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How climate change impacts on local cropping systems: A bioeconomic simulation study for western Switzerland

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Abstract

The Broye catchment, located in the cantons of Vaud and Fribourg, is an important crop production area in Switzerland. In particular, the region's northern plain exhibits very appropriate topographic conditions for intensive and profitable crop cultivation. Due to the region's low precipitation levels irrigation is a common management strategy for certain crops such as potatoes, sugar beets and grain maize. As the required water resources for irrigation are primarily withdrawn from surface water bodies, water scarcity in rivers has become a serious issue in the Broye catchment. Considering the fact that climate change is expected to further increase the region's agricultural water demand, water might become even scarcer in the near future.

In order to overcome future problems associated with water scarcity and to avoid potential losses in agricultural income, it will be important to identify specific adaptation measures with regard to agricultural management strategies and the region's water policy. Therefore, this thesis aimed in a first step to assess the direct impact of local climate change on cropping systems in the Broye catchment and to deduce potential agricultural adaptation options. Considering such optimal adaptation options, forecasts on the region's agricultural water demand were made for different climate and socio-economic scenarios. Finally, this work evaluated different policy measures to reduce the agricultural water demand in the Broye catchment in the context of current and future climate conditions.

To address these objectives, two bioeconomic models were developed operating at the single crop and at the whole farm level, respectively. Both models combine the process-based crop growth model CropSyst with an economic decision model and apply a genetic algorithm for optimization. Furthermore, both of them use the certainty equivalent as target value which enabled the simultaneous consideration of the average income and income risks in the objective function. While maximizing the certainty equivalent, the developed modeling approaches optimized a wide range of agricultural management decisions such as crop choice, land allocation to different crop types, as well as crop-specific nitrogen and irrigation strategies under different climate, crop price and water policy scenarios. Besides changes in optimal management schemes, the use of the bioeconomic models allowed investigation of the effects of the applied scenarios on agricultural income, income variability and agricultural water demand.

Using the single crop model, our simulations results show that climate change will decrease average income and certainty equivalents in winter wheat and grain maize

production in the Broye catchment by up to 25% even considering potential adaptation measures. At farm scale, however, agricultural average income is found to decrease only by 8-12% under the applied climate change scenarios, since also adaptation measures with regard to crop choice and crop land allocation are possible. At the same time, the simulation studies performed in this thesis predict no significant impact of climate change on the farm's income volatility.

Furthermore, our results indicate that crop prices as currently observed in the European Union (EU) are likely to result in much larger changes in the optimal management schemes and agricultural income levels than local climate effects. As a matter of fact, the whole farm model used in this thesis projects losses in average farm income of about 50% under EU crop prices.

Although crop prices have a more significant impact on future agricultural practices and income levels than local climate change, the latter still requires major consideration in the Broye catchment. Irrespective from the chosen crop price scenario, climate change will sharply increase the modeled farm's water demand for irrigation by up to 100%. Interestingly, this increase in agricultural water consumption is not due to an expanded irrigated surface area but solely resulting from higher irrigation water requirements in potato and sugar beet production. For winter crops such as winter wheat or winter barley, irrigation is also under rather strong assumed climate signals not a viable adaptation measure.

Considering these results with regard to irrigation, we finally evaluated different water policies measures to counteract the higher agricultural water demand in the Broye catchment under climate change. Our findings suggest that both, a volumetric water price as well as a water quota, are promising policy measures for the reduction of the region's agricultural water consumption, not only under current but also under future expected climate conditions. Both policies are likely to significantly decrease the modeled farm's water demand while their impacts on the farm income are relatively small since the applied modeling approach accounts for adjustments in the farm's optimal management decisions (e.g., crop choice, crop land allocation).

Overall, this thesis shows that negative climate change effects on arable cropping systems can be mitigated to a large extent by adaptation. Such adaptation measures, however, will cause a sharp increase in the region's agricultural water demand. Thus, provided that water for irrigation purposes will not be withdrawn from other sources, changes in the region's water policy are inevitable in the near future to prevent the frequent occurrence of water scarcity.

