MODELING AGRICULTURAL PRODUCTION RISK AND THE ADAPTATION TO CLIMATE CHANGE

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Abstract

A model that integrates biophysical simulations in an economic model is used to analyze the impact of climate change on crop production. The biophysical model simulates future plant-management-climate relationships and the economic model simulates farmers' adaptation actions to climate change using a nonlinear programming approach. Beyond the development of average yields, special attention is devoted to the impact of climate change on crop yield variability.

This study analyzes corn and winter wheat production on the Swiss Plateau with respect to climate change scenarios that cover the period of 2030-2050. In our model, adaptation options such as changes in seeding dates, changes in production intensity and the adoption of irrigation farming are considered. Different scenarios of climate change, output prices and farmers' risk aversion are applied in order to show the sensitivity of adaptation strategies and crop yields, respectively, on these factors.

Our results show that adaptation actions, yields and yield variation highly depend on both climate change and output prices. The sensitivity of adaptation options and yields, respectively, to prices and risk aversion for winter wheat is much lower than for corn because of different growing periods. In general, our results show that both corn and winter wheat yields increase in the next decades. In contrast to other studies, we find the coefficient of variation of corn and winter wheat yields to decrease. We therefore conclude that simple adaptation measures are sufficient to take advantage of climate change in Swiss crop farming.

Keywords

climate change, robust estimation, yield variation, corn, winter wheat, market liberalization

1 Introduction

In the next decades Swiss farmers will face changing climatic conditions, which are characterized by elevated carbon dioxide concentrations, reduced summer rainfalls and elevated temperatures for the Swiss Plateau region (OCCC, 2005). Furthermore, Swiss agriculture will face changing market conditions due to market liberalization. Both input and output prices are expected to decrease in the next decades. The goal of this paper is to assess

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impacts of climate and price changes on Swiss corn (*Zea mays L.*) and winter wheat (*Triticum L.*) production.

Previous studies that analyzed the effects of climate change (CC) on crop production and crop variability were either based on (crop) simulation or regression models. Crop simulation models simulate and compare crop productivity for different climatic conditions (e.g. TORRIANI ET AL., 2007a). Regression models use historical climate and agricultural data to outline potential effects of climate change on crop productivity (e.g. ISIK AND DEVADOSS, 2006). Both approaches are not sufficient to analyze all aspects of impacts of CC on crop production (ANTLE AND CAPALBO, 2001). If the analysis is restricted to crop physiology, such as in crop simulations, farmer's adaptation actions are not taken into account. But, sufficient inference requires consideration of farmers' reactions to changes in climate and economic conditions. This contrasts the extrapolation of historical farm-level and aggregated data that takes into account farmers' historical reactions to changes in climatic and economic conditions. However, historical data is not able to capture future plant-climate interactions in a sufficient manner, in particular if the crop-weather relationship is restricted to a few variables such as temperature and rainfall. Moreover, such models cannot sufficiently integrate expected CO2 fertilization effects on plants due to low variation in historical CO2 concentrations (ANTLE AND CAPALBO, 2001). In order to overcome these drawbacks, we use a combination of both approaches, simulation of future crop productivity and regression models.

Existing studies show that CC will have particular influence on yield variation (MEARNS ET AL., 1996, TUBIELLO ET AL., 2000, SOUTHWORTH ET AL., 2002, FUHRER, 2003, CIAIS ET AL., 2005, and, TORRIANI ET AL., 2007a). The analysis of yield variation was restricted on climatic variables such as shifts in annual means and intra-annual distributions of climatic variables. These studies do not take adaptation actions of the farmers into account. In contrast, our approach considers farmers' adaptation actions to CC and is thus more sufficient to model the impact of CC on yield variation. An empirical example for corn and winter wheat production on the Swiss Plateau is used to asses the impact of CC on both crop yields and yield variability.

Our model covers no short term adaptation actions (i.e. tactical decisions) of farmers, but adaptation choices with a longer time horizon, i.e. strategic and structural decisions (cp. RISBEY ET AL., 1999). We consider strategic and structural decisions that consist of changes in production intensity, changes in seeding dates and the adoption of irrigation farming. Even though crop yields are influenced by various factors, our analysis is restricted on the crucial inputs nitrogen fertilizer and irrigation water. Thus, the analysis is of particular environmental and economic interest because application of both inputs can lead to the degradation of environmental systems (IEEP, 2000, and, KHANNA ET AL., 2000). Nitrogen fertilizer is furthermore a major source of climate relevant agricultural emissions (HUNGATE ET AL., 2003).

Our model is based on an integrated assessment approach that integrates a biophysical in an economic model. In contrast to other integrated models (e.g. ANTLE AND CAPALBO, 2001), farmers' behavior is simulated using nonlinear programming. The model is divided into three major parts: data simulation, estimation of model parameters and economic simulation. Data simulation describes the yield simulation process which includes the experimental design that enhances yield variability with respect to nitrogen fertilizer and irrigation. Furthermore, current and simulated future daily weather data are crucial inputs for the simulation process. The data simulation results in individual datasets for each climatic scenario and crop that contain yield and input data. These datasets are used to estimate production and yield variation functions, respectively. Subsequently, based on these functions, farmers' adaptation choices under different climate, price and risk aversion scenarios are simulated using nonlinear programming. Final assessment is based on a comparison of optimal input levels and consequential yield levels, yield variation, coefficients of variation and utility of quasi-rents for these scenarios of climate change, future prices and risk aversion.

In Section 2, 3 and 4, the data simulation, the economic model and the estimation processes are described, respectively. Estimation and economic simulation results are presented in Section 5 and 6, respectively. A final discussion of the impact of climate change on Swiss corn and winter wheat production is given in the concluding Section 7.

2 Crop yield simulation and data

Our analysis is based on yield data generated by the deterministic crop yield simulation model CropSyst (e.g. STÖCKLE ET AL., 2003). This is a process-based, multi-crop, multi-year cropping system simulation model. The model simulates above- and belowground processes of a single land block fragment representing a biophysically homogenous area. The model processes are simulated on a daily time step. They comprise the soil water budget, soil-plant nitrogen budget, crop phenology, canopy and root growth, biomass production, crop yield, residue production and decomposition, and soil erosion by water. These processes are simulated in response to weather, soil characteristics, crop characteristics, and management options. The model is therefore highly suitable to analyze the impact of environment and management on crop productivity, and has already been tested for a wide range of environmental conditions (e.g. DONATELLI ET AL., 1997, and, STÖCKLE ET AL., 2003). TORRIANI ET AL. (2007a) provide a model calibration, tests of yield simulation and a documentation of critical crop parameters of corn and winter wheat for the Swiss Plateau that are used in our yield simulation. In general, the comparability of simulated and observed yields is restricted because the simulations do not account for yield reducing events such as hail, disease and insect infestation.

