (Rubas et al., 2008). Thus, the VOI for Spain as estimated in this study could decrease as more regions outside Spain adopt climate prediction.

Climate prediction can enable farmers to use resources more efficiently and affect the cropland area under cultivation and could entail agricultural land surplus. It would be advantageous for farmers and policy makers to take land use change into account when they adopt a climate forecast because land surplus can be utilized for new purposes, e.g. renewable energy production. Our model results show an average land reduction of 2 percent in Spain. With a conservative crop mix, around 5 percent of Spanish agricultural area can be spared. With a proactive crop mix, around 15 percent can be spared, and it is still assured that Spanish agricultural welfare is higher than in the reference scenario and consumers and producers in Spain do not suffer losses. Other studies (Hill et al., 1999; Mjelde and Hill, 1999; Hill et al., 2004) also qualitatively show climate and market condition-dependent changes of cultivated land area and commodity production. They indicate that climate information could affect cultivated land changes. If farmers want to sustain their income with other agricultural crops, they should know what to grow as alternatives - e.g. more heat resistant crops or biofuel crops. If severer climate extremes become more frequent due to climate change, and market profitability is poor, farmers may abandon farming, and seasonal forecasts could stimulate this development. The resulting land surplus could then be utilized for more resilient biofuel crop cultivation on seasonal basis, or for a permanent transition to solar energy production, depending on policy options.

2.9 Conclusion

This study shows that the value of climate forecasts is variable and that a country using forecasts can become more competitive than the ROW. It is more beneficial for Spain to react proactively in crop mix decisions to climate forecasts, and to share climate forecasts in adverse climate conditions. However, climate forecasts serve best to optimize agricultural management under favorable conditions, but fail to address problems pertaining to negative climate variability impacts in conservative crop mix scenarios. Additionally, climate forecasting could entail a land surplus, so that new land use plans considering sustainable agriculture and demanding renewable energy targets need to be established. The negative VOI is not much discussed in the field of climate forecasting adaptation and the potential chance of negative VOI should be considered before its implementation. Thus the learning of a strategic use of climate forecasts is essential for farmers to make proactive decisions. For its proper utilization in agriculture, further interdisciplinary studies are necessary to investigate its effect on marketing, international trade and plausible land use changes of cropland area. The side effects of using climate information, e.g. negative VOI, distributional effects of VOI on other farmers or countries could be examined in various conditions.

2.10 Appendix – model equations

Indexes

Symbol	Description
$r, \tilde{r}$	aggregated international regions {Spain and 28 other regions}
n	NUTS-2 regions in Spain
h	homogeneous response units
$e, \tilde{e}$	crops {Barley, Corn, Rice, Wheat, Potato, Cotton}
p	commodities {six crops and one aggregated livestock good ('lv')}
$t, \tilde{t}$	technologies (rain-fed, irrigation)
f	livestock feed {Barley, Corn, Rice, Wheat, Potato, Cotton}
a	crop mix alternatives
s	states of nature (30 years climate)

Linear Coefficients

Symbol	Description
β	maximum arable land area (1000 ha)
κ	land allocation to crop management system in base period (1000 ha)
ψ	historical crop areas (1000 ha)
φ	maximum crop shares
γ	crop yields (tonnes/ha)
ω	irrigation water requirements (1000 m^3/ha)
μ	feed requirements per unit of aggregate livestock product (tonnes/Gcal)
ς	crop management cost (\$/ha)
η	new cropland expansion cost (\$/ha)
α	abandoned cropland cost (\$/ha)
ρ	probability of climate state

Non-linear Functions

Symbol	Description
ϕ^d	integral of inverse demand function
ϕ^t	integral of trade cost function
ϕ^m	integral of management change cost function
ϕ^w	integral of inverse water supply function
ϕ^a	integral of livestock production cost function

Variables

Symbol	Description
D	demand quantity (1000 tonnes, Tcal)
L	land management (1000 ha)
A	livestock production (Tcal)
T	trade quantity (food, 1000 tonnes, Tcal)
F	livestock feed quantity (1000 tonnes)
C	management change area (1000 ha)
W	irrigation water use (km^3)
S	crop mix choice (unitless)
M	new land management area (1000 ha)
X	abandoned management area (1000 ha)

Objective function[2]

$$\max \quad \sum_{s} \left(\rho_s \cdot \left[\begin{array}{l} +\sum_{r,p} \phi^{d}_{r,p}\left(\mathbf{D}_{r,p,s}\right) \\ -\sum_{r,\tilde{r},p} \phi^{t}_{r,\tilde{r},p}\left(\mathbf{T}_{r,\tilde{r},p,s}\right) \\ -\sum_{r} \phi^{w}_{r}\left(\mathbf{W}_{r,s}\right) \\ -\sum_{r} \phi^{a}_{r}\left(\mathbf{A}_{r,s}\right) \\ -\sum_{r,n,h,e,t} \left(\varsigma_{n,h,e,t} \cdot \mathbf{L}_{r,n,h,e,t,(s)}\right) \\ -\sum_{r,n,h,t,\tilde{t}} \phi^{m}_{r,n,h,t,\tilde{t}}\left(\mathbf{C}_{r,n,h,t,\tilde{t},(s)}\right) \\ -\sum_{r,n,h,t} \left(\eta_{r,n,h,t} \cdot \mathbf{M}_{r,n,h,t,(s)}\right) \\ -\sum_{r,n,h,t} \left(\alpha_{r,n,h,t} \cdot \mathbf{X}_{r,n,h,t,(s)}\right) \end{array} \right] \right)$$

Constraints

1. **Crop land limits** $\forall r,n,h,(s)$

$$\sum_{e,t} \mathbf{L}_{r,n,h,e,t,(s)} \le \beta_{r,n,h}$$

2. **Water use accounting equations** $\forall r,s$

$$\sum_{n,h,e,t} \left(\omega_{r,n,h,e,t,s} \cdot \mathbf{L}_{r,n,h,e,t,(s)}\right) - \mathbf{W}_{r,s} \le 0$$

3. **Crop mix restrictions** $\forall r,n,h,e,(s)$

$$\sum_{t} \mathbf{L}_{r,n,h,e,t,(s)} - \sum_{a} \left(\psi_{r,n,e,a} \cdot \mathbf{S}_{r,n,h,a,(s)}\right) = 0$$

4. **Maximum crop share restrictions** $\forall r,n,h,e,(s)$

[2] Note the model has two decision modes: probabilistic model with and without seasonal climate forecasting. In absence of forecasting, all climate state indexes given in parentheses vanish.

$$\sum_{t} \mathbf{L}_{r,n,h,e,t,(s)} - \varphi_e \cdot \sum_{\tilde{e},t} \mathbf{L}_{r,n,h,\tilde{e},t,(s)} \leq 0$$

5. Crop management balance equations $\forall r,n,h,t,(s)$

$$\sum_{e} \mathbf{L}_{r,n,h,e,t,(s)} + \sum_{\tilde{t}} \mathbf{C}_{r,n,h,t,\tilde{t},(s)} - \sum_{\tilde{t}} \mathbf{C}_{r,n,h,\tilde{t},t,(s)} = \kappa_{r,n,h,t}$$

6. Land use change balance equations $\forall r,n,h,t,\ (s)$

$$\sum_{e} \mathbf{L}_{r,n,h,e,t,(s)} + \mathbf{X}_{r,n,h,t,(s)} - \mathbf{M}_{r,n,h,t,(s)} = \kappa_{r,n,h,t}$$

7. Crop product supply demand balance $\forall r, p, s$

$$\mathbf{D}_{r,e,s} + \mathbf{F}_{r,e,s} + \sum_{\tilde{r}} \mathbf{T}_{r,\tilde{r},e,s} - \sum_{\tilde{r}} \mathbf{T}_{\tilde{r},r,e,s} - \sum_{n,h,t} \left(\gamma_{r,n,h,e,t,s} \cdot L_{r,n,h,e,t,(s)} \right) \leq 0$$

8. Feed product supply demand balance equations $\forall r, f \in p, s$

$$\mu_{r,f} \cdot \mathbf{A}_{r,s} - \mathbf{F}_{r,f,s} \leq 0$$

9. Livestock product supply demand balance equations $\forall r, s$

$$\mathbf{D}_{r,'lv',s} + \sum_{\tilde{r}} \mathbf{T}_{r,\tilde{r},'lv',s} - \sum_{\tilde{r}} \mathbf{T}_{\tilde{r},r,'lv',s} - \mathbf{A}_{r,s} \leq 0$$

Chapter 3. Climate change impacts on cropland area and adaptation: case study Spain using a stochastic model framework

Abstract

Climate change alters the productivity of agricultural land and consequently induces land use changes. To quantify the effect, we analyse climate change impacts on the agricultural sector in Spain, explore how two different land use policies influence total acreage, consumer surplus and gross producer revenue, and evaluate the benefit of seasonal climate predictions. We consider annual climate impacts by employing physically and temporally consistent daily weather data from three Regional Climate Models (REMO, RegCM, and Aladin) of the ENSEMBLE project for the SRES A1B scenario. Climate impacts on crop productivity are projected with the process-based crop model Environmental Policy Integrated Climate (EPIC) and subsequently used in a stochastic partial equilibrium for the agricultural sector model.

The results show that already in the period of 2020-2039, the average consumer surplus and gross producer revenue are more than 1 standard deviation below the mean of the baseline period (1995-2014). A statistically significant deviation from baseline values is reached only in the period of 2080-2099, however, where consumer surplus decreases by 2 – 3 percent, gross producer revenue decreases by 5 to 20 percent, and cultivated land declines by 20 – 50 percent.

An analysis of adaptation options shows that a land retaining policy in Spain would benefit Spanish consumers by increasing production. Keeping marginal land in production, however, imposes a resource overuse, and the overall costs for land retention are thus higher than those of land abandonment by a factor of two. Climate predictions have two effects: If land abandonment is an option, consumers benefit from climate predictions. For producers, their revenue decreases. Furthermore, under moderate climate change scenarios, the value of climate predictions decreases over time because cultivated land can be abandoned. However, under strong climate change scenario, producers react to keep their land and revenue loss decreases. With a land retaining policy, on the other hand, the value of climate predictions becomes minimal for consumers than with a land abandonment policy because production increment is smaller with climate information.

Climate change induced crop productivity changes put pressures on Spanish agricultural land. Future land use policy should consider that land retention in Spain under climate change leads to increasing costs because of over production and the benefit of using climate predictions is shrinking.

3.1 Introduction

Climate change is anticipated to have adverse impacts on agriculture in large parts of the world. Yet future climate change assessments still face large uncertainties due to factors such as the emergence of extreme climate events, CO_2 fertilization effects, technological progress in new cultivars, and farmers' adaptation to climate variability (Tubiello et al., 2007; Ackermann, 2013). Among these factors, changes in the frequency and magnitude of climate extremes and their impact on agricultural sectors are major concerns for stakeholders (Katz and Brown, 1992; Easterling et al., 2007). In the last decades already, heat waves increased globally (Coumou et al., 2013) and manifested on ever larger areas of land (Hansen et al., 2012), causing economic damages (Coumou and Rahmstorf, 2012). Developing countries experienced price shocks and social instability, partially attributable to climate extremes. The 2010 heat wave in Russia substantially reduced wheat production, and the Russian government banned wheat exports (Godfray et al., 2010; Arezki, 2011; Trostle, 2011). These events show that climatic extremes and their influence on production and markets have to be taken into account, and adaptation policies formulated accordingly are needed to supply not only food in adequate quantities in future, but also energy and ecosystem services.

In climate impact research on agriculture, studies on the economic impacts of extreme climate and weather are rare. Most of the economic studies have estimated the impact of climate change on agriculture at continental or global scale (Table 3-1). In those analyses, averaged climate change impacts were used as input to economic assessments to evaluate long term market equilibrium. Coarse resolution monthly mean temperature and precipitation sums were used as input to production functions. Thus, impacts of extreme events and their consequences on markets could not be taken into account. Recently, Willenbockel (2012) attempted to simulate price responses to extreme events in the decade of the 2030s by employing production shock scenarios. He could show that historical weather related shocks to crop exporting countries could increase export prices and impact food importing countries; but a limitation of the study is that it uses historically observed yield variability and future climate change is not considered.

Table 3-1 Benchmark study for climate impacts on agriculture

	Region	Climate model	Climate data	Impact model	Crop Yield	Economic model	Period
Reilly et al. (2003)	US	GCM×2	Monthly average	Crop model	Averaged impacts	FASOM (PE)	2030, 2090
Darwin (2004)	World	GCM×8	Monthly average	Land classes (growing seasons)	Averaged impacts	FARM (CGE)	End of 21st century
Parry et al. (2005)	World	GCM	Averaged trends	Yield response function	Averaged impacts	BLS(CGE)	2060
(Willenbockel, 2012)	World	GCM	Averaged trends	Yield response function	Averaged impacts + stochastic	GLOBE(CGE)	2030
Iglesias et al. (2012)	Europe	RCM×4	Monthly average	Yield response function	Averaged Impacts	GTAP(CGE)	2071-2100

* '×' in climate model column denotes the number of climate model used in the analysis.
* FASOM (Forest and Agricultural Sector Optimization Model), FARM (Future Agricultural Resources Model), BLS (Basic Link System), GLOBE (A SAM Based Global CGE Model using GTAP Data), GTAP (Global Trade Analysis Project)

Another approach is to use ensemble climate scenarios to conduct probabilistic impact assessments on biophysical factors, e.g. crop yields or growing degree days (Tebaldi and Lobell, 2008; Goergen et al., 2013; Tao and Zhang, 2013). Such probabilistic biophysical assessments have not yet been linked to an economic model at national level to assess annual market impacts. Reasons for this could be that stochastic weather generation does not produce spatially and temporally coherent daily weather data at larger scales. Statistically downscaling global weather data to regional levels weakens the correlation between temperature and precipitation (Piani and Haerter, 2012). Dynamic downscaling, however, can provide weather variables which are physically consistent on a daily basis and spatially consistent over multiple sites (STARDEX, 2005). These daily weather time series can be used to run process-based crop growth models for impact simulations. This way, both climate scenario and agricultural decision model work on the same scale, facilitating a consistent analysis of potential climate change impacts on a national agricultural sector.

In this context it is important to not only assess the impacts of climate change, but also to explore different adaptation strategies. Land use change, for example, is essential for rural economic viability and also for the energy sector, as land surplus can be used for renewable energy production. The seasonal climate anomaly prediction is regarded as an effective measure to avoid production risks induced by climate extremes (Hansen et al., 2011; Hellmuth et al., 2011). However, the value of climate predictions in decades to come has not yet been investigated.

To address the limitations of current research outlined in the previous paragraphs, in this study we want to assess the economic consequences of different land use policies and of climate predictions, all in the framework of a model sequence from a regional climate scenario to a crop model to a stochastic partial equilibrium model for Spain. Spain is selected as the study region because the country is expected to be most vulnerable in Europe (Iglesias et al., 2012).