CropSyst requires daily values of maximum and minimum temperature, solar radiation, and maximum and minimum relative humidity. In CropSyst, phenology is determined by thermal time, i.e., a specific development stage is reached when the required daily accumulation of average air temperature above a base temperature and below a cutoff temperature is reached. Daily climate input as required by CropSyst is obtained from the monitoring network of the Swiss Federal Office of Meteorology and Climate (MeteoSwiss). We use data from six meteorological stations distributed over the Swiss Plateau ranging from 06°57' to 08°54' longitude (FINGER AND SCHMID, 2007). To simulate current climate conditions, we use climate data of the years 1981 to 2003. Compared to an approach with one single location, the use of observations from six different weather stations broadens the data base. For the atmospheric CO2 concentration input we use recordings from the years 1981 to 2003. They range from 339 ppm to 379 ppm (SCHRÖTER ET AL., 2005).

Two climate change scenarios are applied to generate crop production functions for the coming decades. Climate scenarios with projections for the years 2030 and 2050 were taken from OCCC (2005). OcCC climate projections are based on simulations with two CO2 emission scenarios, four global climate models, and eight regional climate models. These simulations with totally 16 scenario-model combinations on a grid of 50x50 km over the whole European continent were performed within the scope of the PRUDENCE project (CHRISTENSEN ET AL., 2001). The OcCC climate projections used in this study represent the median of the simulations with the 16 scenario-model combinations for the years 2030 and 2050. The scenarios are abbreviated in the following as 2030 and 2050. The baseline for these climate anomalies is the year 1990. They include seasonal changes of temperature and precipitation for northern Switzerland (Table 1).

Table 1: Seasonal anomalies of temperature and precipitation

	2030				2050			
	DJF	MAM	JJA	SON	DJF	MAM	JJA	SON
Temperature	+ 1	+ 0.9	+ 1.4	+ 1.1	+ 1.8	+ 1.8	+ 2.7	+ 2.1
Precipitation	1.04	1.00	0.91	0.97	1.08	0.99	0.83	0.94

*) Anomalies of temperature in °C (absolute value) and of precipitation in relative values with respect to the climate of the year 1990. DJF: December-February; MAM: March-May; JJA: June-August; SON: September-November.

Source: OcCC (2005)

Based on today's weather data and the anomalies of temperature and precipitation (Table 1), a set of climate data are generated for each of the climate change scenarios using the stochastic weather generator LARS-WG (Semenov and Barrow, 1998). To achieve monthly anomalies as required by LARS-WG, the seasonal anomalies are linearly interpolated. For the 2030 scenario, the CO2 concentrations (IPCC, 2000) range from 437 ppm to 475 ppm. For the 2050 scenario, CO2 concentrations in the range of 495 ppm to 561 ppm are assumed. Within the simulation years, the atmospheric CO2 concentration is varied randomly within the defined range.

For each location and scenario, the same soil type is assumed. It follows Torriani et al. (2007a) where this soil is used to calibrate the CropSyst model for Switzerland. The soil texture is characterized with 38% clay, 36% silt, and 26% sand. Based on the texture, CropSyst assesses the hydraulic properties of the soil. Soil depth amounts to 1.5 m and the soil organic matter content is at 2.6% weight in the top soil layer (5 cm) and 2.0% in lower soil layers.

The applied management scenarios are uniform on the simulated crop area and include nitrogen (N) fertilization and irrigation. The amount of N applied per year ranged between 0 and 320 kg ha^{-1} for corn and between 0 and 360 kg ha^{-1} for winter wheat. Currently applied amounts of N fertilizer (Walther et al., 2001) are expanded in the simulation in order to cover potential future N fertilization strategies. For corn (winter wheat), there are three fertilizer applications per year if $N \leq 160$ kg ha^{-1} ($N \leq 180$ kg ha^{-1}) and four fertilizer applications per year if $N > 160$ kg ha^{-1} ($N > 180$ kg ha^{-1}), respectively, as shown in Table 2. For higher N amounts, however, an additional application date is introduced between the second and third date. In the simulations, fertilizer application dates are defined relative to the seeding date and derived from Dubois et al. (1998) and Walther et al. (2001).

Table 2: Distribution of annual fertilizer amounts

	Distribution of annual fertilizer [kgN ha^{-1}] to the dates of application
Corn	up to 160 kg: 1 : 1 : 0 : 2
	up to 320 kg: 1 : 1 : 1 : 2
Winter Wheat	up to 180 kg: 6 : 7 : 0 : 5
	up to 360 kg: 6 : 7 : 5 : 5

To simulate irrigation, we chose the automatic irrigation option of CropSyst. With this option, irrigation is triggered as soon as soil moisture is lower than a specific user-defined value. The degree of soil moisture is expressed as a value between 0 (permanent wilting point) and 1 (field capacity). When soil moisture falls below the previously defined value, water is added to the soil until field capacity is reached. However, there is an upper limit of irrigation water of 20 mm per irrigation event. Irrigation starts one day after seed and ends on the day of

harvest. The simulated experimental framework is equal for each climate scenario. This allows for comparability of results.
For simulations under current climate we use seeding dates provided by DUBOIS ET AL. (1999) and TORRIANI ET AL. (2007a). The temperature increase under the climate change scenarios leads to a shift of the annual temperature pattern and thus to a shift of the period of optimal crop development (TORRIANI ET AL., 2007a). Therefore, seeding dates are placed according to the temperature offset of the climate change scenario (Table 3). Even though seeding dates are placed earlier, CC leads to shorter maturity periods. Thus, shifts in average dates of maturity, which are equal to dates of harvest, are larger than for seeding dates (Table 3).

Table 3: Seeding and average harvesting dates for the applied climate scenarios.

	Climate Scenario	Current climate	2030	2050
Corn	Seeding date	10th May (130)	7th May (127)	4th May (124)
	Average Day of Maturity (Harvest)	17th September (263)	4th September (250)	28th August (240)
Winter Wheat	Seeding date	10th October (283)	13th October (286)	16th October (289)
	Average Day of Maturity (Harvest)	05th August (217)	27th July (208)	18th July (199)

*) Numbers in brackets are days of year.

Source: CropSyst Simulations.

For each location and year one simulation is conducted without application of fertilizer and irrigation. Furthermore, to broaden variability, the amount of fertilizer and the degree of soil moisture that triggers irrigation was varied randomly within the defined range. The datasets contain, depending on the crop and climate scenario, between 527 and 541 observations. A dry matter content of 85% and 90% is assumed for corn and winter wheat yields, respectively.