3.2 Methods

3.2.1 Three regional climate models (RCMs)

For the analysis of climate change impacts on local crop productivity, the resolution of global circulation models (GCM) is too coarse. To estimate local climate developments, three downscaling methods can be applied: statistical downscaling, stochastic weather generation, and dynamic downscaling. Statistical downscaling is computationally inexpensive and can be applied to a wide range of GCM experiments. It is useful in addressing uncertainty issues by considering model differences, yet it assumes that the statistical relationship between large scale predictors and local predictands remains unchanged even under altered climatic conditions, which can be problematic for the projection of future climate extremes (Luo and Yu, 2012). Stochastic weather generation methods produce daily weather series independently for every site in a region by using perturbed parameters from GCMs; yet for multisite crop impact studies spatially and temporally consistent weather data should be employed (Wilks, 2012). In the dynamic downscaling method, a regional climate model (RCM) is applied to generate daily weather data at high resolution from coarse resolution boundary GCM circulations, considering local topography and land surface. Dynamic downscaling was chosen for this study, because it has the advantage that the climate variables are physically, temporally, and spatially consistent over the entire study region. Some limitations remain, however, as RCMs show weaknesses in hindcasting and are computationally costly (Luo and Yu, 2012).

The specific daily weather time-series (1995-2100) we use were generated with three different RCMs within the FP6-ENSEMBLE project (http://ensemblesrt3.dmi.dk/). The spatial resolution of the data is 25 km, and the scenario is SRES A1B. Table 3-2 shows the respective combinations of GCM and RCM. The RCMs – REMO, Aladin, and RegCM –

were chosen for their relatively high performance on the Iberian Peninsula (Lorenz and Jacob, 2010). We use daily maximum and minimum temperature, precipitation, solar radiation, and relative humidity for the EPIC simulations.

Table 3-2 RCMs from ENSEMBLE project in A1B scenario (1951~2100)

Institution	RCM	Driving GCM	Horizontal resolution
MPI-M	REMO	ECHAM5-r3	25km
CNRM	Aladin	ARPEGE_RM5.1	25km
ICTP	RegCM	ECHAM5-r3	25km

* MPI-M : Max Planck Institute for Meteorology, CNRM : Meteo France, ICTP : The Abdus Salam Intl. Centre for Theoretical Physics

3.2.2 Crop productivity simulations

For the simulation of crop productivity we use the EPIC model (Environment Policy Integrated Climate), which is a process-based crop growth model, widely used for regional and global climate impact analysis (Williams and Singh, 1995). Simulation units for Spain are derived by intersecting Homogeneous Response Units (HRU), land cover data, and NUTS2 (nomenclature of territorial units for statistics) regions. HRUs are delineated by clustering units within the same altitude, soil, and slope class (Schmid et al., 2006). Irrigated sites are identified through the Land Use/Cover Area frame Statistical Survey, LUCAS (Stolbovoy and Montanarella, 2007). Crop calendar data come from the MARS (Monitoring Agricultural ResourceS) project. We simulate five crops (winter wheat, spring barley, rice, corn, and potato) with an automatic fertilization scheme on all sites and water-stress induced automatic irrigation on irrigated sites. We use the automatic fertilization option because we assume that farmers adapt to climate change by minimizing nutrient deficits. Crop rotations are set according to observed crop maps. EPIC simulations are repeated on each simulation unit with different crop sequences until each crop is grown at least once in each year. Crop yields are scaled to NUTS2 region level by multiplying the simulation unit yields with the actual crop area in the year 2005. A bias correction is done with multiplicative factors for crop yields also on NUTS2 level.

3.2.3 **Spanish agricultural sector model**

We use a partial equilibrium economic model for the agricultural sector for five crops and one aggregated livestock pool. Conversion factors from livestock feed quantity to produced livestock calorie are estimated and used in the livestock supply equation. The model uses explicit demand curves with price-demand elasticities for each commodity, and Leontief production functions for every simulation unit. Land expansion and land abandonment costs are also considered for each simulation unit.

We use and compare three modes of economic decision making: deterministic, stochastic, and stochastic with perfect information. The deterministic model calculates the market equilibrium for climate change impacts averaged over four distinct time periods in the future. The stochastic model computes the market equilibrium taking into account producer uncertainty about future climate conditions. Thus, this model version maximizes the expected market welfare over different states of nature with a specific probability. Conceptually, the stochastic model version is analogous to the Discrete Stochastic Programming with Recourse (Lambert et al., 1995). The stochastic model with perfect information represents the use of seasonal climate anomaly predictions. Farmers are provided with information on projected crop yields for the current year, and choose crop mixes and management options accordingly.

We estimate welfare changes in the Spanish agricultural sector by calculating the changes in Marshallian consumer surplus and the changes in Marshallian water resource surplus. In addition, we calculate impacts on gross producer revenue. The Rest of the World (ROW) regions are explicitly depicted using the same regional disaggregation as the GLOBIOM model (Sauer et al., 2010). The sum of consumer, resource, and trade surplus changes over all regions yields a measure of global welfare changes. Climate change impacts are only applied to Spain; productivities in the ROW remain as in the reference period. The base model is calibrated to FAO data of the year 2005. We consider five distinct time periods: baseline 2005s (1995 – 2014), 2030s (2020 – 2039), 2050s (2040 – 2059), 2070s (2060 – 2079) and 2090s (2080 – 2099). We employ a comparative static approach to assess the climate change impacts for each time period. The other socio-economic factors such as GDP growth, income changes, and technological changes are not considered and only climate change induced productivity changes are taken into account. Land area and management levels are recursively transferred to the next time slice.

3.2.4 Deterministic, Stochastic decisions and stochastic decisions with perfect information

Most agricultural sector models are deterministic, mainly due to the limits of data availability and computational efficiency. Deterministic models can reproduce long-term market equilibrium, but are of limited use in the endogenous depiction of short term market variability of e.g. crop yields and prices. In reality, agricultural decision makers consider historical climate and market conditions, but deterministic decisions do not take into account expected market instabilities. In a deterministic model, the control variable X (management decisions) is computed with respect to parameter $\bar{\alpha}$ (e.g. crop yield) by maximizing the welfare:

$$\underset{X}{Max} \quad W(\mathbf{X}, \bar{\alpha}) \tag{1}$$

Stochastic decisions are different from deterministic decisions in that they take into account the probability of certain decision-relevant variables p, e.g. yield and price (equation 2), and that decision outputs are also related to decision makers' risk preferences. This is an important feature, as many studies have shown that at farm level decisions change under various yield and market conditions. However, it is challenging to build a stochastic model at sector level with high resolution geophysical data due to increasing data requirements for each state of nature (i). In this study, only crop yield variability in each 20 year time slice is set as state of nature.

$$\underset{X}{Max} \sum_{i} p_i W(\mathbf{X}, \alpha_i) \tag{2}$$

The model with stochastic decisions with perfect information depicts yet another situation. Farmers are given information on projected crop yields α every year prior to management decision making, which facilitates the implementation of management strategies tailored to the market situation and climate. In each year, farmers make the best possible decisions, yielding the highest welfare levels of all three modes (Gollier, 2001).

$$\sum_{i} P_i \underset{X_i}{Max} W(\mathbf{X}_i, \alpha_i) \tag{3}$$

See Figure 3-1 for a graphical summary of the different decision modes.

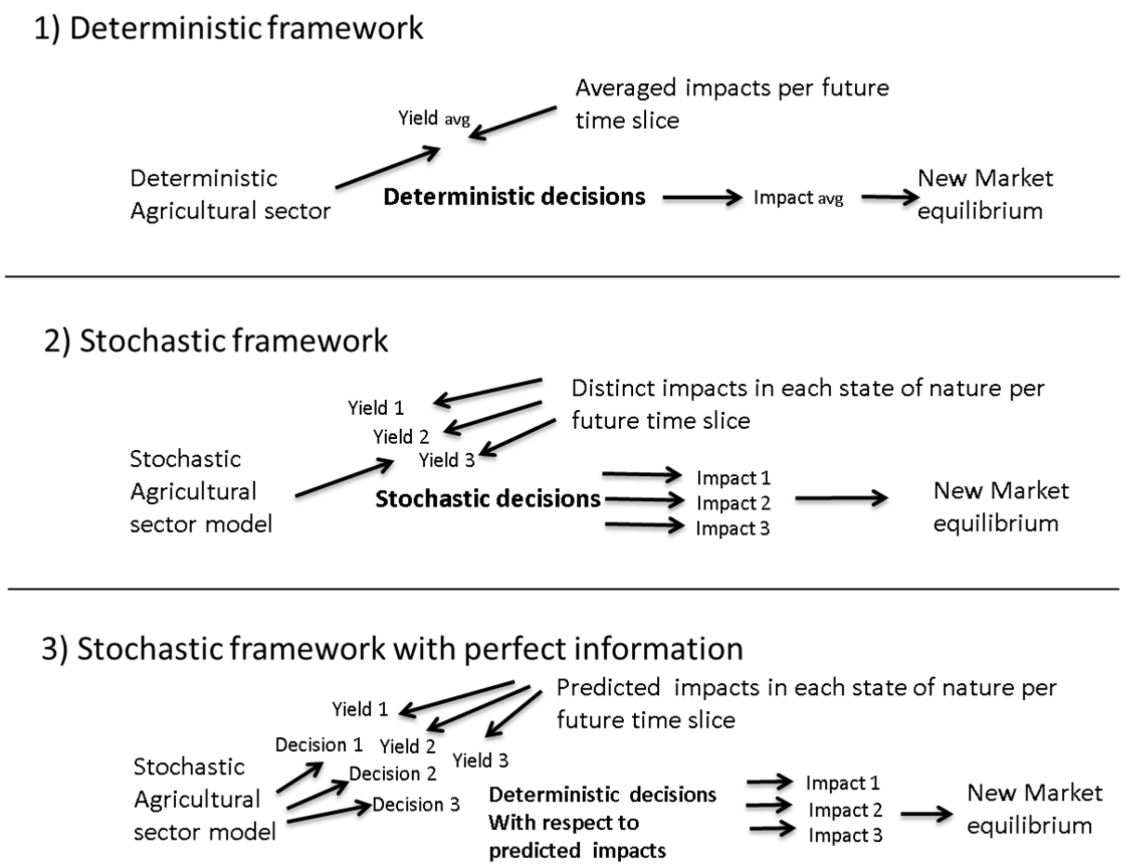

Figure 3-1 Decision modes used in this study. Most of the previous analyses use the deterministic mode.

3.2.5 Scenarios for adaptations to climate change

We consider two adaptation measures: cropland change and the use of climate predictions seasonal climate prediction. Cropland change has two cases: land abandonment and land retention at present level. The “Land abandonment’ scenario indicates that cropland is endogenously determined under climate change induced productivity changes and liberalized trade. Spanish farm land is abandoned when the marginal revenue is less than marginal cost. The ‘Land retention’ scenario indicates that the government supports farmers if they continue cultivating the same land area they also cultivated in the baseline time slice.

In the climate prediction scenario, the same two cropland change scenarios are used, but this time the farmers employ the climate information to flexibly expand or abandon cultivated land. This depicts the situation in which farmers leave the market easily. The other scenario is that farmers continue cultivation on the same area and instead employ the climate information to increase production. In this scenario, farmers are inclined to stay in agricultural business.

3.3 Results

3.3.1 Climate change impacts on crop productivity for Spain

The three regional climate models show different patterns of change regarding temperature and precipitation (see Appendix, Figure 3-10, Figure 3-11). The Aladin time series generally shows a smaller increase in temperature than the RegCM and REMO time series. Regarding precipitation, Aladin and RegCM show a slight increase in the spring season, whereas REMO shows a decrease in April and June. The simulated precipitation reduction in REMO is generally higher than in the two other models, and stays like this over the whole century.

Due to these differences, the resultant crop yields show different trends (Figure 3-2). Crop yields simulated with Aladin data show higher mean values and a larger deviation, especially for barley and wheat. Runs with REMO and RegCM data show smaller deviations in crop yields. An analysis of the results reveals that some years of the daily weather data generated with Aladin facilitate near ideal crop growth in EPIC, so that yields are exceptionally high. On average, the REMO weather data shows stronger and more consistent negative climate impacts on all crops than the other two time series.

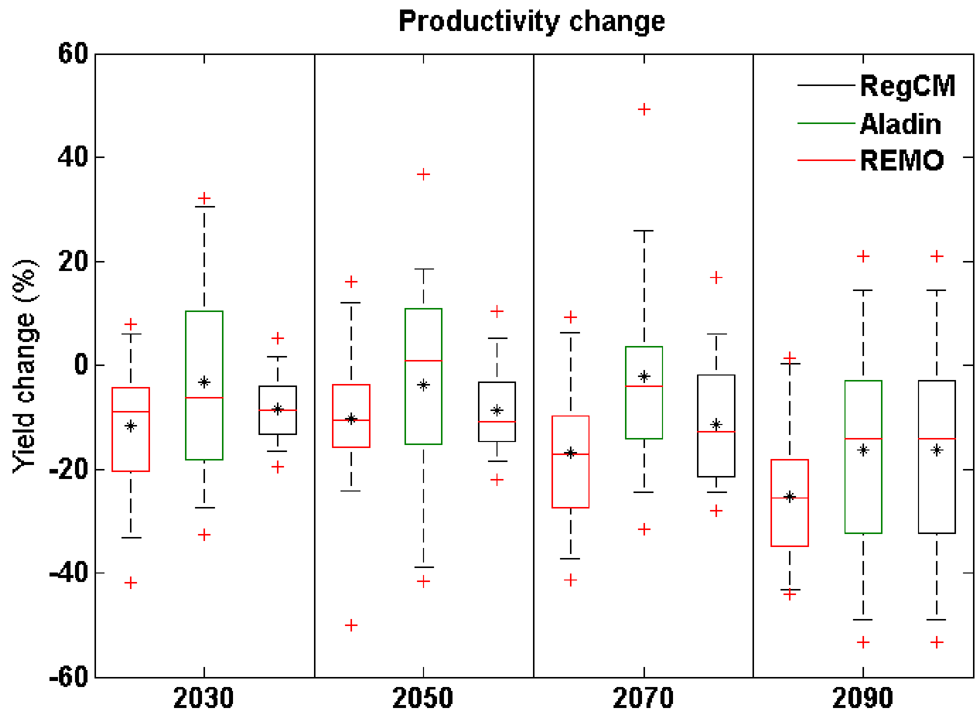

Figure 3-2 Aggregated yield changes for all five crops simulated with three different regional climate model outputs in comparison to the baseline period (1995 – 2004). Asterisk: mean; upper whisker: 95th percentile; lower whisker: 5th percentile; upper box: 75th percentile; lower box: 25th percentile; centerline: median.

If one looks at the changes in yield over time, in the early decades (2030s − 2070s), climate change impacts are consistent and do not exhibit clear differences. In the 2090s the negative impacts are prevalent, and barley yield e.g. decreases by 30 to 40 percent on average, but winter wheat moderately benefits from climate change in Spain and yields increase by 5 to 10 percent on average (Figure 3-3). Unlike mean yield values, the 5th percentile of crop yields does not steadily decline. For barley, the minimum yield simulated with REMO data e.g. stays constant at levels of around -60 percent compared to baseline values. For the other crops and climate models, low extreme values decline over time, but they do not decline consistently.

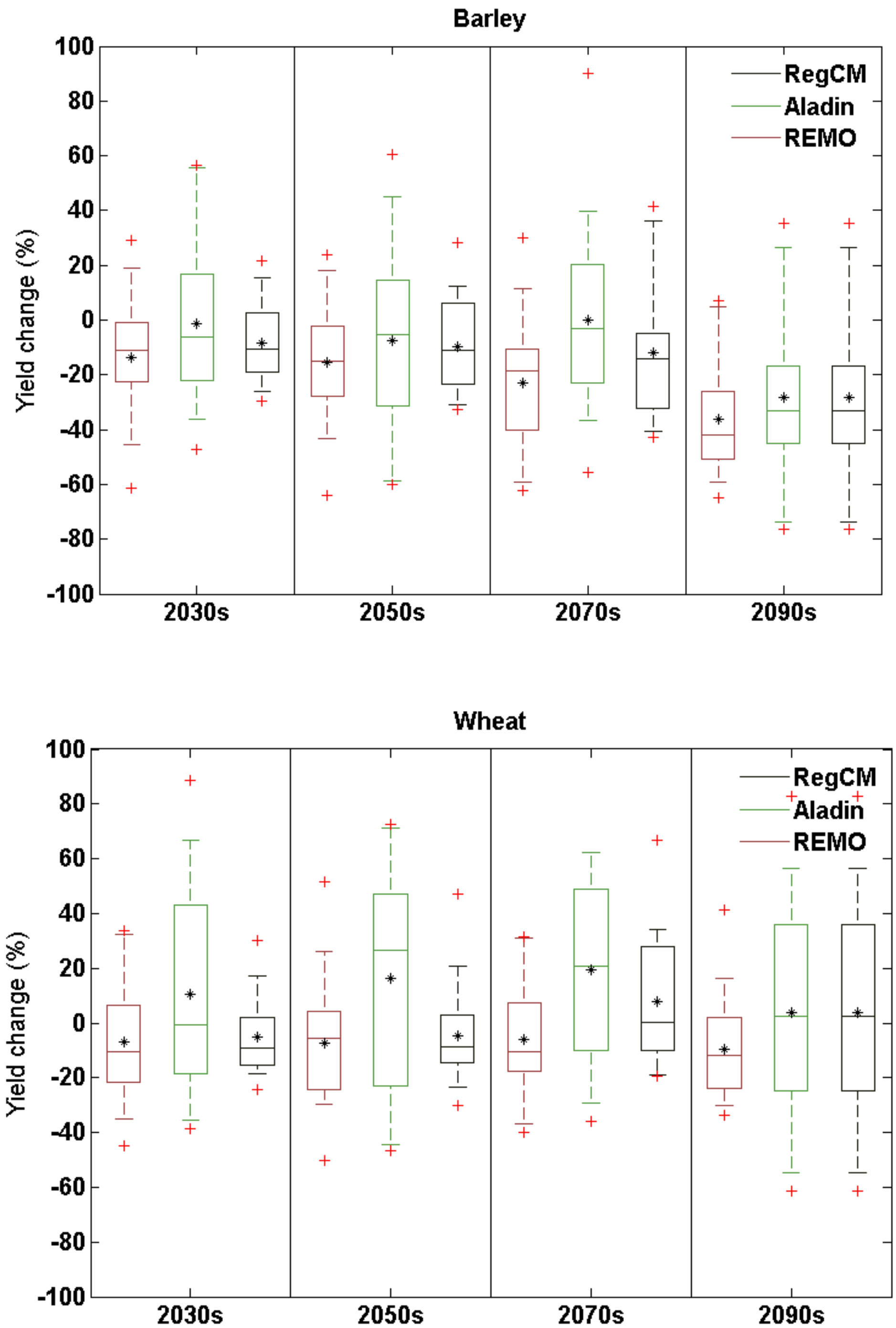

Figure 3-3 Barley and wheat yield changes simulated using three different regional climate model outputs and a comparison to the baseline period (1995 – 2004). Asterisk: mean; upper whisker: 95th percentile; lower whisker: 5th percentile; upper box: 75th percentile; lower box: 25th percentile; centerline: median.

3.3.2 Cropland change and economic impacts

The simulations with all three RCMs show that cropland area in Spain decreases over time, until only 50 − 80 percent of the original area remains in the 2090s (Figure 3-4). Farmers abandon land when the marginal revenue is less than the marginal cost, both in the deterministic and the stochastic model. In the stochastic model with perfect information, farmers abandon even more land, because they know of adverse climatic condition in advance and act accordingly.

Consumer surplus follows a similar trend and decreases by 2 − 3 percent over the time course, whereas gross producer revenue decreases by 5 – 20 percent (Figure 3-5). These damages are attributed to changes in productivity caused by changes in climate, and also cropland reductions. Simulations done with climate data from Aladin, which is driven by a different GCM than the other two RCMs, show slight benefits in the early periods. All models agree, however, that by the 2090s, climate change impacts are negative. The deterministic model and the stochastic model do not show much difference in consumer Surplus, but it show higher impacts on gross producer revenue. The stochastic model with perfect information, however, shows a slight benefit for consumer surplus and a more pronounced loss for gross producer revenue in comparison to the other two models. With climate predictions, farmers abandon cropland more, causing revenue losses for producers. In this study, technological progress to use climate information is not considered and farmers make decisions to reduce cultivated land with respect to adverse climate conditions. Finally, the Aladin output (Figure 3-5) shows high anomaly of consumer surplus and producer revenue in 2070s. This shows that projected climate in 2070s from Aladin do not contain rather favourable conditions and crop yield output also shows less pronounced impacts in 2070s from Aladin (Figure 3-2).

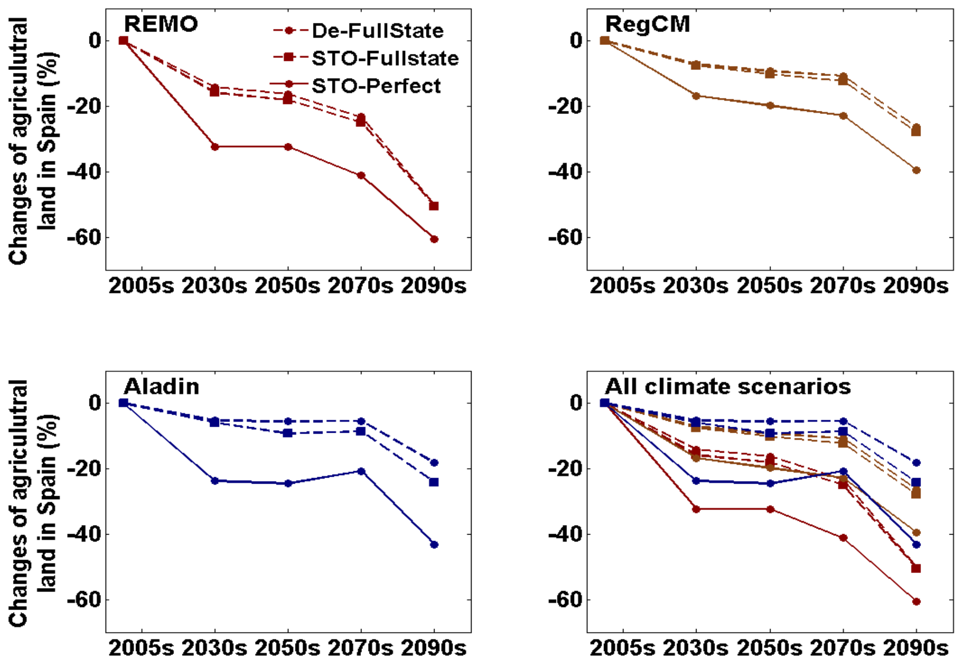

Figure 3-4 Simulated changes of cultivated land in Spain using three RCM outputs (REMO, RegCM, Aladin) and different decision modes. Baseline cultivated land area is 5.8 mil. ha in 2005s. 'De' indicates deterministic mode decisions, 'STO' indicates stochastic mode decisions and 'STO-Perfect' indicates perfect information output.

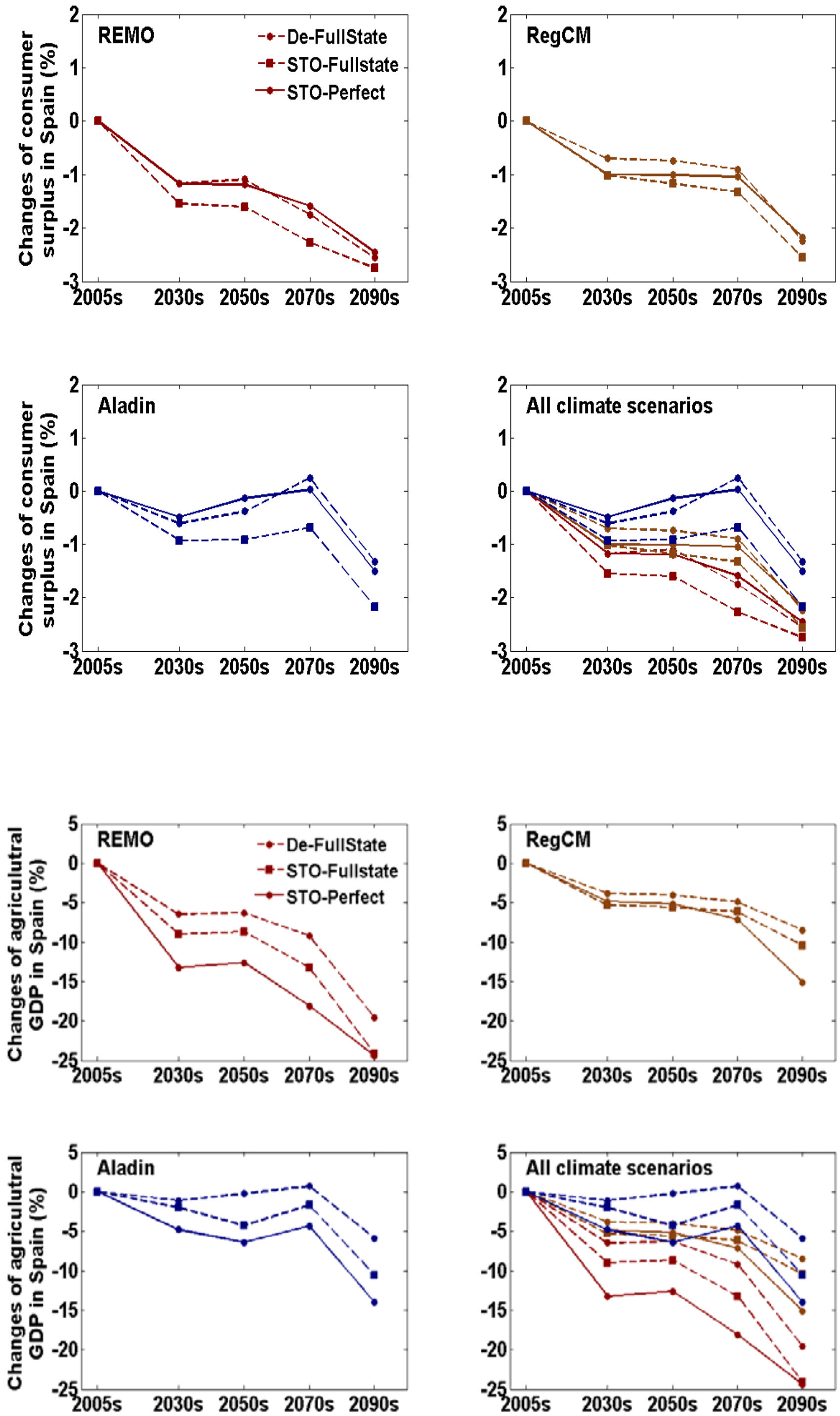

Figure 3-5 Simulated changes of consumer surplus and gross producer revenue in Spain using different RCM outputs (REMO, RegCM, Aladin) and decision modes. 'De' indicates deterministic mode decisions, 'STO' indicates stochastic mode decisions and 'STO-Perfect' indicates perfect information output.

3.3.3 Climate variability impacts on the market and adaptation using climate prediction

Figure 3-6 shows climate variability impacts on consumer surplus and gross producer revenue in each year from stochastic model solutions. Both changes are fitted with a linear regression. Changes in producer revenues simulated with data from REMO show a steeper slope than changes simulated with RegCM and Aladin. The Aladin scenario shows a wider range of confidence bounds, whereas the REMO scenario shows stronger negative climate change impacts on consumer surplus and gross producer revenue. Both REMO scenarios exhibit extreme values outside of confidence bounds.

Figure 3-7 shows the same data as Figure 3-6, but this time aggregated to four time slices and with all three decision modes. In the 2030s, the REMO and RegCM scenarios show gross producer revenue decreases of more than 1 standard deviation, whereas values in the Aladin scenario stay above that level. By the 2090s, average impacts amount to changes of -1 to -2 standard deviations. Changes in the 5th percentile producer revenue levels show stronger declines than average levels, but no consistent pattern of decline is visible over time.

Seasonal climate anomaly predictions (stochastic mode with perfect information) markedly affect gross producer revenue. In the ‘Land abandonment’ scenario, producer revenue could decrease visibly, as land abandonment due to forecasts of adverse conditions diminished farm production. In the ‘Land retention’ scenario, on the other hand, negative impacts are lessened because farmers do not abandon cropland, yet total management costs increase due to the use of less productive lands.

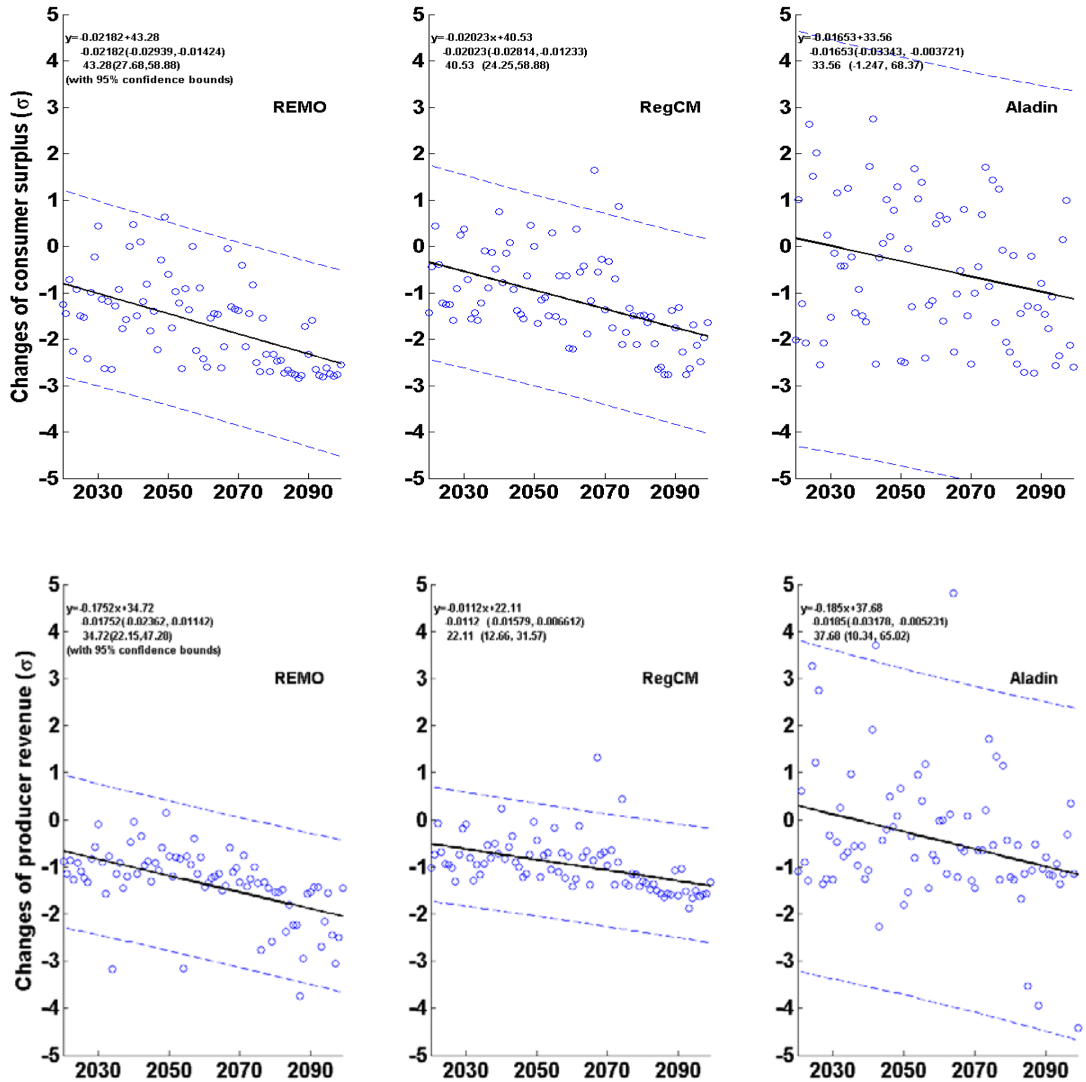

Figure 3-6 Linear regression fits on consumer surplus and gross producer revenue change from the stochastic model solutions. Consumer surplus and gross producer revenue anomalies are compared with the standard deviation (σ) of the baseline value.