3 The economic model

Our analysis is based on utility-maximization with expected utility *E(U)* defined as follows:

$$E(U(\pi)) = \int_0^\infty U(\pi) f(\pi) d\pi \quad (1)$$

Where *E* is the expectation operator and $U(\pi)$ is the utility of quasi-rents π (revenue minus variable costs). The latter is treated as a random variable with density function $f(\pi)$. The stochastic character of quasi-rents can be the result of both stochastic yields and stochastic prices. Input and output prices are assumed to be deterministic in our analysis. Only crop yields are stochastic, with yield variation σ_y. Production and yield variation functions are assumed to be known. Yield variation is therefore treated as risk and not as uncertainty. Risk preferences are incorporated with a preference parameter towards variation of quasi-rents (σ_π). The utility function, which is linear in quasi-rents, is defined as follows (following HAZELL AND NORTON, 1986):

$$U(\pi) = E(\pi) - \gamma\sigma_\pi \quad (2)$$

Where γ is the coefficient of risk aversion (defined as $-(\partial U / \partial \sigma_\pi)/(\partial U / \partial \pi)$) which indicates risk-averse, risk-neutral and risk-taking behavior if $\gamma > 0$, $\gamma = 0$, and $\gamma < 0$, respectively.
An indicator function, I, is used to model farmers' adoption of irrigation farming: $I = 1$ for adoption of an irrigation system and $I = 0$ for crop farming without irrigation. Farmers are

assumed to implement an irrigation system if expected utility minus adoption costs is higher than expected utility of crop farming without application of irrigation. That is, $I = 1$ iff $E(U(\pi_{I=1})) - K > E(U(\pi_{I=0}))$, where K are the variable costs of adoption, e.g. the rental costs of the irrigation system. Expected quasi-rent $E(\pi)$ is defined as

$$E(\pi) = pE(y(X)) - ZX - IK \tag{3}$$

Where *y(X)* denotes the functional relationship, i.e. production function, between output scalar *(y)* and the vector of inputs *(X)*, *p* the output price scalar and *Z* an input price vector. The input vector consist of two inputs: nitrogen (*N*) and irrigation water (*W*). The decision on adoption of irrigation farming leads to two types of production functions in this model: one with and one without irrigation, respectively. This distinction is omitted in this section to ensure lucidity. The standard deviation of quasi-rent is defined as:

$$\sigma_\pi = \left| E((\pi - E(\pi)) \right| \tag{4}$$

Under assumption of deterministic prices and by rearrangement of (4), the standard deviation of quasi-rent simplifies to $\sigma_\pi = p\ \sigma_y$. Expected yields (i.e. solutions on the production function) are used to derive yield variation, $\sigma_y(X)$. The latter is defined as the absolute difference between observed yields (i.e. simulated observations) and expected yields (eqn. 5).

$$\sigma_y(X) = \left| y(X) - E(y(X) \right| \tag{5}$$

Therefore, the difference between observed and predicted yields for observation i is the absolute residual of the regression analysis, e_i, i.e. $\sigma_{yi}(X_i) = |e_i| = |y_i(X_i) - y_i(X_i)|$. Yield variation is determined by weather and soil conditions and input use, $\sigma_y(X) = f(I \cdot W, N)$. In this model, the intercept captures weather and soil effects on yield variability. Irrigation water is part of yield variation functions only for irrigation farming, i.e. $I = 1$. Substitution of eqn. (3) and (5) in (2) leads to the following final optimization problem:

$$\max_{X,y} E(U(\pi)) = pE(y(X)) - ZX - \gamma\, p\sigma_y(X) - IK \tag{6}$$

Expected utility (eqn. 6) is maximized subject to the production function constraint *y(X)*. The first order condition for utility maximization is presented in section 6.

4 Estimation methodology and functional forms

The production function, $y = f(X)$, is fitted to a square root functional form (eqn. 7), following FINGER AND HEDIGER (2007).

$$Y = \alpha_0 + \alpha_1 \cdot N^{1/2} + I \cdot \alpha_2 \cdot W^{1/2} + \alpha_3 \cdot N + I \cdot \alpha_4 \cdot W + I \cdot \alpha_5 \cdot (N \cdot W)^{1/2} \tag{7}$$

Y denotes corn yield in kilogram, *N* the amount of nitrogen applied (kg ha^{-1}), and *W* irrigation water applied in mm. The α_i's are parameters that must satisfy the subsequent conditions in order to ensure decreasing marginal productivity of each input factor: $\alpha_1, \alpha_2 > 0$ and $\alpha_3, \alpha_4 < 0$. If $\alpha_5 > 0$, the two input factors are complementary. They are competitive if $\alpha_5 < 0$, while $\alpha_5 = 0$ indicates independence of the two input factors.

The estimation of model parameters is a two step procedure that is described in the following. First step is the estimation of production function coefficients (eqn. 7) using robust regression. These estimates are used to calculate robust regression residuals for the entire dataset. Subsequently, robust regression residuals are used to estimate yield variation functions in a second step of estimation (eqn. 5).

4.1 Robust Regression and the Production Function

In this study, robust regression is used to estimate the coefficients of production functions (eqn. 7). This estimation technique was found to increase the accuracy of estimation and to expose the true underlying input-output relationship (FINGER AND HEDIGER, 2007).
The main idea of robust regression is to give little weight to outlying observations in order to isolate the true underlying relationship. Outliers are characterized by exceptional yield levels and exceptional input-output relationships, respectively, i.e. they deviate from the relationship described by the majority of the data. The further away an observation is from the true relationship, the smaller is the corresponding weight of contribution to the robust regression analysis. The identification of the true relationship and of outliers, respectively, is a non-trivial challenge, in particular, if the situation exceeds the simple regression case. We use the Reweighted Least Squares (RLS) regression for the robust estimation. RLS is a weighted least squares regression, which is based on an analysis of Least Trimmed Squares regression residuals that gives zero weights to observations identified as outliers (see ROUSSEEUW AND LEROY, 1987 for details). An observation is identified as outlier if the standardized residual exceeds the cutoff value of 2.5 (HUBERT ET AL., 2004).
Extreme yield events, e.g. caused by extreme climatic events such as droughts, negatively affect risk-averse decision makers. Such extreme yield events increase yield variation and lead thus to decreasing levels of utility. The modeling of extreme yield events is inefficient if Ordinary Least Squares (OLS) regression is used for the estimation of coefficients and related residuals. One outlier can be sufficient to move the coefficient estimates arbitrarily far away from the actual underlying values (ROUSSEEUW AND LEROY, 1987, and, HUBERT ET AL., 2004). Thus, analyses based on regression residuals derived by OLS estimation are inefficient and can produce misleading results. In contrast, robust regression and robust regression diagnostics enable efficient estimation in the presence of outliers.
In order to correct for heteroscedasticity, feasible generalized least squares (FGLS) regression is applied. Thus, weights are generated with respect to both, outliers and heteroscedasticity in the final estimation of production functions. The estimation is conducted with the ROBUSTREG and MODEL procedure, respectively, of the SAS statistical package (SAS INSTITUTE, 2004).

4.2 Yield Variation Function

Observations which are identified as outliers are not taken into account for the final estimation of production function coefficients. However, these observations are of particular interest for the estimation of yield variation because they increase yield variation. Therefore, residuals are calculated for the entire dataset, including the observations identified as outliers. The inclusion of outliers in the further analysis is possible if and only if no typing, copying or measuring errors but exceptional climatic events are source of the here identified outliers as proved for the here analyzed datasets by FINGER AND HEDIGER (2007). Residuals are the difference between observed (here: CropSyst simulations) and predicted observations (input-output combinations on the production function), $|e_i| = |Y_i(X_i) - \hat{Y}_i(X_i)|$. Yield variance is, among other factors such as weather and soil, determined by input use. This relationship is modeled using a square root function (eqn. 8) for corn. Irrigation water (*W*) is only an element of yield variation functions for irrigation farming ($I = 1$).

$$\sigma_y(X) = \beta_0 + I \cdot \beta_1 \cdot W^{0.5} + \beta_2 \cdot N^{0.5} \tag{8}$$

Where β_0 is the yield variation solely determined by weather and soil conditions. β_1 and β_2 quantify the influence of irrigation and nitrogen application on yield variation, i.e. $\beta_i = \partial\sigma_y(X)/\partial X_i^{0.5}$. An input is risk decreasing if $\beta_i < 0$ and risk increasing if $\beta_i > 0$, respectively. For winter wheat, a quadratic specification was found to be most adequate (eqn. 9).

$$\sigma_y(X) = \beta_0 + I \cdot \beta_1 \cdot W + \beta_2 \cdot N^2 + \beta_3 \cdot N \tag{9}$$

Interpretation of coefficients β_0 and β_1 remains as for eqn. 8. However, the influence of nitrogen on yield variation was found to have a quadratic shape for winter wheat, first decreasing, than increasing yield variation (coefficients β_2 and β_3 in eqn. 9).

The yield variation function is estimated using the MODEL procedure of the SAS statistical package and FGLS regression in order to correct for heteroscedasticity. In contrast to other studies, which focus on heteroscedasticity correction (JUST AND POPE, 1979) and take simultaneous equation biases into account (ISIK AND KHANNA, 2003), our estimation approach focuses on efficient estimation in presence of extreme events. Taking into account that such events are more likely to occur along with changing climate (e.g. FUHRER ET AL., 2006), this property is of particular interest.

5 Estimation Results

This section is devoted to the presentation and interpretation of regression analysis results which are input for the economic model. Simulation results of the economic model that are used for final assessment are presented in Section 6.

Coefficient estimates of the corn and winter wheat production functions (eqn. 7) for the assumed climate scenarios are presented in Table 4 and 5, respectively. It shows that coefficient estimates have the correct (i.e. the expected) sign. The intercept, i.e. the base yield where neither nitrogen nor irrigation is applied, shows an increase from the baseline scenario to the 2050 scenario for both crops. This is because of more favourable climatic conditions for crop growth. In particular an increased CO2 concentration leads to higher yield levels (FUHRER, 2003). Higher yield levels are furthermore the result of applied shifts in seeding days as this is a powerful adaptation option to avoid negative effects of climate change (cp. SOUTHWORTH ET AL., 2002, and, TORRIANI ET AL., 2007a). However, we are aware that current parameterizations of the CO2 effects as implemented in many crop models such as CropSyst have recently been questioned by LONG ET AL. (2006).

The analysis of base yields, where neither irrigation nor nitrogen fertilization takes place, is purely hypothetical. Both winter wheat and corn farm management without any input use is inexistent in Switzerland. Therefore, conclusions of the impact of climate change on yield levels can be drawn if and only if optimal input levels and according optimal yield levels are calculated in the subsequent section.

Table 4 shows furthermore a constant increase of the interaction parameter $(NW)^{1/2}$ from the baseline to the 2050 scenario for corn. Independency of nitrogen fertilizer and irrigation water in the baseline and 2030 scenario shifts to significant complementary interaction in the 2050 scenario. The interaction is important, as nitrogen is taken up in a water solution (LIU ET AL., 2006). In the first two scenarios, nitrogen uptake is sufficiently ensured by rainfall. In the latter scenario, which is characterized by lower amounts of rainfall (Table 1), optimal nitrogen uptake is only ensured if irrigation takes place. Moreover, nitrogen leaching is reduced if rainfall is substituted by irrigation that never exceeds field capacity as in our CropSyst simulations (not shown). Therefore, climate change is expected to increase the application of nitrogen fertilizer in presence of irrigation but to decrease nitrogen application if no irrigation is available.

Table 4: Coefficient Estimates: Production Function for Corn.

Coefficient	Climate scenario		
	Baseline	2030	2050
Intercept	6601.924 (162.13)**	6972.651 (180.68)**	7053.137 (165.17)**
$N^{1/2}$	313.0936 (16.34)**	347.6081 (19.79)**	309.8714 (16.36)**
$W^{1/2}$	67.1385 (4.17)**	59.65229 (4.69)**	71.58906 (5.50)**
N	-10.544 (8.15)**	-10.9985 (9.38)**	-9.59084 (7.60)**
W	-2.49922 (2.17)*	-0.93264 (1.09)	-1.0195 (1.19)
$(NW)^{1/2}$	0.364377 (0.45)	1.04329 (1.55)	3.522244 (4.92)**
Coefficient of det. (adj.)	0.7330	0.8403	0.8371

*) Note: Statistics in parentheses are t statistics

(**) – indicates significance at the 1% level

(*) – indicates significance at the 5% level

Table 5: Coefficient Estimates: Production Function for Winter Wheat.

Coefficient	Climate scenario		
	Baseline	2030	2050
Intercept	4582.359 (67.37)**	4894.397 (80.81)**	5142.069 (81.35)**
$N^{1/2}$	161.2262 (9.34)**	178.4068 (11.93)**	151.3398 (9.64)**
$W^{1/2}$	25.48017 (1.18)	70.16545 (3.73)**	68.29841 (3.38)**
N	-5.23933 (5.43)**	-5.96726 (7.16)**	-5.18194 (5.90)**
W	-0.85541 (0.56)	-2.93945 (2.19)*	-3.47498 (2.36)*
$(NW)^{1/2}$	0.508462 (0.59)	-0.35761 (0.48)	0.535636 (0.67)
Coefficient of det. (adj.)	0.3877	0.4663	0.3715

However, Table 5 shows that this is not the case for winter wheat. The interaction parameter $(NW)^{1/2}$ is not affected by CC and remains insignificantly low. The different seasonal shifts in rainfall and temperature patterns (Table 1) and different timing of maturity stages (Table 3) lead to this difference between corn and winter wheat. TORRIANI ET AL. (2007a) already pointed out that irrigation will become more important for spring than for winter crops at the Swiss Plateau.