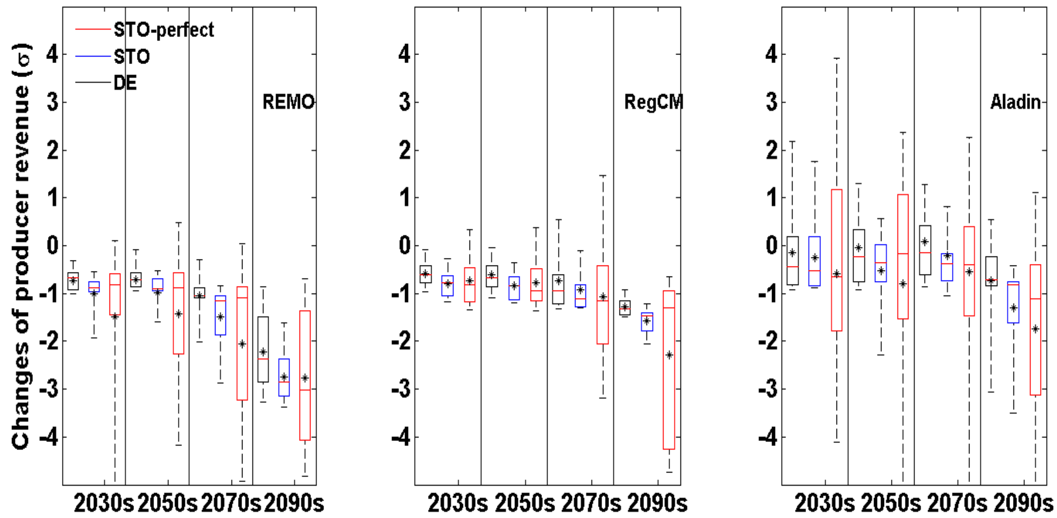

Figure 3-7 Impacts of climate variability and climate extremes on gross producer revenue in Spain. 'DE': deterministic model outputs, 'STO': stochastic model outputs, 'STO-perfect': stochastic model outputs with perfect information. (Asterisk: mean; upper whisker: 95th percentile; lower whisker: 5th percentile; upper box: 75th percentile; lower box: 25th percentile; centerline: median)

To test whether the observed differences in producer revenues are statistically significant, we applied a Kruskal-Wallis test to the data. The test is a non-parametric method for testing whether samples originate from the same distribution, which can be applied to non-Gaussian distributions. P-values smaller than 0.01 indicate that the null hypothesis has to be rejected and that the samples come from different distributions. The test result (Table 3-3) shows that gross producer revenue changes from all RCMs do not make significant differences between 2030s and 2050s. RegCM outputs show that the period from 2030s to 2070s have the same impact distribution and Aladin outputs have the same impact distributions from the baseline to 2070s. Only REMO shows distinct distributions from one period to the next, except 2030s – 2050s).

Table 3-3 Kruskal-Wallis test results on gross producer revenue changes over each pair of neighboring periods from each regional climate model output. Statistical test is applied to each climate scenario on a group of periods at the 1% significance level. The p-value below 0.01 rejects the null-hypothesis that comparing samples are from the same distribution (d.f. : Degree of Freedom, M.S. : Mean Squared error)

	Climate	Group of periods	D.F	M.S.	P
Gross Producer revenue	REMO	Baseline, 2030s	1	3240	<<0.0001
		2030s, 2050s	1	3.6	0.8711
		2050s, 2070s	1	1822	0.0003
		2070s, 2090s	1	2856	<<0.0001
	RegCM	Baseline, 2030s	1	2340	<<0.0001
		2030s, 2050s	1	25.6	0.6652
		2050s, 2070s	1	490	0.0583
		2030s, 2050s, 2070s	2	583.55	0.0609
		2070s, 2090s	1	3312	<<0.0001
	Aladin	Baseline, 2030s	1	313	0.1298
		2030s, 2050s	1	4.9	0.8498
		2050s, 2070s	1	8.1	0.8077
		Baseline, 2030s, 2050s, 2070s	3	337	0.5987
		2070s, 2090s	1	1587	0.0007

3.3.4 Adaptation effects with cropland and climate prediction

In Figure 3-8, the effects of the adaptation scenario ‘Land retention’ is shown in relation to the scenario ‘Land abandonment’. In the ‘Land retention’ scenario, consumer surplus is higher than in the ‘Land abandonment’ scenario, as Spanish producers retain more land in production and thus produce more food. Yet, the scenario also induces higher additional (‘over-production’) costs, because producers are forced to cultivate marginal land with higher management costs, while market prices decline simultaneously with the rising production. Regarding resource effects by land retention, water surplus increases in Spain when a larger irrigated area is cultivated under water-stressed conditions.

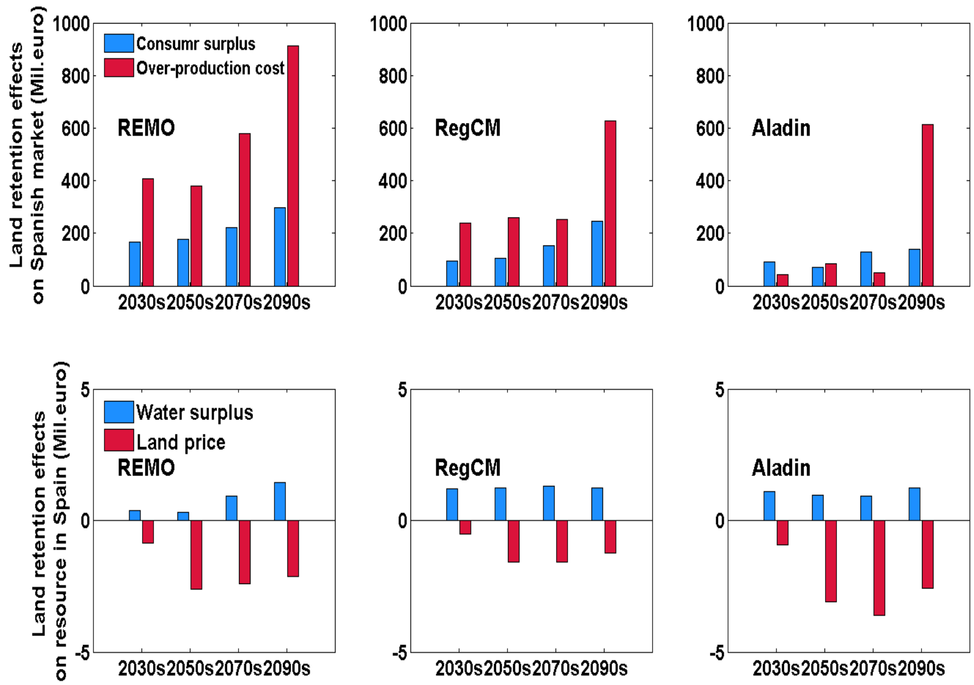

Figure 3-8 Time-dependent land retention effects on consumer surplus, over-production costs, water surplus and land price on marginal cropland in comparison to the land abandonment scenario.

Figure 3-9 shows climate prediction effects on consumer surplus and gross producer revenue for each land scenario. In the 'Land abandonment' scenario, consumer surplus increases and gross producer revenue decreases when climate predictions are used. Climate predictions lead to a higher rate of land abandonment (see Figure 3-4), and domestic production decreases as a consequence. The consumer surplus increases in this situation due to food commodity imports from more productive regions at lower prices. However, when the more benign Aladin model output is considered, both consumers and producers benefit from climate predictions. In the 'Land retention' scenario, prediction effects are smaller. Less productive land is still cultivated, and a restriction of the crop mix to historically observed states also contributes to the smaller value of climate predictions. Even though the changes are less pronounced, the results show a higher diversity of effects, differing from time period to time period and RCM to RCM. In the REMO and RegCM scenarios in the 2090s, the value of prediction is negative for both consumers and producers, because climate information does not help farmers to increase their production. In the Aladin scenario, the values are positive, because the Aladin weather time series includes a higher number of climatically favorable years in the 2090s (see also Figure 3-5, Figure 3-6).

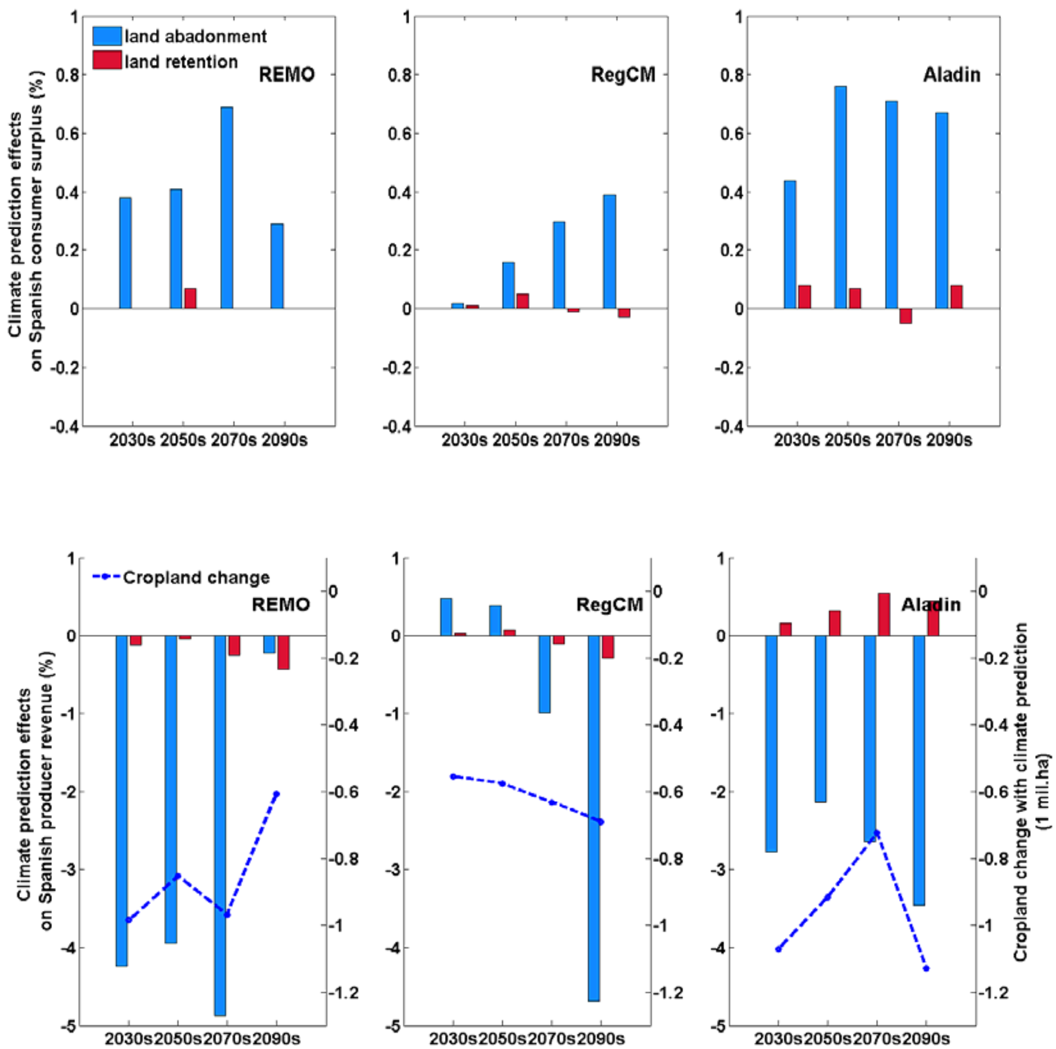

Figure 3-9 Climate prediction effects for 'land abandonment' and 'land retention' scenarios. Consumer surplus and gross producer revenue are compared in each time period with climate prediction and without climate prediction in Spain. 'Cropland change' with use of climate prediction is plotted on the bottom figure.

The value of climate predictions also depends on the land use scenarios. Under the 'Land abandonment' scenario, the prediction value for consumer surplus remains stagnant or increases, whereas the value for gross producer revenue is on a downward trend, again due to land abandonment rates, except for the REMO scenario. For the REMO scenario, in 2090s, negative impacts on gross producer revenue is smaller than in previous periods because farmers abandon less land with climate prediction because Spain already abandoned 50 percent cropland and climate prediction leads to production increase compared with previous periods. Consumers benefit as long as international trade compensates for the domestic production deficit. Under the 'Land retention' scenario, the value of climate predictions decreases or remains stagnant for consumer surplus, and the values for gross producer revenue are ambiguous.

3.4 Discussion

3.4.1 Climate data

For the evaluation of annual climate change impacts on regional or national scale high quality regional climate data are required. To assess annual climate change risks for the Spanish agricultural sector, we thus use climate data from three different regional climate models. The risks calculated with our model framework are different depending on the RCM used, even though all three were run with the SRES A1B scenario. Two RCMs (REMO, RegCM) use input from the ECHAM5 GCM and exhibit similar results, while Aladin, which is run with data from the ARPEGE GCM, shows different trends in the results. GCMs provide boundary conditions for RCMs, and substantially influence the projection of precipitation. It is thus not surprising that different GCMs run with the same scenario still show large differences in climate impact assessment (Olesen et al., 2007; Turco et al., 2013). RCMs, too, include large biases in the model output (Turco et al., 2013), and the large variability of crop yields presented in this study can be explained by direct use of climate model outputs. If bias-corrected climate data are used, the yield variability becomes smaller (Olesen et al., 2007). The results thus show that for near-term climate change impact analyses, the climate model output should be carefully considered, and that for economic damage analyses, a bias correction considering all correlations between climate variables should be performed.

Concerning our results, they indicate that by the end of the century agricultural GDP (producer revenue) loss amounts to approximately $5 - 20$ percent, and yield loss to an average of 19 percent. Other impact studies report a total GDP loss of 1.3 percent and a yield change of −27 percent with a 5.4 degree warming by 2080s in southern Europe (Ciscar et al., 2011; Ciscar et al., 2012). However, the studies are not directly comparable to our SRES A1B scenario, as Ciscar et al. used the emission scenarios SRES A2 and B2 and RCMs from the PRUDENCE project (Christensen et al., 2007a) and also a Computable General Equilibrium (CGE) model in comparison to our Partial Equilibrium (PE) model. The CGE measures welfare based on utility derived from household consumption, whereas the PE uses a Marshallian surplus. Moreover, climate impacts on the agricultural supply can be mitigated by macroeconomic adjustments in the CGE, but the PE directly absorbs the supply change impacts.