5.1 Input use and yield variation

In Table 6 and 7, final coefficient estimates for the yield variation functions for corn and winter wheat (eqn. 8 and 9) are presented. For both crops, the coefficient β_0, i.e. yield variation solely determined by weather and soil conditions, decreases from the baseline to the 2030 scenario and increases in the 2050 scenario. If neither irrigation nor nitrogen fertilizer application takes place, yield variation increases from the 2030 to the 2050 scenario.

Table 6: Coefficient Estimates: Yield Variation Function for Corn (Eqn.8).

Coefficient	Climate scenario		
	Baseline	2030	2050
β_0 (Intercept)	409.0276 (14.78)**	381.7547 (18.33)**	468.5082 (19.52)**
β_1 ($N^{0.5}$)	38.98357 (10.78)**	39.2059 (11.82)**	39.81619 (11.26)**
β_2 ($W^{0.5}$)	-8.1252 (2.41)*	-12.7453 (5.32)**	-20.2869 (8.19)**
Coefficient of det. (adj.)	0.1901	0.2441	0.2718

Table 7: Coefficient Estimates: Yield Variation Function for Winter Wheat (Eqn.9).

Coefficient	Climate scenario Baseline	2030	2050
β_0 (Intercept)	789.2329 (23.11)**	680.4995 (22.21)**	728.5457 (23.60)**
β_1 (W)	-0.49937 (1.63)	-0.40804 (1.50)	-0.45408 (1.62)
β_2 (N^2)	0.004154 (2.37)*	0.006181 (3.97)**	0.008927 (5.75)**
β_3 (N)	-2.19199 (3.85)**	-2.50537 (4.97)**	-3.37643 (6.69)**
Coefficient of det. (adj.)	0.0659	0.0548	0.0829

For corn, irrigation causes a decrease ($\beta_2 < 0$) and nitrogen fertilizer causes an increase ($\beta_1 > 0$) in yield variation (Table 6). The property of irrigation to lower corn yield variation ($|\beta_2|$), continuously increases along our climate change scenarios. Higher temperatures and decreased rainfalls make irrigation to a more risk decreasing activity in future. The coefficient β_1, the property of nitrogen fertilizer to increase yield variation, is nearly constant under different climate conditions (Table 6). There is no impact of climate change on the relationship of yield variation and nitrogen for corn production.
For winter wheat, nitrogen first causes a decrease, than an increase in yield variation (Table 7). Irrigation causes a decrease of the latter. In contrast to results for corn, the relationship between input use and yield variation is not affected of CC for both inputs nitrogen and irrigation (Table 7). However, conclusions on the impact of climate change on the yield variation can be drawn if and only if utility maximizing input levels and according yield variations are calculated in the subsequent section.

6 Optimal Input Use, Yield, Expected Utility, Yield variation and Adoption Rates

Prediction of influence of climate change upon yield, input use and farmers' utility requires modeling of farmers' behavior, i.e. maximization of expected utility (eqn. 6). The derived optimal input levels provide the highest expected utility per hectare. The input price vector *W* is restricted on variable costs. Therefore, total variable costs *ZX* consist of variable nitrogen costs (nitrogen applied times nitrogen price) and the variable irrigation costs (irrigation water applied times price of irrigation water). Other costs are assumed constant and thus irrelevant for the profit maximizing input combination. The optimization problem of eqn. (6) leads to the following first order condition:

$$\partial f(x_i^*)/\partial x_i - z_i / p - \gamma \cdot \beta_i = 0 \qquad (10)$$

Where z_i denotes the price and x_i^* the optimal level of input i. A risk premium is included in the tangency condition if $\gamma \neq 0$. The risk premium is the product of the coefficient of risk aversion and the influence-coefficient of input i on yield variation, i.e. $\gamma\beta_i$. This is the difference between expected marginal productivity and the ratio of input and output prices at the optimal level of input use. Therefore, the optimal level of factor use for an input that increases (decreases) yield variation is smaller (larger) for a risk-averse than for a risk-neutral agent. Eqn.10 is solved for both irrigation and non-irrigation farming independently.

6.1 Prices and Risk Aversion

Due to market liberalization, Swiss agriculture will face diminishing output-input price ratios in crop production down to levels of, for instance, the European Union (EU). The differences between current Swiss and EU prices are much smaller for inputs such as nitrogen fertilizer than for outputs such as corn and wheat. Price forecasts for the periods of interest in our analysis, i.e. 2030 to 2050, are impossible. In order to show the sensitivity of adoption processes to both climate and economic variables, we assume three price scenarios for 2030 and 2050: current EU prices (P_{EU}), 1.5 x P_{EU} and 2 x P_{EU}. Price assumptions are presented in Table 8 and are documented more detailed in FINGER AND SCHMID (2007).

Table 8: Price Scenarios (in CHF)

Price Scenario	Corn kg^{-1}	Wheat kg^{-1}	Nitrogen kg^{-1}	Irrigation (mm per ha)
Current	0.396	0.57	1.33	0.6
P_{EU}	0.185	0.182	0.91	0.6
1.5 x P_{EU}	0.2775	0.273	0.91	0.6
2 x P_{EU}	0.37	0.364	0.91	0.6

Specifying a parameter towards farmers' risk attitude is crucial for the analysis. Various studies estimated farmers' risk parameter γ with widely differing results (HAZELL AND NORTON, 1986). However, no such case study exists for Swiss farmers. Therefore, we restrict numerical analysis on two cases of constant (i.e. independent from the level of utility) risk aversion: $\gamma = 0.5$ and $\gamma = 1$, respectively.

6.2 Results

There are 3 x 2 scenarios for each crop (price and risk aversion scenarios). For reasons of lucidity, not all results are presented in detail. For one scenario ($\gamma = 0.5$, P_{EU}) optimal input levels, expected utility, optimal yield levels and optimal yield variation are presented in Table 9 and 10. In these tables, results are presented for both irrigation and non-irrigation farming. Furthermore, differences in input levels, utility, yields and yield variation between irrigation and non-irrigation farming are presented. All results are within the range of the data.

Table 9 shows that the assumed combinations of price and climate change scenarios have only small effects on optimal use of nitrogen fertilizer for corn. In contrast, the optimal amount of applied irrigation water more than doubles from the baseline and the 2030 scenario to the 2050 scenario. Future levels of utility are lower for both climate scenarios mainly due to the decline in output prices. Yield levels increase by up to twenty percent from the baseline to the 2050 scenario for irrigation farming ($I = 1$). In contrast, optimal levels of corn yields decline from the 2030 to the 2050 scenario for non-irrigation farming. Corn yield variation decreases from the baseline to the 2050 scenario for irrigation farming but increases for non-irrigation farming.