3.4.2 **Decision modes**

The results in cropland and management change differ slightly between the deterministic and the stochastic model. However, the stochastic model higher economic impacts on agricultural GDP than the deterministic models. Lambert et al. (1995) also showed that the stochastic agricultural sector model yielded greater climate change impacts than the deterministic model, but was not greatly different. Each time period considered has 20 states of nature, represented by 20 years of climate variability, which influence land change decisions. A low probability and strong climate impacts affect land management decisions although the total cropland remains at the similar level. In addition, the climate scenario has stronger impact on economic parameter than the decision modes. Finally, the stochastic model output could yield higher producer surplus Adams et al. (2003b) and resource surplus (Figure 3-8) as farmers make decision to avoid a wider range of risks.

3.4.3 **The value of climate predictions**

The 'stochastic decision with perfect information' mode shows considerable effects on cropland area and the market in Spain (Figure 3-4 and Figure 3-5). The value of climate prediction is substantially affected by climate conditions. More frequent occurrences of adverse climate conditions, as seen in the REMO scenario, induce detrimental effects on producers given that they have no adaptation measures to cope with them. On the other hand, a relatively favorable climate (Aladin scenario) could be beneficial to both consumers and producers, more so if land is free to be abandoned. If the cultivated area is fixed ('Land retention'), climate predictions have a lower value. This indicates that policies like farm subsidies, which promote agricultural land in cultivation, lower the value of climate prediction.

The change in the value of climate prediction is rarely investigated. Chen and McCarl (2000) show that the future value of climate predictions may slightly increase with changes in ENSO frequency and intensity. In his study, land use change due to the climate prediction is not reported. We show that the value of information decreases when climate conditions become adverse to agriculture and no efficient adaptation measures are at hand, as producers then lose profits regardless of climate prediction availability. Our model shows large cropland abandonment with the use of climate information regarding adverse climate conditions. Hill et al. (1999) also show the same effects with using of climate information. Unless other profitable crops are substituted on the cropland, the total area would decrease and it leads to negative value of information.

3.5 Conclusions

In this work, we integrated annual crop productivity changes, based on data from ensemble regional climate models (3 members, 3 RCM, 2GCM), with a Spanish agricultural sector model, and could thus compare impacts of climate change in terms of distributions of annual stochastic damages. This work represents a new attempt to quantify impacts from extreme climate events on the agricultural market. The results show that, based on the RCM used, economic impacts differ in the early decades of the 21st century, but all models agree that strong negative impacts will be observed late in the century. Annual climate variability impacts on consumer surplus and gross producer revenue also show a large variance depending on the RCM. All RCMs do not show significant difference between 2030s and 2050s. GCM and RCM should be selected judiciously, bias correction methods should be applied, and ensemble simulations should be done to get a measure of uncertainty.

Cropland in Spain may be reduced by 20 to 50 percent, and producer revenue may decrease by 5 to 20 percent. By implementing a cropland retaining policy, consumers in Spain gain, but the cost of the policy is more than twice higher than the consumers' gain. Climate predictions increase consumer benefit, but decrease producer revenues when farmers can abandon cropland. With a cropland retention policy, prediction effects substantially decrease.

Climate change impacts from different RCMs show that Spain has to confront negative impacts under climate change. Climate prediction may decrease agricultural producers' revenue if farmers abandon cultivating without right strategic adaptation measures to adverse climate condition in the future. Farm support programs have to be designed to efficiently use cropland with climate prediction or to stimulate land use transitions to other sectors e.g. afforestation, renewable energy.

3.6 Appendix - regional climate data and EPIC results

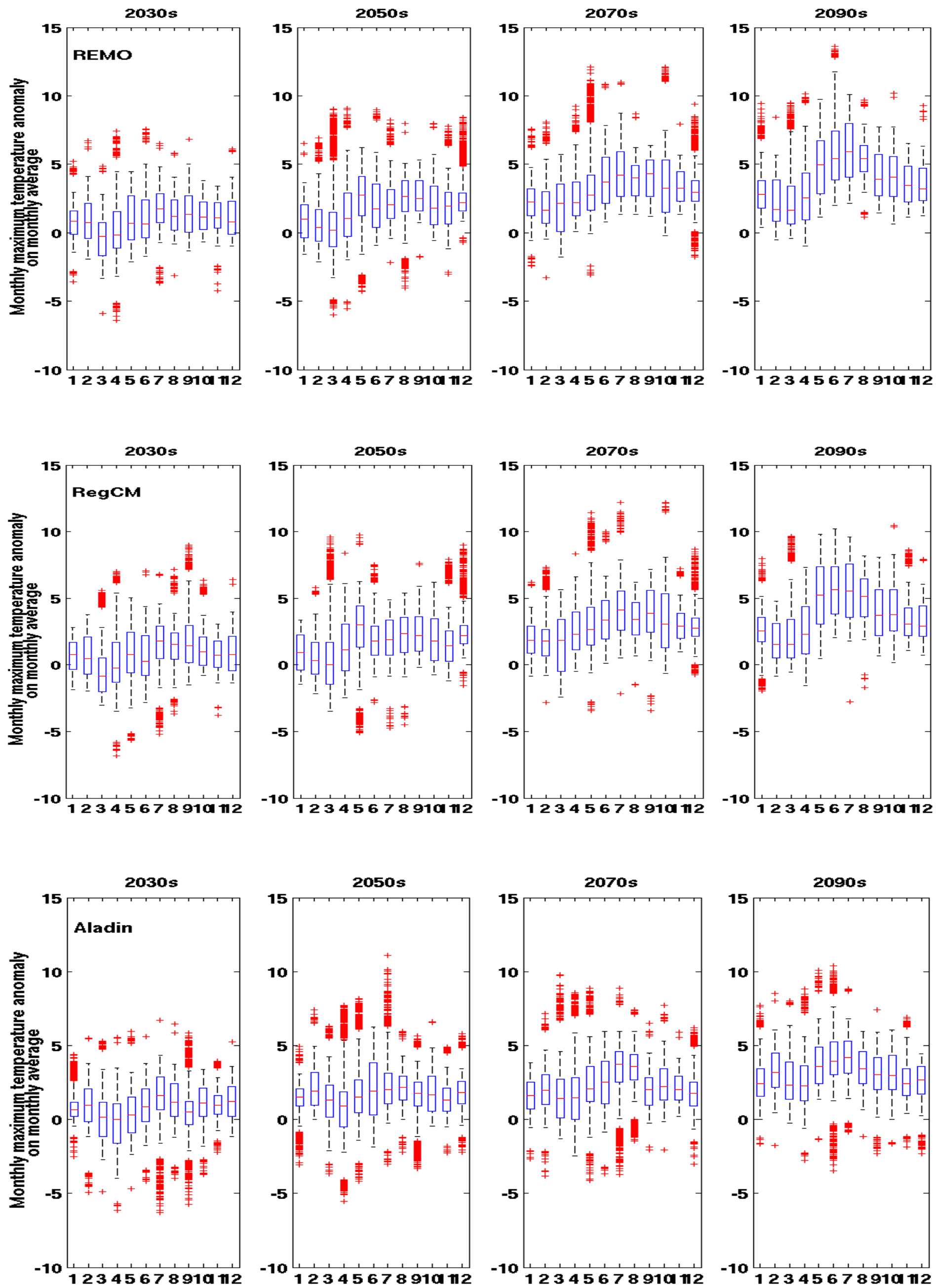

Figure 3-10 Monthly maximum temperature anomalies to the baseline mean monthly maximum temperature. The values are averaged over the cultivated land in Spain. upper whisker: 95th percentile; lower whisker: 5th percentile; upper box: 75th percentile; lower box: 25th percentile; centerline: median

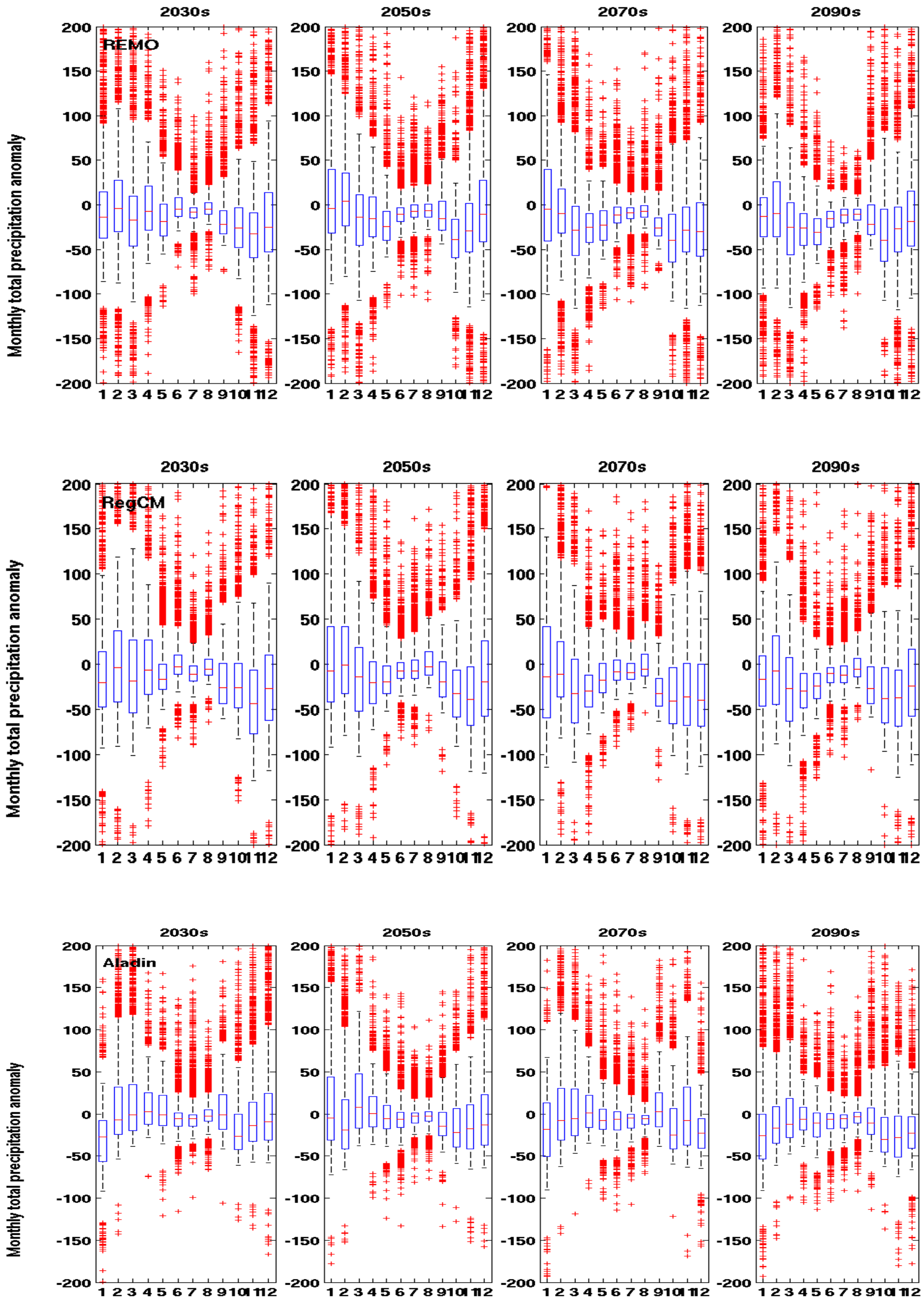

Figure 3-11 Monthly precipitation sum anomalies to the baseline mean monthly precipitation sum. The values are averaged over the cultivated land in Spain. upper whisker: 95th percentile; lower whisker: 5th percentile; upper box: 75th percentile; lower box: 25th percentile; centerline: median

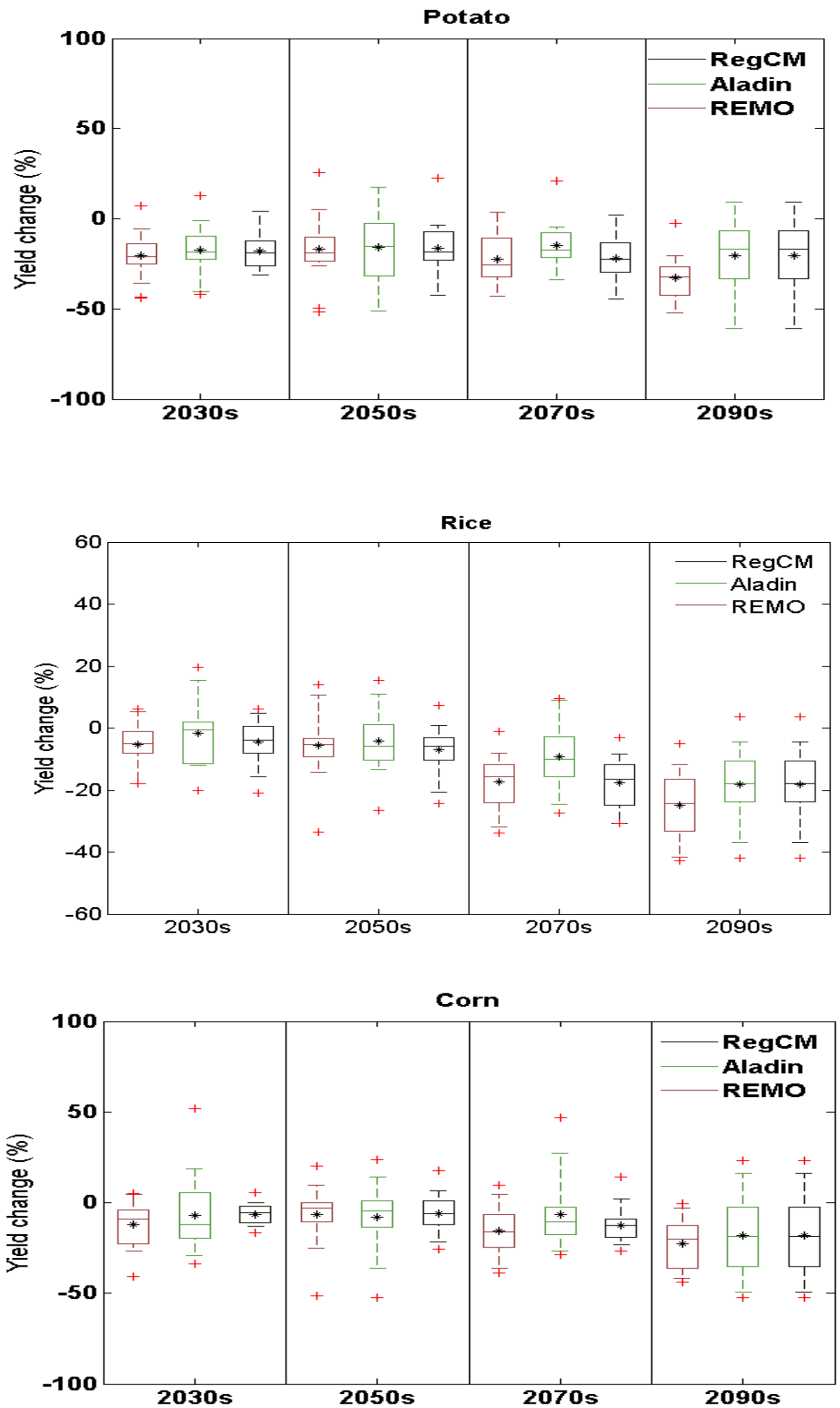

Figure 3-12 Potato, Rice and Corn (Maize) yields simulated with three different regional climate model outputs compared to the baseline period (1995 – 2004). Asterisk: mean; upper whisker: 95th percentile; lower whisker: 5th percentile; upper box: 75th percentile; lower box: 25th percentile; centerline: median.