For winter wheat (Table 10), optimal amounts of nitrogen and irrigation water are smaller for the future scenarios compared with the baseline scenario mainly because of the reduced output/input price ratio. Both climate change and irrigation farming have only small impacts on yield variation of winter wheat. Therefore, differences between irrigation and non-irrigation farming are much smaller for winter wheat than for corn. In particular the increase of expected yield levels due to irrigation is in maximum 307 kg ha^{-1} for winter wheat (2050 scenario, Table 10) but 1596 kg ha^{-1} for corn (2050 scenario, Table 9).

Table 9: Corn: Optimal input levels, expected utility, yields and yield variation.

Irrigation Indicator Climate Scenario	Nitrogen (kg ha^{-1})	Irrigation Water (mm)	Expected Utility per ha	Optimal Yield (kg ha^{-1})	Optimal Yield Variation
I=1					
Baseline	114.10	87.48	3286.2	9189	749.4
2030	112.48	85.20	1632.79	9995	679.9
2050	137.93	208.49	1685.66	10788	643.2
I=0					
Baseline	111.5	0	3147.22	8732	820.7
2030	106.16	0	1567.24	9387	785.7
2050	99.84	0	1529.5	9192	866.4
Difference I=1 and I=0					
Baseline	2.6	87.48	138.98	457	-71.3
2030	6.32	85.2	65.55	608	-105.8
2050	38.09	208.49	156.16	1596	-223.2

*) Scenario: $\gamma = 0.5$, P_{EU}. For irrigation ($I = 1$) and non-irrigation farming ($I = 0$).

Table 10: Winter Wheat: Optimal input levels, expected utility, yields, yield variation.

Irrigation Indicator Climate Scenario	Nitrogen (kg ha^{-1})	Irrigation Water (mm)	Expected Utility per ha	Optimal Yield (kg ha^{-1})	Optimal Yield Variation
I=1					
Baseline	138.59	90.01	3019.59	5976	520.3
2030	75.03	30.87	1007.01	6274	514.7
2050	71.33	30.92	1023.44	6348	519.1
I=0					
Baseline	131.72	0	2934.92	5743	572.6
2030	76.58	0	973.16	5999	524.9
2050	68.93	0	986.67	6041	538.2
Difference I=1 and I=0					
Baseline	6.87	90.01	84.67	233	-52.3
2030	-1.55	30.87	33.85	275	-10.2
2050	2.4	30.92	36.77	307	-19.1

*) Scenario: $\gamma = 0.5$, P_{EU}. For irrigation ($I = 1$) and non-irrigation farming ($I = 0$).

Adoption of irrigation farming is triggered by utility differences between irrigation and non-irrigation farming in our model. For both crops, utility differences $E(U(\pi_{I=1})) - E(U(\pi_{I=0}))$ decrease from the baseline to the 2030 scenario due to the decline of output prices (Table 9 and 10). In contrast to winter wheat, this difference increases for corn in the 2050 scenario. Even though the output price is lower, CC leads to a higher profitability of irrigation in corn farming.

Results of the other scenarios can be summarized as follows. Higher output prices lead, in general, to higher input use, higher yield levels, lower yield variation and higher levels of utility. Furthermore, this leads to larger utility differences between irrigation and non-irrigation farming for both crops. That is, an increase of output prices increases the profitability of irrigation farming. The increase of the coefficient of risk aversion from 0.5 to 1.0 leads to lower amounts of nitrogen for corn, but higher optimal nitrogen use for winter wheat. This leads furthermore to an increase of the optimal amount of irrigation water and the profitability of irrigation farming. Yield variation decreases for both crops if risk aversion increases. The effect of changes in risk aversion on yield levels is ambiguous.

6.3 Adoption of Irrigation Farming

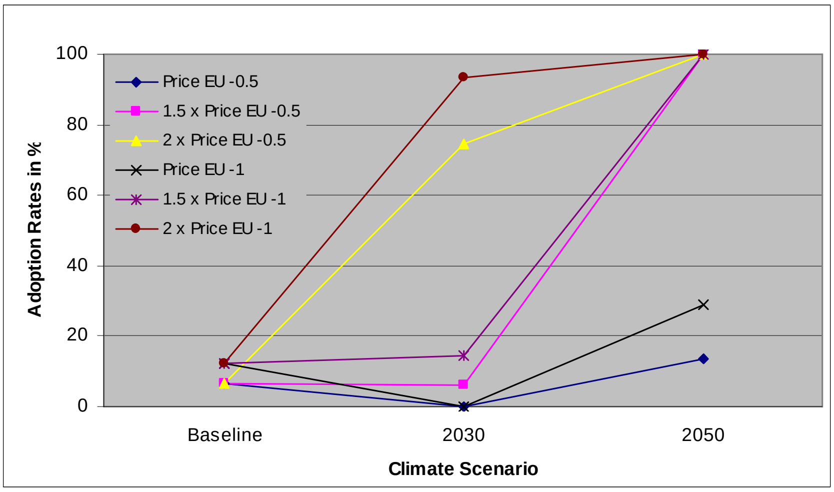
Farmers' are assumed to adopt irrigation farming, $I=1$, if and only if $E(U(\pi_{I=1}))-K > E(U(\pi_{I=0}))$, where K denotes the variable adoption costs for e.g. renting of equipment. Adoption costs are modeled stochastically to reflect heterogeneous adoption costs for farmers due to, for example, differences in farm size, access to irrigation water and infrastructure endowments (KULSHRESHTHA AND BROWN, 1993). 100000 draws are made from a normal distribution $N(200,40)$. This results in simulated costs that range between 20 and 385 with an interquartile range between 173 and 226. Even though this distribution of costs is not representative, it avoids corner solutions compared with a single value for adoption costs. Thus, this approach is more suitable to highlight the sensitivity of the model. Comparability between the scenarios is ensured by applying equal distribution of costs for each scenario.

Every simulated observation adopts irrigation farming if the utility difference between irrigation and non-irrigation farming (see Table 9 and 10) is larger than the simulated costs:

The simulated adoption rates never exceed one percent for winter wheat. Irrespective of the price and risk aversion scenarios, the assumed CC scenarios lead not to adoption of irrigation farming in winter wheat production because of shifts in maturity stages (Table 3) and only small reductions of relevant spring rainfall in the applied climate change scenarios (Table 1). This is consistent with the results of TORRIANI ET AL. (2007a) that show only marginal benefits of irrigation in winter wheat farming.