Chapter 4. Agricultural land abandonment under climate change and its potential use for renewable energy - A case study for Spain

Abstract

Land abandonment is a future concern that may occur due to climate change or technological progress in Europe. We investigate potential agricultural land abandonments in Spain induced by climate change. We use a stochastic agricultural sector economic model coupled with crop yield changes driven by an ensemble of regional climate model outputs. We also examine the potential use of abandoned agricultural land for renewable energy such as solar and biomass. The results show that cropland in Spain will decreases by 5 to 20 percent in the 2030s and by 10 to 70 percent in the 2090s by climate change induced productivity changes. By granting subsidies to land owners, abandoned cropland could further increase up to 30 percent of total agricultural area in the 2030s. Photovoltaic potential on abandoned cropland in Spain is estimated to be 50 percent of current total EU electricity consumption (2010 values) and biofuel potential is estimated to be 40 percent of biofuel target of Spain from PRIME energy scenarios. Land use and energy policy should consider such tremendous difference in energy potential for adaptation and mitigation policy decisions.

4.1 Introduction

Land resource is essential not only for food production, but also for renewable energy production. As more lands are used for biofuel production, competition for agricultural land between food and biofuel energy production increases (Smith et al., 2010). With regards to food production, agricultural land will have to be able to feed a population of about 9 billion by 2050 and food production will need to increase by 60 percent globally (OECD/FAO, 2012c). Global agricultural land is required to increase by 5 to 10 percent (excluding biofuel needs) in order to meet global demand by 2050, simultaneously with higher yields and cropping intensity (OECD/FAO, 2012a; Spiertz, 2012). On the other hand, in 2007, an estimated 1.6 percent of the global cultivated land or 25.1 million ha was devoted to the production of biofuel feedstock (FAO, 2008). First generation biofuel feedstock is grown on agricultural land and directly competes with food cropland, creating conflicts with food production (Howard et al., 2009; Gomez et al., 2011). Globally, biofuel production affects food production and increases the pressure on food prices (Harvey and Pilgrim, 2011).

On the other hand, other renewable energy sources such as solar and wind also occupy land with low fertility, while solar panels are also installed on rooftops. For the future expansion of solar energy to meet renewable energy target, more ground area may be required (Nonhebel, 2005). Due to climate change, the productivity of biofuel feedstock is declining in vulnerable regions and in southern Europe; all temperate oilseeds, starch crops, cereals, and solid biofuel crops are predicted to decline substantially (Tuck et al., 2006). Solar photovoltaic (PV) energy has much larger energy intensity than biofuels, by a factor of 42, taking energy input into account (Dijkman and Benders, 2010). Land use competition would be affected by future climate change impacts on crop productivity and technical progress in renewable energy.

For land use change studies, previous research mainly considered socio-economic drivers (e.g., technological changes, biofuel production and trade policies) and biophysical pressures (e.g., climate change, and soil erosion) (Busch, 2006; Smith et al., 2010; Banse et al., 2011). Many studies report that in Europe, significant cropland reduction of up to 10 percent by 2080 may occur due to technological changes and liberalized international trade (Rounsevell et al., 2006). Up to 74 percent decline of cropland in Spain is projected in the SRES A1f1 scenario by 2080 provided rapid technological development (Rounsevell et al., 2005). On the other hand, it may increase due to lower technical progress and local sustainability policies (Rounsevell et al., 2005; Rounsevell and Reay, 2009; Hermans et al., 2010).

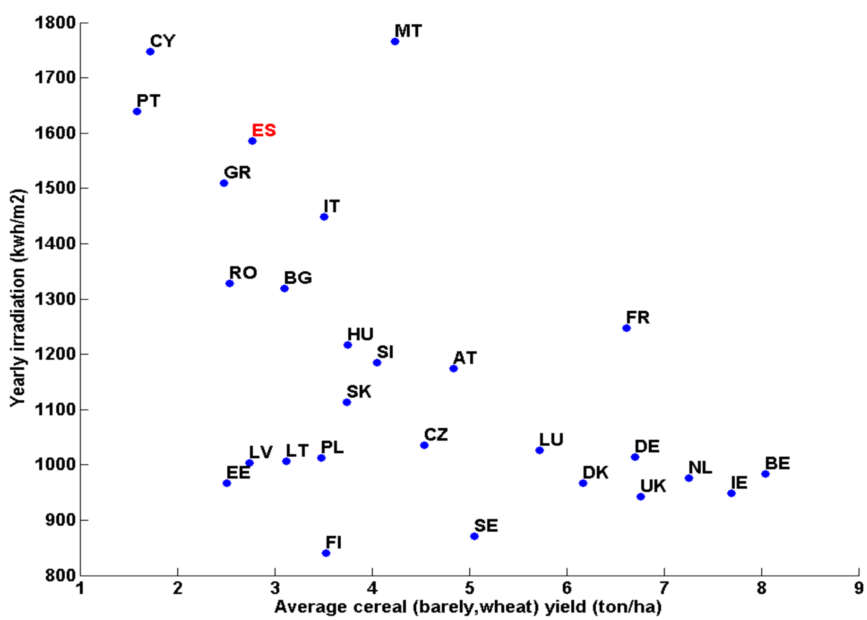

Figure 4-1 Comparison of yearly solar irradiation and cereal yields in EU countries. Solar irradiation data source (PVGIS © European Communities, 2001-2008) and cereal yield data source (FAO). (AT:Austria, BE:Belgium, LU:Luxemburg, BG:Bulgaria, CY:Cyprus, CZ:Czech Republic, DK:Denmark, DE:Germany, EE:Estonia, ES:Spain, FI:Finland, FR:France, GR:Greece, HU:Hungary, IE:Ireland, IT:Italy, LV:Latvia, LT:Lithuania, MT:Malta, NL: Netherlands, PL:Poland, PT:Portugal, RO:Romania, SK:Slovakia, SI:Slovenia, SE:Sweden, UK:United Kingdom)

Land abandonment draws attention especially under climate change impacts. It is a complex process including economic, social aspects and environmental changes (Rounsevell and Reay, 2009; Keenleyside, 2010; Renwick et al., 2013). Climate change especially, is expected to induce negative impacts on crop yields as the severity and frequency of extreme climate events increase. Fertile lands are expected to decrease due to desertification and soil degradation. Land abandonment can also damage rural economic viability and degrade ecosystem in rural area. FAO (2006) argues that maintaining land in production is likely to be an ineffective and inefficient means to address the perceived negative consequences of land abandonment, but it provides new economic opportunities for renewable energy (Keenleyside, 2010).

In this study, we focus on two subjects: the likely magnitudes of agricultural land abandonment under climate change in Spain and the potential of abandoned cropland for solar and bioenergy use. Spain has the highest solar energy potential and the lowest bioenergy feedstock productivity in the EU (Table 4-1). Due to climate change, heat waves and droughts will be more frequent and could lower biomass productivity (Tuck et al., 2006).

We aim to show integrated views on land use change, land abandonment and renewable energy potential under climate change. The advantages and disadvantages of solar and bioenergy production are examined. We use a global warming scenario, A1B in a climate-crop-stochastic economic model framework and consider climate variability changes for periods in the 2030s (2020 – 2039), 2050s (2040 – 2059), 2070s (2060 – 2079) and 2090s (2080 – 2099) by three regional climate models (RCM): REMO, Aladin, and RegCM. Climate data are taken from EU-FP6 ENSEMBLE (http://ensemblesrt3.dmi.dk/). The stochastic economic model computes future agricultural market equilibrium, cultivated land changes and land abandonment, taking into account climate change risks in the market.

4.2 Methodology

4.2.1 EPIC simulation for Spain

We use ensemble climate data outputs from three RCMs (REMO, RegCM, and Aladin) from the EU-FP6 ENSEMBLE project. Horizontal resolution is 25 km. Regional climate outputs are dynamically downscaled from different GCMs. We use maximum and minimum temperature, precipitation, solar radiation, and relative humidity to evaluate future climate change impacts on crop yields with a process-based crop model EPIC (Environmental Policy Integrated Climate). EPIC is a process-based crop growth simulation model (Williams et al., 1989a) and it was previously employed to analyze climate change impacts on crop productivity. EPIC simulates the daily crop growth in five crops: barley, wheat, corn, potato, and rice. Simulation units are delineated with geographical, soil property, and land category. They are used as inputs for EPIC simulations and as a link to the agricultural economic model. Crop area is distributed on each simulation unit based on observed cropland and 2005 level yields (EUROSTAT). We simulate EPIC with automatic fertilizer and automatic irrigation modes on the assumption that farmers adapt to nutrient deficit under climate change.

4.2.2 Crop area distribution

National statistics usually provide aggregated cropland area data at province level. In order to assess the regional land use change, however, higher resolution data are needed as inputs to the agricultural economic model. Here, we use a mathematical model to distribute crop area on simulation units for this study. Variable **X** depicts the proportion of land for a specific crop from the observed arable land in each simulation unit (Area) and **X**·Area indicates the selected arable land area for cropland. The objective function minimizes the sum over crop area gap between observed cropland area (**OBS_A**) and assigned simulation unit area (**X**· Area) at NUT2 level. The indices *c*, *id,* and *n* denote the set of crops, simulation unit, and NUT2 regions.

$$\min_{X} \sum_{n,id,c} (\boldsymbol{X}_{n,id,c} \bullet \text{Area}_{id} - \text{OBS\_A}_{n,c})^2 \tag{1}$$

Crop area selection is constrained by observed crop area at NUT2 level (*OBS_A*) (2) and production (3) at NUTS2. *Y* denotes simulated crop yields on each simulation unit and *OBS_Y* indicates observed yield at NUT2 level.

$$\sum_{id} \boldsymbol{X}_{n,id,c} \bullet Area_{id} \leq OBS\_A_{n,c} \qquad \forall n,c \tag{2}$$

$$\sum_{id} \boldsymbol{X}_{id,c} \bullet Area_{id} \bullet Y_{id,c} \leq OBS\_A_{n,c} \bullet OBS\_Y_{n,c} \qquad \forall n,c \tag{3}$$

In addition, the variable **X** is determined by maximum crop share rules (*Max_share*) (4) within the range of 0 and 1 (5) at all simulation units.

$$\boldsymbol{X}_{n,id,c} \leq Max\_share_{c} \qquad \forall\ n,id,c \tag{4}$$

$$\sum_{c} \boldsymbol{X}_{id,c} \leq 1 \qquad \forall id \tag{5}$$

4.2.3 **Stochastic agricultural sector model**

Stochastic agricultural sector model computes the market equilibrium with expected market welfare and risk neutral concepts. As the model considers climate variability in decision making, it results in different outputs and economic consequences. Lambert et al. (1995)

show that stochastic models yield slightly higher climate change impacts than deterministic ones. This model contains five crops and one aggregated livestock commodity. Agricultural production and trade is explicitly represented. Five crops constitute 5.8 million hectares and constitute around 60 percent of total agricultural land in Spain. Agricultural land area changes between the cultivation land for food and land abandonment. Thus, it is restricted by land abandonment and land expansion costs. Here, the land abandonment implies financial loss of capital investments. We consider financial loss of farm land based on land rent prices in Spain which ranges from 70 – 130 euro on rainfed cropland (Střeleček and Lososová, 2011) while abandonment costs are 20 euro/ha higher for irrigated land than for rainfed. We also apply the same costs to land expansion. We consider 20 alternative states of climate in each period. Only future climate scenarios affect the baseline economic model and farmers change land management and area with respect to this new climate state. Other future socioeconomic scenario changes are not taken into account. This model is calibrated to the year 2005.

4.2.4 Calculation of technical bioenergy potential

We use three biomass feedstocks: food crops, poplar coppice, and miscanthus (Table 4-1). Food crops are such as wheat, barley, and corn, which can be converted to ethanol by fermentation. Poplar coppice and miscanthus are energy crops which have higher biomass yields than food crops. These could be combusted to produce heat and electricity for home and industry. We compare the biofuel, heat, and electricity generation on abandoned cropland and compare these with PRIME energy scenarios (EU, 2010) for Spain in 2030.

Table 4-1 Biomass conversion efficiency to final fuel

Biomass	Process	Final fuel	GJ/ton
Food crops	Fermentation	Ethanol	8.0
Poplar coppice	Combustion	Heat	5.4
Poplar coppice	Combustion	Electricity	2.7
Miscanthus	Combustion	Heat	5.4
Miscanthus	Combustion	Electricity	2.7

Table 4-2 PRIME energy scenario in biomass for Spain

Final fuel		Unit	2010	2015	2020	2025	2030
Biofuel	Biomass	Ktoe	1783	2840	3191	3296	3163
Heat	Biomass & Waste	Ktoe	1972	2661	3365	3755	4118
Electricity	Biomass & Waste	Gwh	7706	11013	14018	15336	17559

4.2.5 Calculation of technical solar electricity potential calculation

We use Photovoltaic Geographic Information System (PVGIS) data (http://re.jrc.ec.europa.eu/pvgis/) to estimate technical annual total solar electricity potential E (kWh/ m^2) in Spain (Suri et al., 2007).

$$E = P_k \mathrm{PR} G$$

P_k is peak unit power of 1kWp of a polysilicon solar cell, PR is the system performance ratio, and G is the yearly sum of global irradiation on a horizontal, vertical or inclined PV module (kWh/m^2). The area of 1kWp system is assumed to be approximately 9.5 m^2. The system performance ratio (PR) is the difference between the nominal output and actual output. PR is approximately 0.75. The horizontal PV module has a lower power output than the one at an optimum angle. We use horizontal PV module output data to prevent the overestimation of solar electricity on abandoned cropland. Average value of PV electricity potential at NUT2 level in Spain is calculated and used for PV electricity potential estimation at each NUT2 region. Finally, we compare the PV electricity potential with EU electricity consumption level in 2010 (3,635,604 GWh/yr, EUROSTAT).

4.3 Results

4.3.1 Cultivated land change

Figure 4-2 shows cultivated land changes in Spain through adaptation to climate change with free trade. Cultivated land area in Spain decreases under climate change. In the 2030s, the land area reduction is sensitive to land abandonment costs and climate models. REMO output shows more than 20 percent reduction, but Aladin shows around 10 percent. However, in the 2090s, cultivated land area in most scenarios will decrease by 10 to 70 percent. In all climate models, low abandonment cost (70 euro/hectare) yields higher land reductions, while high abandonment cost (130 euro/hectare) shows lower land reductions.

The stochastic model (SM) had a tendency of decreasing less land in the early decades and decreasing more land in the later decades than the deterministic model (DM). This is due to low probability risks being not less pronounced in the earlier decades than in the later decades. The SM also computes the land equilibrium at higher level than the DM. DM may have overestimated the land reductions in comparison to the SM. In Aladin and RegCM runs, SM does not yield results much different from the DM from the 2030s to 2070s. However, in the 2090s, SM yields around 50 percent more land declines than DM.