In contrast, the baseline adoption rate for corn is 6.5 % ($\gamma=0.5$) and 12.3% ($\gamma=1$), respectively. As shown in Figure 1, the future adoption rates are mainly determined by future prices and future risk aversion of farmers. In general, higher prices and higher risk aversion lead to higher adoption rates. As a consequence, all farmers switch to irrigation (corn) farming in 2050 for the 1.5 x P_{EU} and 2 x P_{EU} scenarios. Assuming P_{EU}, however, the highest adoption rate is 29% for the 2050 scenario with $\gamma=1$. That is, even in 2050 the adoption of irrigation farming will be relatively small if Swiss farmers' face current EU prices.

Figure 1: Adoption Rates of Irrigation Farming for Corn.



*) Note: Price EU -1 denotes the P_{EU}, $\gamma=1$ scenario.

To obtain final results, the adoption rates are combined with the results for input use, yield level, yield variation and utility. For instance, the final result for optimal yields (Y^*) is calculated as follows: $Y^* = \textit{adoption rate} \cdot Y^*(I=1) + (1-\textit{adoption rate}) \cdot Y^*(I=0)$. In order

to derive utility for farmers that adopt irrigation farming, the average costs of the adopters in the simulated sample are subtracted from the expected utility (e.g. in Table 9).
Final model results for yield levels, yield variation, coefficients of variation, nitrogen use and utility of quasi-rents are shown in Figure 2 and 3. It shows that both yield levels and utility of quasi-rents are less affected by levels of risk aversion than by output prices. That is, differences between risk aversion scenarios for a single price scenario are smaller than vice versa. In contrast, nitrogen use and yield variation are clearly affected by both risk aversion and output prices.
Figure 2 shows increasing yields and decreasing yield variation for future corn and winter wheat production. Even though corn yield variation increases for two scenarios ($\gamma = 0.5$, P_{EU} in 2050; and; $\gamma = 0.5$, 1.5 x P_{EU} in 2030, Figure 2), the coefficients of variation, i.e. the ratio of yield variation and yield level, for all scenarios are unambiguously decreasing (Figure 2). Figure 2 further shows that an increase of both risk aversion and output prices leads to a decrease of the coefficient of variation for corn and winter wheat, respectively.
The optimal amount of applied nitrogen for winter wheat decreases mainly due to output price reductions (Figure 3). Increasing output prices lead, however, to increasing optimal amounts of applied nitrogen. In contrast, the latter increases up to 250 kg ha^{-1} for corn in the 2050, $\gamma = 0.5$, 2 x P_{EU} scenario. High adoption rates of irrigation farming (Figure 1) and the positive interaction between nitrogen use and irrigation in the 2050 scenario (Table 4) lead to this strong increase of nitrogen use. Utility of quasi-rents for winter wheat depends on output prices but not climate change as shown in Figure 3. Neither adoption of irrigation farming nor changes in production intensity are profitable (i.e. used) adaptation strategies to CC in winter wheat farming. In contrast, for high corn prices the adaptation possibility of adoption of irrigation farming enables even increasing utility levels for climate change scenarios (Figure 3).

Figure 2: Final Model Estimates for Yield, Yield Variation and Coefficient of Variation for Corn and Winter Wheat.

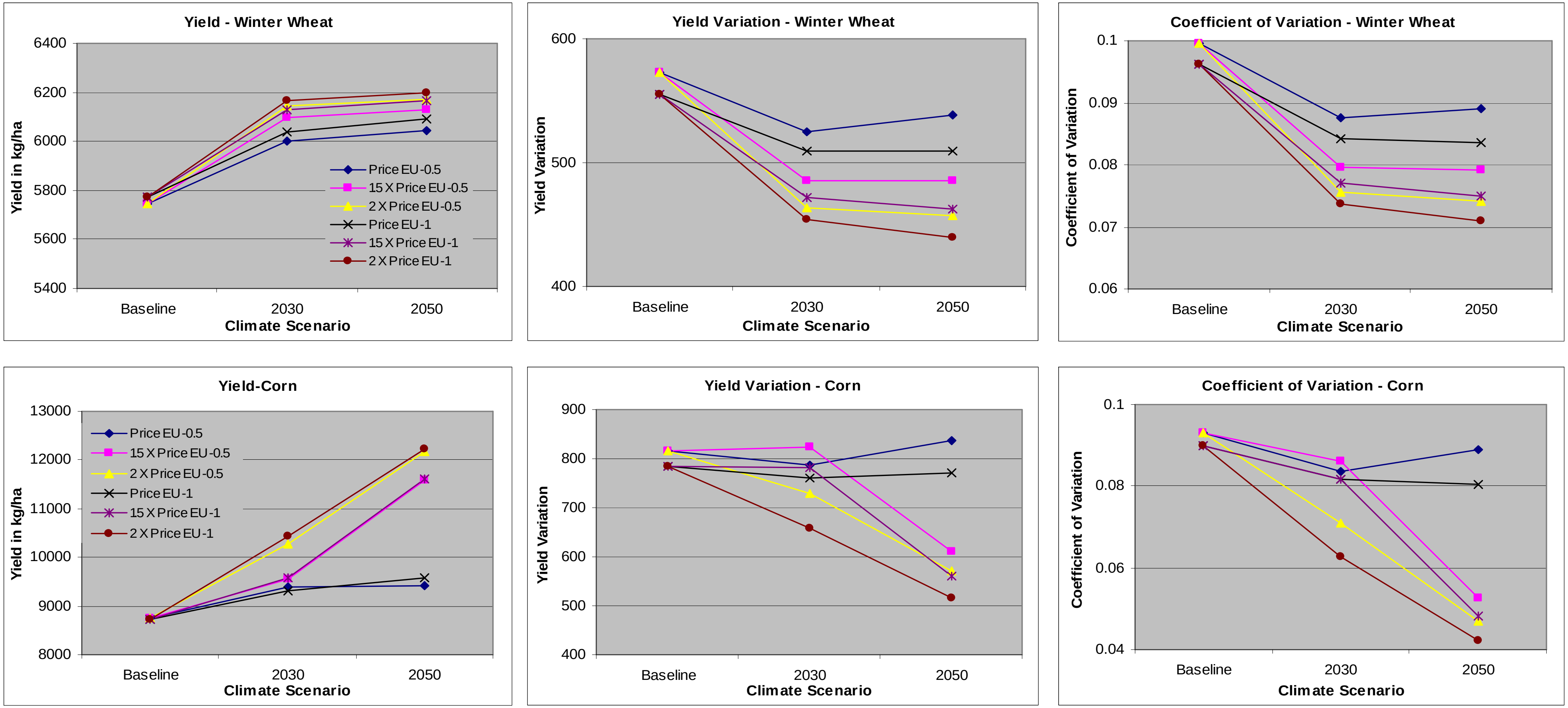
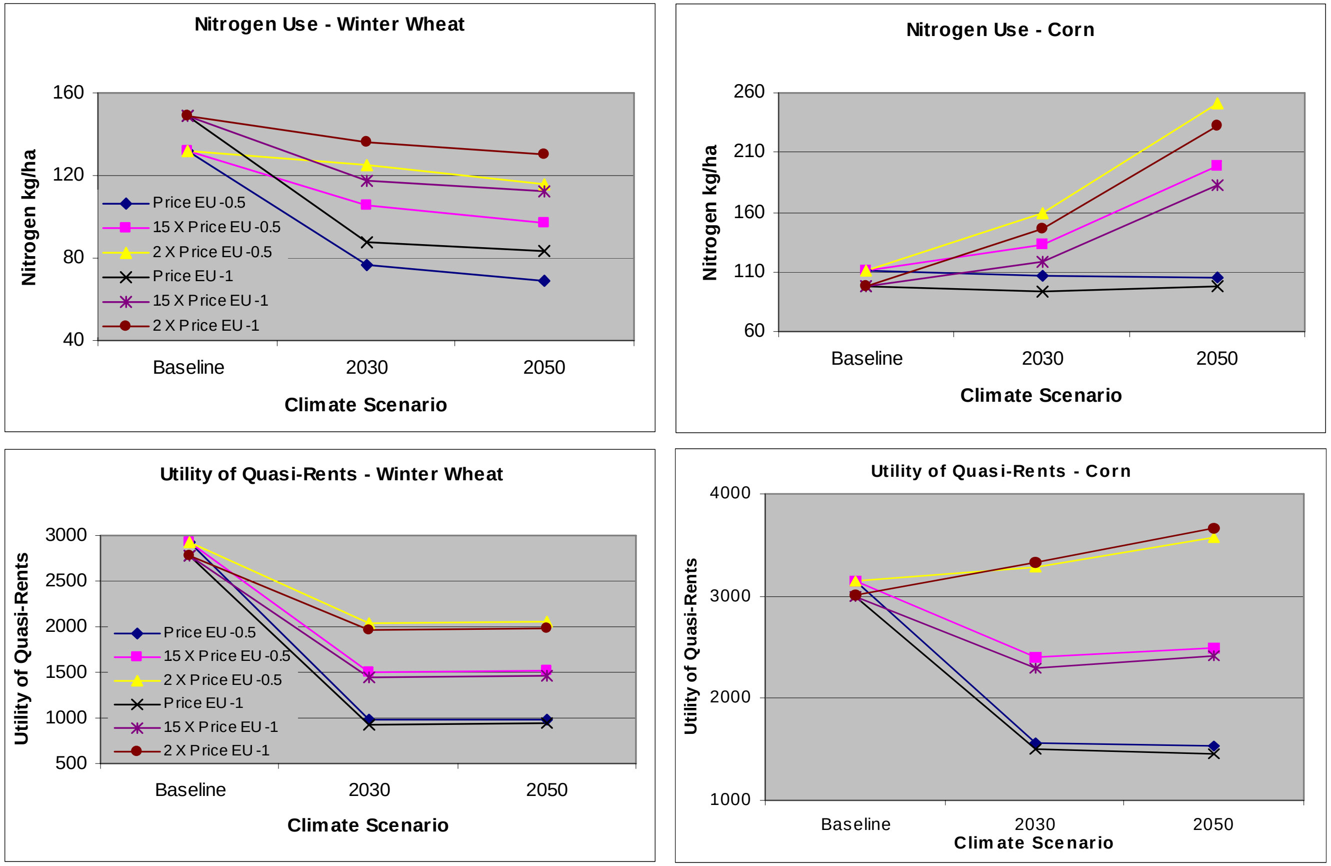


Figure 3: Final Model Estimates for Nitrogen Use and Utility of Quasi-Rents for Corn and Winter Wheat.



7 Discussion and Conclusions

Approaches of earlier studies that analyzed the impact of climate change on crop production were not able to incorporate both future climate-plant interactions and adaptation measures simultaneously. To overcome this drawback, we use a modeling approach that combines predicted climate-plant relationships (crop simulation modeling) and an economic model that focuses on strategic adaptation.

We found beneficial effects of climate change if adaptation measures such as changes in seeding dates, changes in production intensity and implementation of irrigation systems are taken into account. For the time horizon considered in this analysis (2030-2050) we found corn and winter wheat yields to increase above current levels. FLÜCKIGER AND RIEDER (1997) projected decreasing corn and increasing winter wheat yields in Switzerland using a regression modeling approach. For winter wheat this is consistent with our analysis because the adaptation options considered in our study do not significantly change the impact of climate change on winter wheat production. The difference for corn yield projections is due to adaptation measures that are taken into account in our analysis but are not considered in FLÜCKIGER AND RIEDER (1997).

Yield variation of corn is projected to increase but decrease for winter wheat in the analysis of TORRIANI ET AL. (2007a). The latter result is consistent with our findings. The increase of corn yield variation contrasts our results because in particular changes in production intensity are not taken into account in TORRIANI ET AL. (2007a). However, it has to be taken into consideration that the applied climate change scenarios in FLÜCKIGER AND RIEDER (1997), TORRIANI ET AL. (2007a) and our analysis are different.

Altogether, higher and less variable yields projected from our analysis lead to a decrease of the coefficient of variation for future corn and winter wheat production at the Swiss Plateau. We chose numerical examples of constant risk aversion. However, several studies (see SERRA ET AL., 2006) point out decreasing instead of constant risk aversion of farmers. That is, risk aversion of farmers increases with decreasing utility. All but one of the scenarios assumed in our study leads to lower utility levels in future. Thus, farmers are expected to be more risk averse in future than currently. An increase of risk aversion causes lower coefficients of variation. Therefore, even higher reductions in the coefficients of variation for corn and winter wheat are expected than indicated by our study.

In order to validate the here presented results, further soil types and further CC scenarios should be considered. Further climate change scenarios should emphasize the altitude of future extreme climatic events such as droughts. The here applied estimation procedure for model parameters, using robust regression, is in particular suitable for the incorporation of such extreme climatic events.

In conclusion, our approach of modeling impacts of climate change on crop production and production risk is valuable for further research, because it enables the simultaneous analysis of climate change, price and risk aversion scenarios. It can be extended with further adaptation measures. Our case study shows that simple adaptation measures such as changes in seeding dates, changes in production intensity and adoption of irrigation farming are sufficient to generate positive effects of climate change for corn and winter wheat production at the Swiss Plateau. Taken into account that further adaptation measures such as breeding and financial instruments such as weather derivates were found to be valuable adaptation strategies for Swiss crop production (TORRIANI ET AL. (2007a,b), the latter will take advantage of climate change.

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