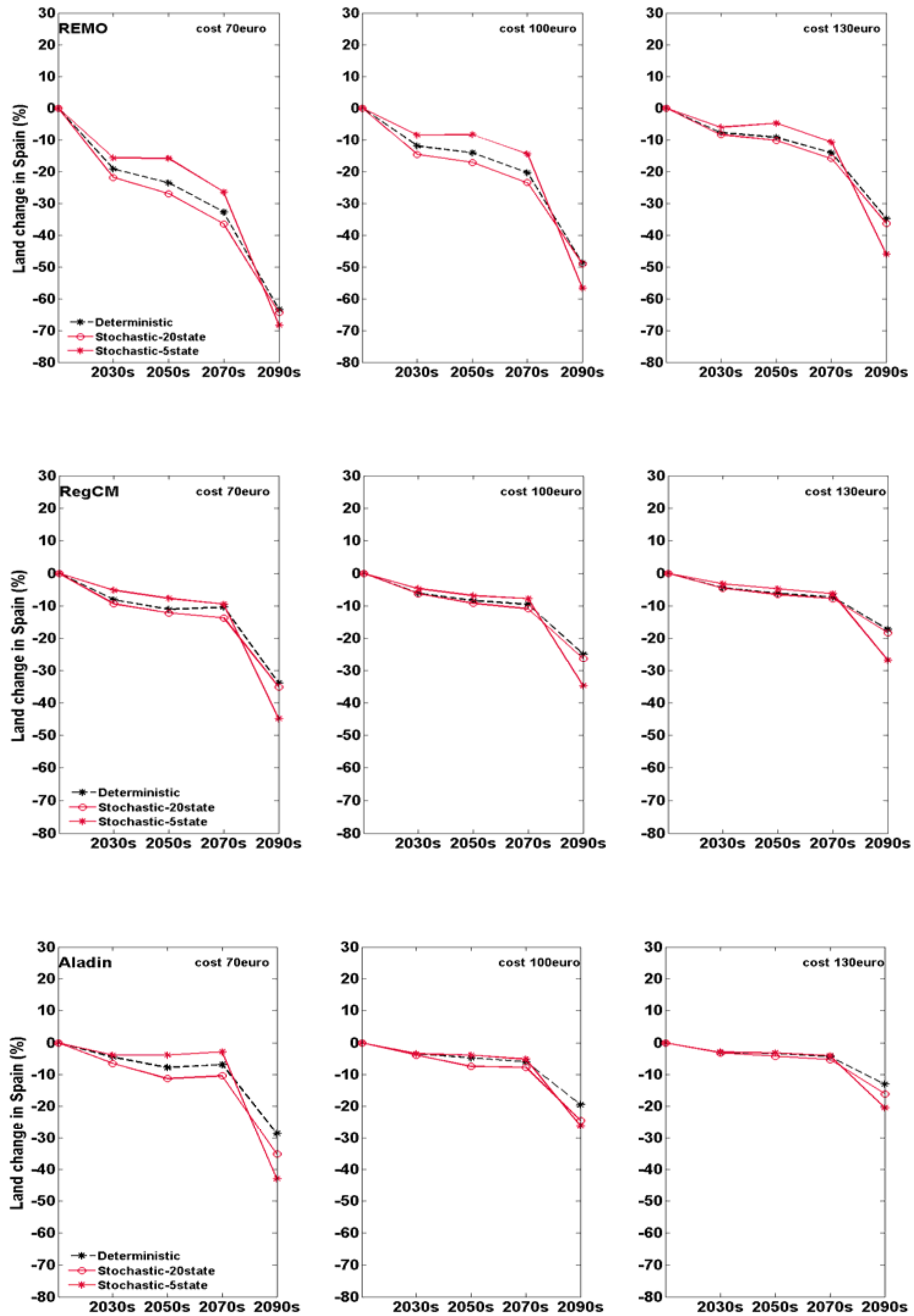

Figure 4-2 Total cultivated land changes of five crops in Spain with different climate models, land abandonment costs, and decision modes (Baseline crop area is 5.8 mil. ha, left: 70 euro, middle: 100 euro, right: 130 euro).

4.3.2 Land price changes

Figure 4-3 shows that shadow prices of land on each simulation unit. Shadow price levels are ranked in order, and the area is accumulated by the rankings of shadow price level. Shadow prices of land here indicate effects on objective value in case an additional one hectare of land is added to each land site. Due to climate change, crop productivity is aggravated and land value decreases, but it depends on the climate scenarios. REMO shows very strong climate change impacts and in large land areas, the shadow price of land becomes negative. Even though farming is maintained, land profitability is lower than baseline period. It implies that most of the land is at risk to be abandoned if additional fertile cropland is supplemented. On the other hand, Aladin data shows that in the earlier decades, climate change increases land value, becoming higher than the baseline value, and in the 2090s it is expected to drop below the baseline. All climate model results show that shadow price has substantial impacts in 2090s.

4.3.3 Land supply curves for renewable energy

Figure 4-4 shows how potential land use shifts from agriculture to renewable energy by granting subsidies for land owners. With the free trade scenario, cropland area could be abandoned and transformed for renewable energy use, of up to 0.5 to 2 million ha with a subsidy level of 100 euro/ha. A subsidy level above 200 euro/ha, transformed land considerably, with an increase of up to 4 million ha for renewables. Until the 2070s, land transformation shows similar impacts with subsidies, but in the 2090s, it distinctly increases compared with previous years based on all climate models. On the other hand, with the limited trade scenarios, much less land area is converted to renewable energy. Only 0.1 million ha is transformed for renewables with a 200 euro/ha subsidy.

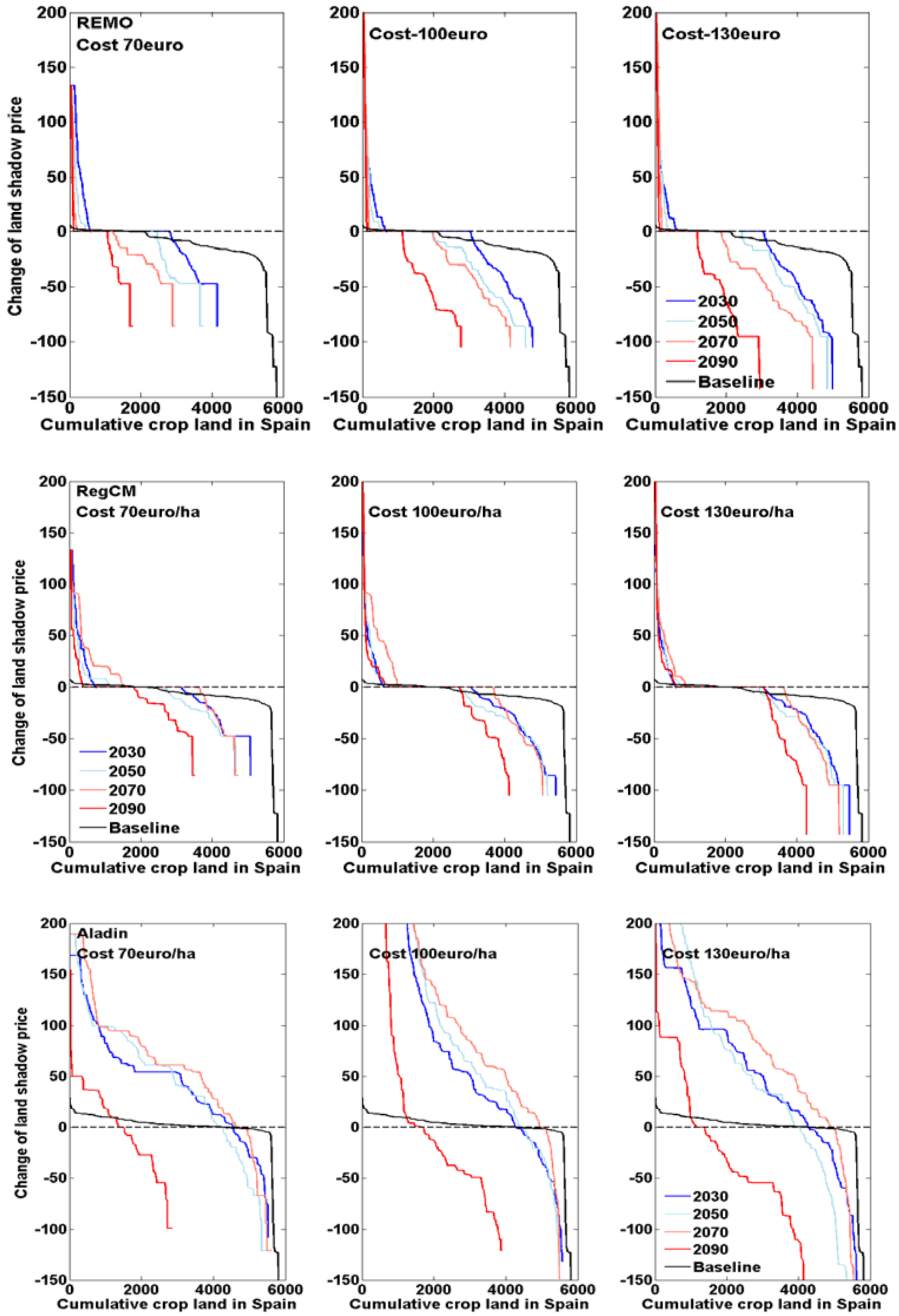

Figure 4-3 Change of the shadow price of cultivated land on simulation units with different abandonment costs (left: 70 euro, middle: 100 euro, right: 130 euro).

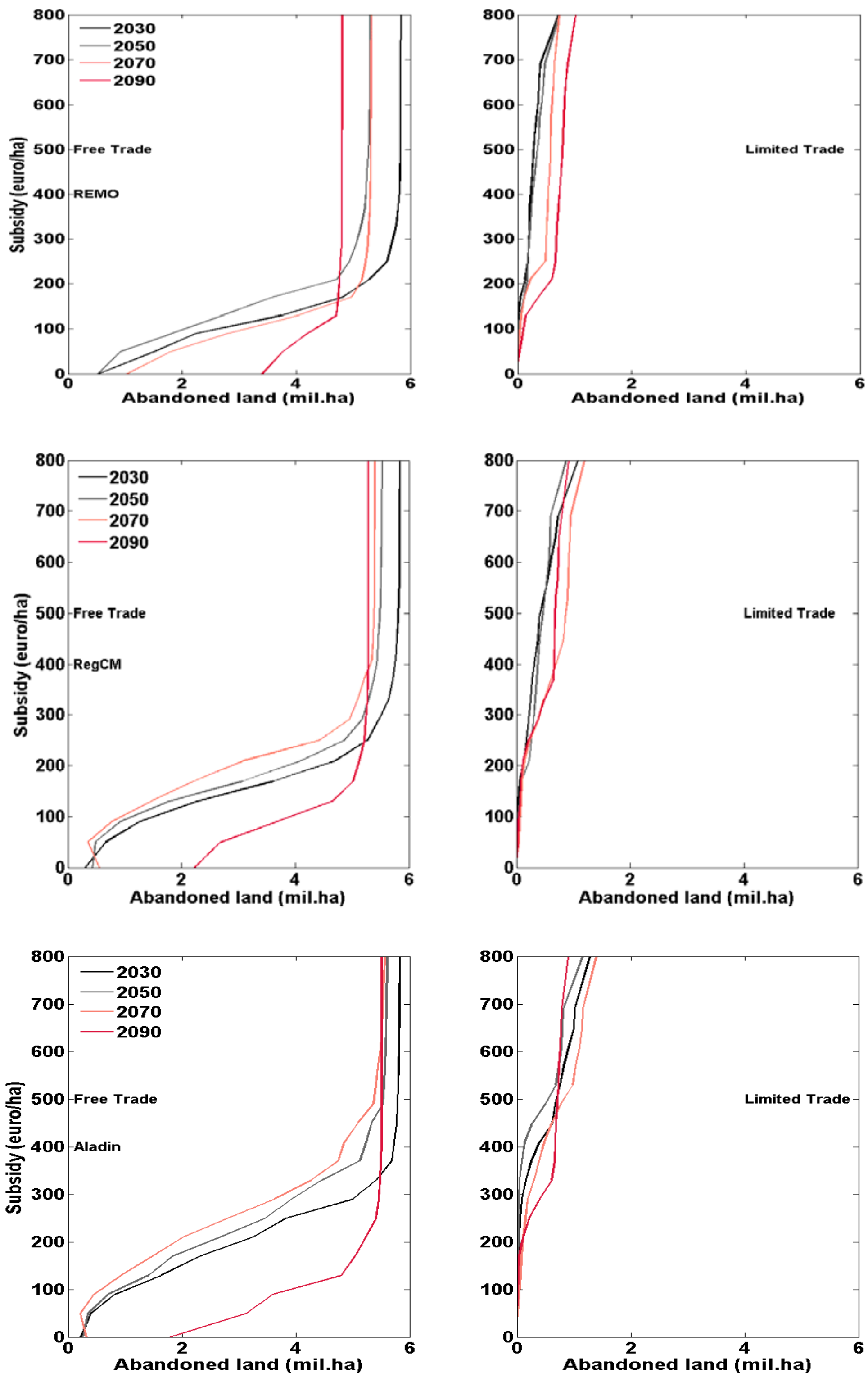

Figure 4-4 Land subsidy effects on agricultural transitions to land abandonments (left: free trade, right: limited trade).

The solar electricity (Figure 4-5) shows very large potential. With a 100 euro/ha subsidy, the transformed land could produce 10^6 GWh/yr from solar photovoltaics, amounting to ~50 percent of the total EU electricity consumption. At a maximum, with a 400 euro/ha subsidy, land dedicated to solar energy potential could make up to ~250 percent of the total EU market.

On the other hand, biofuel potential from food crops on the same abandoned land has 1000 ktoe energy with a 100 euro subsidy (Figure 4-6). This energy could supply 30 percent of biofuel energy targets in 2030. Furthermore, the utilization of energy crops such as poplar coppice and miscanthus produces a larger volume of energy than the biofuel ethanol process from food crops (Figure 4-7), because energy crops had higher feedstock productivity than food crops and the conversion efficiencies from biomass to heat and electricity is higher. However, energy productions from all biomass scenarios show much lower energy potential than PV electricity in Spain.

Table 4-3 Comparison of energy input and outputs of Bioethanol and Solar Photovoltaic (PV) in Sweden, Netherlands and Spain. Data source from Dijkman and Benders (2010).

Country	Energy source	Input	Net energy density (NED) GJ/ha/yr	Ratio of Solar PV to Bioethanol in NED
Sweden	Bioethanol from Sugar beet	47 t/ha/yr	10.9	32.6
	Electricity from Solar PV	824 kWh/kWp	356	
Netherlands	Bioethanol from Sugar beet	62 t/ha/yr	15.5	27.2
	Electricity from Solar PV	873 kWh/kWp	421	
Spain	Bioethanol from Sugar beet	27 t/ha/yr	4.8	252.7
	Electricity from Solar PV	1473 kWh/kWp	1213	

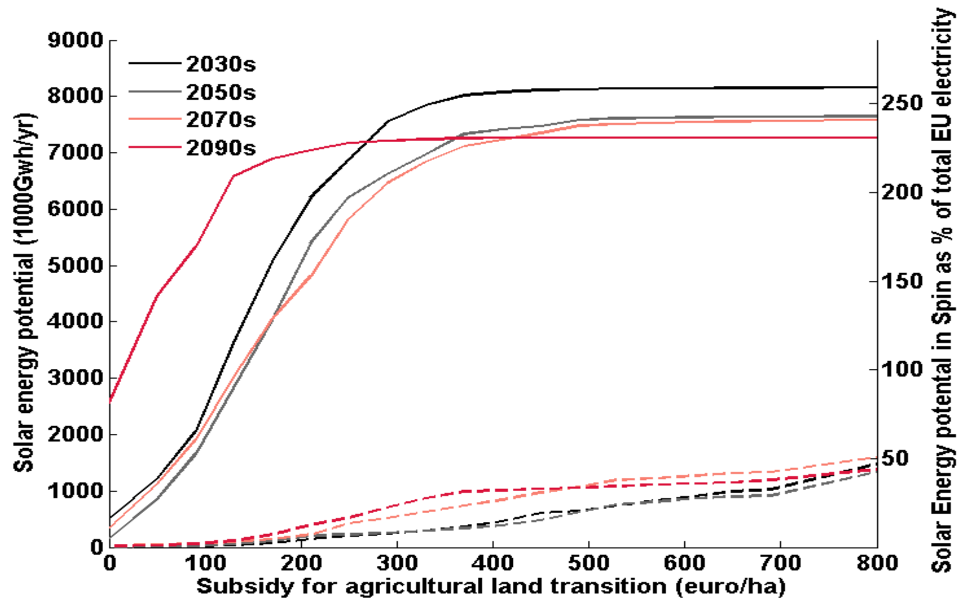

Figure 4-5 Mean solar energy potential on abandoned cropland in Spain from three RCMs climate impacts. Bold line: free trade scenario, Dotted line: limited trade level to the baseline level (year 2005).

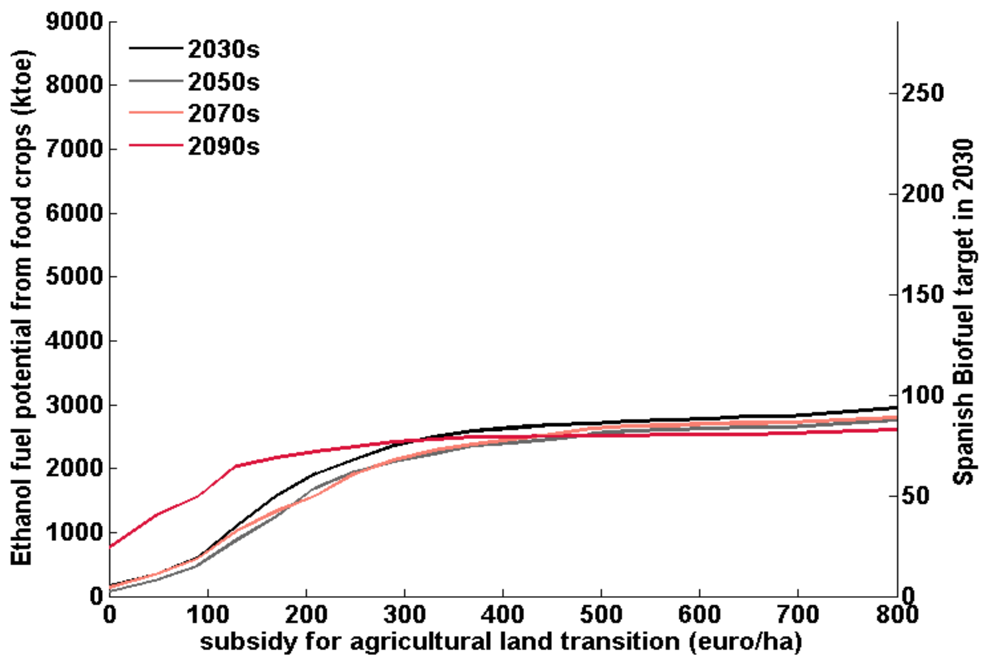

Figure 4-6 Mean biofuel potential from food crops on abandoned land in Spain from three RCM climate scenarios. Left axis: bio-ethanol potential, right axis: bio-ethanol potential as percentage of biofuel target from PRIME scenarios.

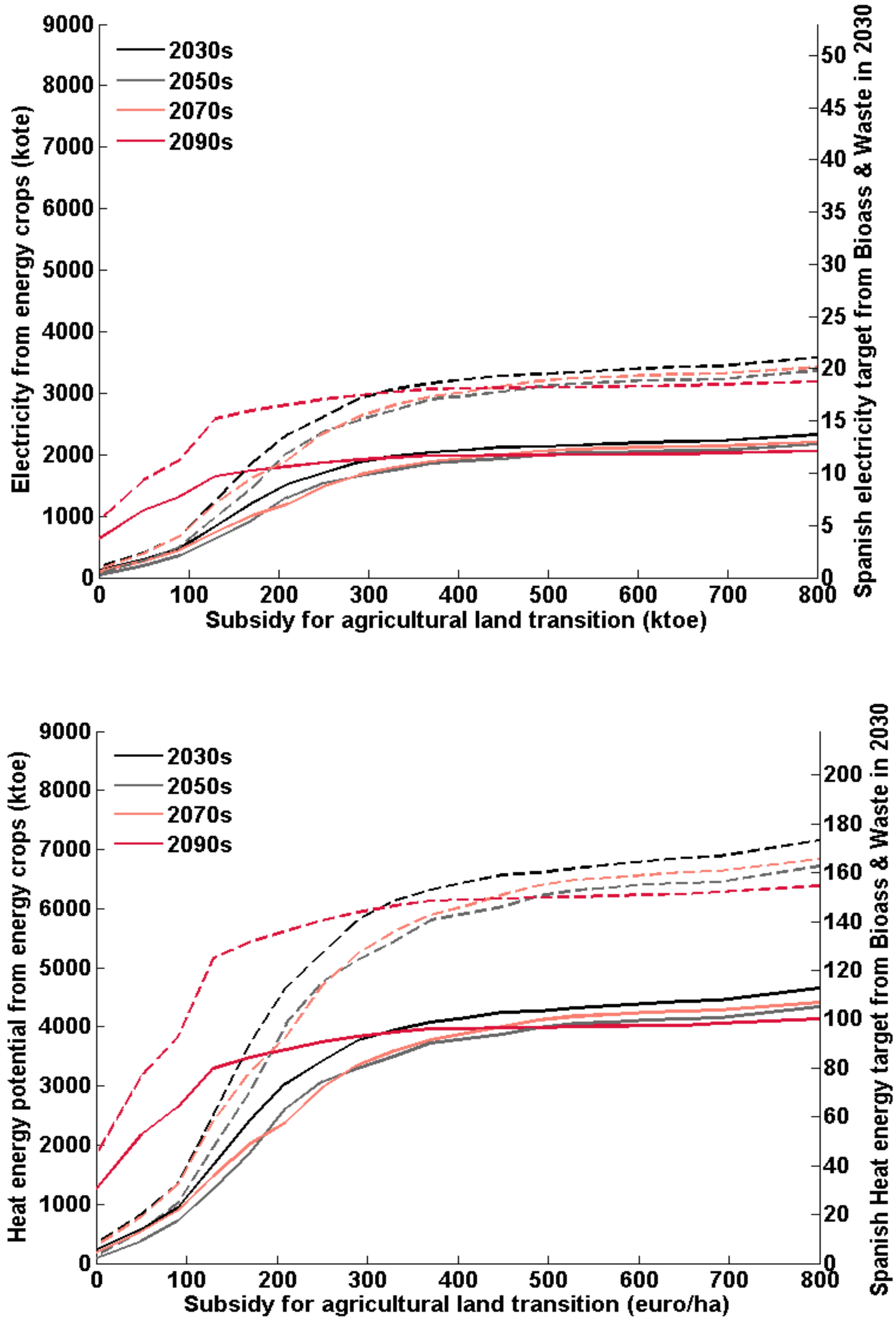

Figure 4-7 Mean heat and electricity potential from energy crops (poplar coppice: bold line, miscanthus: dotted line) on abandoned land in Spain from three RCM climate scenarios. Left axis: heat and electricity potential, right axis: heat and electricity potential as percentage of heat and electricity target from biomass from PRIME scenarios.

4.4 Discussion

Different climate model outputs in the same emission scenarios (A1B) affect the cultivated land change in Spain in different manners. Two climate model outputs (Aladin and RegCM) show slight benefits in the early decades of the 21st century and lower damages in later decades than REMO outputs. Three models agree on climate change impacts for the 2090s. There are some problems for the regional climate models in early decade climate impact applications because the impact results diverged. Regional climate model validation and consistent projection are required within certain boundaries.

Cultivated land in Spain decreases and is strongly affected by climate change impacts without considering technological progress in agriculture. Previously, many studies only assume that technological progress induces land reduction (Ewert et al., 2005; Rounsevell et al., 2005). These studies put high weights on technological progress based on historical rate and low weights on climate change impacts. However, we counter that climate change induced productivity change may also cause land abandonments, unless significant progress in genetically modified crops is fulfilled. In the worst climate change scenarios (A1B), cropland area in Spain may decline by about -20 percent in 2030s and by -70 percent in 2090s from the baseline level.

Agricultural land profitability also decreases through climate change, whereas fertile and productive land decreases by a significant amount. Climate change would affect farm revenue and profitability. A great deal of land would face land abandonments and may require other income substitutes to protect rural area. For adaptation, one option is to replace or improve crop cultivars. In addition, biofuel feedstock can quickly replace the existing cropland.

However, under climate change, biofuel feedstock will also experience climate change impacts; all crops suffer from these negative impacts in Spain (Tuck et al., 2006).

Bioenergy intensity is much lower than solar energy potential. Energy intensity of solar photovoltaics is ~40 times larger than biofuel on average. In Spain, the net solar energy output per unit area is up to 250 times larger than net bioenergy outputs (Table 4-3). Solar energy cost is likely to decrease further in the future. Harnessing solar energy on abandoned cropland could be considered as an alternative option to bioenergy. It is required to harmonize Common Agricultural Policy (CAP) and energy policy to develop renewable energy in rural areas.

4.5 Conclusion

Climate change can strongly affect land productivity in Spain and its consequent effects on cropland and land abandonment should be significant in terms of adaptation policies. Without technical progress, crop productivity will decrease over time and cropland in Spain would decrease by 10 to 20 percent in the 2030s and up to 70 percent in the 2090s. Biofuel production could be an alternative for utilization on abandoned cropland, but under the aggravating climate condition, harnessing solar photovoltaic energy could also be considered. For further research, technological changes in agricultural system should be considered in crop growth simulations. It should include the changes of biofuel feedstock productivity under climate change explicitly from high resolution climate scenarios.

Chapter 5. Summary and main conclusions

The main objective of this thesis was to assess climate change impacts on Spanish agriculture from the perspective of climate anomaly prediction, welfare, and land use change. To address these issues, a stochastic model was developed for a Spanish agricultural sector model. The new model contains large datasets and numerous simulation units which represent regional crop management and cultivated area. Climate variability impacts on crop yields in Spain were simulated using a biophysical crop growth model with inputs from multiple regional climate models. Using this framework, stochastic decisions with no climate information and with perfect climate information were compared. In the following, the main findings and limitations of this framework will be summarized, and recommendations for future work will be given.

Seasonal climate prediction is considered as a potential adaptation measure to address the changes of climate variability under global warming, provided it will become available at useful skill for Europe. Under historical climate variability (1961-1990), both consumers and producers in Spain can generally benefit from climate prediction for their agricultural sector but the magnitude of these benefits depends on (i) farmers' responsiveness and (ii) the nature of the predicted climate condition. However, production and welfare shifts to foreign countries could lead to slightly negative values of information for the Spanish agricultural sector as a whole due to predictions of adverse climate conditions and Spanish farmers' conservative reactions to climate information (chapter 2). However, if foreign farmers have access to climate anomaly predictions and act accordingly, both global agricultural welfare and Spanish agricultural producer benefits increase regardless of the nature of the predicted climate anomaly for Spain (chapter 2). This picture changes slightly when climate change is considered. Here, when farmers are free to abandon unproductive cropland, climate prediction may decrease their revenue, whereas consumers may benefit. If a subsidy is paid to retain all cropland, the effects of climate anomaly prediction become minimal (chapter 3).

In economic impact assessments for Spain, consumer surplus decreases by 2 – 3 percent and producer revenue decreases by 5 to 20 percent in 2080 – 2099. Climate extremes from regional climate models decrease producer revenue by two standard deviations in 2020 – 2039 and more than three standard deviations in 2080 – 2099 in comparison to baseline values (chapter 3). A statistically significant deviation from baseline values is only reached in the period between 2080 and 2099, however.

Land is an essential resource for food supply and renewable energy production. Future land use change is a key factor to achieve food security and to meet renewable energy targets. Seasonal climate prediction promotes agricultural efficiency. Climate prediction could maintain the current level of agricultural welfare with a national cropland reduction of 2 percent on average under past climate variability (chapter 2). With climate prediction under changing climate variability, agricultural land could be further reduced and consumer surplus increased (chapter 3). Cropland in Spain may decrease by 5 to 20 percent in 2030s and by 10 to 70 percent in the 2090s by climate change induced productivity changes with different land abandonment costs and RCM scenarios (chapter 4). Land retention policy would incur over-production costs to Spain which are higher than consumer surplus gain by a factor of two (chapter 3). A subsidy on productive agricultural land may cause less productive farm land to be abandoned, which could facilitate land transition to renewable energy use under a liberalized trade environment (chapter 4).

Photovoltaic (PV) electricity potential on abandoned cropland in Spain is 150 - 300 times higher than bioenergy such as ethanol. By the 2030s, a 100 euro/ha subsidy on cropland may lead to 1 to 2 mil. ha of land being abandoned because receiving a subsidy is more economical than cultivating unproductive land where marginal revenue is less than marginal costs. Technical potential of PV electricity on this land amounts to approximately 50 percent EU electricity consumption in 2010. PV electricity generation could be considered an alternative use for abandoned cropland due to its high energy intensity and rural economic viability, rather than biofuel feedstock which is expected to become more vulnerable under climate change (chapter 4).

The research results should be interpreted with caution. First of all, even though the new stochastic model for the agricultural sector model added a lot of complexity, the model still has difficulties conducting uncertainty analyses with respect to climate variability. To address this issue, it is required to harmonize climate states and obtain numerous geographical management datasets. Agricultural production functions could then be developed by combining these data with specific climate factors such as temperature and precipitation. Different types of model frameworks should be investigated and compared for these purposes.

It is further assumed in the studies that the seasonal climate anomaly prediction is perfectly accurate. Future studies need to account for the intrinsic uncertainty of climate predictions. It is also important to investigate more realistic producer behaviors to uncertain climate predictions and weather events – e.g. droughts – taking into account farmers' income and fluctuating market prices. Furthermore, only climate change induced productivity change is considered as a main driver in land use change. Various socio-economic factors, e.g. dietary preferences, income growth or technological progress in adopting new cultivars should be considered as well.

For further studies, the effects of decadal predictions or scenario developments of major climate variability, i.e. ENSO (El Niño–Southern Oscillation) and NAO (North Atlantic Oscillation), and their use for long term investment decisions in agriculture or in other sectors are of interest as well. For enhanced impact analyses, consistent bias correction of climate model outputs should be conducted and extreme value statistics can be applied to estimate possible climate extreme impacts. The geographical and technical constraints of installing PV systems on Spanish rural area should be studied. Economic potential of PV electricity with a feed-in tariff scheme should also be investigated not only for Spain, comparing with other countries in Europe.

In conclusion, this work showed that countries whose agricultural sectors are expected to be severely impacted by climate change will face substantial challenges in future. All policies and adaption strategies such an land use policy and climate anomaly prediction, devised to meet these challenges should to be carefully scrutinized for their advantages and disadvantages before implementation, and the instruments for evaluation should also be chosen with care. Lastly, in any decision support for stakeholders, the inherent uncertainty about the future should always be considered.

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Eidesstattliche Versicherung

Declaration on oath

Hiermit erkläre ich an Eides Statt, dass ich die vorliegende Dissertationsschrift selbst verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt habe.

I hereby declare, on oath, that I have written the present dissertation by my own and have not used other than the acknowledged resources and aids.

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