Zusammenfassung

Das Einzugsgebiet der Broye, welche in den Kantonen Waadt und Fribourg liegt, zählt zu den wichtigsten Ackerbaugebieten der Schweiz. Vor allem die Topographie der nördlichen Ebene der Region weist eine sehr gute Eignung für den Ackerbau auf, was intensive und profitable landwirtschaftliche Anbausysteme ermöglicht. Da die jährlichen Niederschlagsmengen im Broye Einzugsgebiet relativ tief sind, ist die Bewässerung von einigen landwirtschaftlichen Kulturen wie z.B. Kartoffeln, Zuckerrüben oder auch Körnermais gängige Praxis. In den letzten Jahren hat dies jedoch wiederholt zu Wasserknappheit in den Flüssen, aus welchen das benötigte Wasser normalerweise entnommen wird, geführt. In Anbetracht der Tatsache, dass der Klimawandel wohl zu einer Erhöhung des landwirtschaftlichen Wasserbedarfes führen wird, kann man davon ausgehen, dass Wasserknappheit in den nächsten Jahren zu einem noch grösseren Problem in der Broye Region werden dürfte.

Um in Zukunft Wasserknappheit und etwaige Verluste im landwirtschaftlichen Einkommen möglichst zu vermeiden, ist es wichtig Anpassungsstrategien in Bezug auf lokale landwirtschaftliche Produktionsformen und die lokale Wasserpolitik zu entwerfen. Zu diesem Zwecke wurden in dieser Arbeit in einem ersten Schritt direkte Folgen des Klimawandels im Ackerbau und mögliche Anpassungsmassnahmen untersucht. In einem zweiten Schritt wurde ausgehend von den identifizierten Anpassungsmassnahmen abgeschätzt, wie sich der landwirtschaftliche Wasserbedarf im Broye Einzugsgebiet unter verschiedenen Klimawandel- und sozio-ökonomischen Szenarien entwickeln wird. Schliesslich wurde auch analysiert, wie sich die landwirtschaftliche Wassernachfrage unter aktuellen und zukünftigen Klimaszenarien durch geeignete Politikmassnahmen verringern lässt.

Diesen Forschungsfragen wurde mittels zweier bioökonomischen Modellen, welche für Untersuchungen auf der Einzelkultur- resp. auf der Betriebsebene entwickelt wurden, nachgegangen. Beide Modelle verknüpfen das mechanistische Pflanzenwachstumsmodell CropSyst mit einem ökonomischen Entscheidungsmodell und verwenden einen genetischen Algorithmus als Optimierungstechnik. Zudem wurde in beiden Modellen das Sicherheitsäquivalent als Zielwert definiert, so dass nicht nur das Durchschnittseinkommen, sondern auch das Einkommensrisiko in der Zielfunktion der Optimierung berücksichtigt wurde. Mit dem Ziel das Sicherheitsäquivalent zu maximieren wurde eine Vielzahl verschiedener landwirtschaftlichen Managemententscheidungen (z.B. Kulturwahl, Flächenallokation, sowie Düngungs- und Bewässerungsintensität) unter verschiedenen Klimawandel-, Agrarpreis- und Wasserpolitikszenarien optimiert. Neben der Optimierung der genannten Managemententscheidungen konnte mithilfe der

bioökonomischen Modelle auch simuliert werden, wie sich das landwirtschaftliche Einkommen, die Einkommensvariabilität sowie die landwirtschaftliche Wassernachfrage unter den verwendeten Szenarien verändert.

Die Resultate des Einzelkulturmodelles veranschaulichen, dass sich das Durchschnittseinkommen und auch das Sicherheitsäquivalent im Winterweizen- und Körnermaisanbau unter den verwendeten Klimawandelszenarien um bis zu 25% verringert, obwohl Anpassungen der optimalen landwirtschaftlichen Managemententscheidungen berücksichtigt wurden. Dagegen zeigen Simulationen des Betriebsmodell, dass der Klimawandel das Durchschnittseinkommen eines gesamten Ackerbaubetrieb nur um 8-12% reduziert, da auf Betriebsebene auch Anpassungen in der Kulturwahl, sowie der optimalen Flächenallokation möglich sind. Gleichzeitig lassen sich aufgrund unserer Simulationen keine signifikanten Veränderungen in der Variabilität des landwirtschaftlichen Betriebseinkommens unter Klimawandel erkennen.

Tiefere Agrarpreise haben nicht nur auf die optimalen Managemententscheidungen, sondern auch auf das landwirtschaftliche Betriebseinkommen viel grössere Effekte als der Klimawandel. So sagt das Betriebsmodell unter der Annahme von EU Agrarpreisen eine Reduktion des landwirtschaftlichen Betriebseinkommens von etwa 50% voraus.

Obschon das gewählte Preisszenario eine wichtigere Rolle bezüglich optimaler Managemententscheidungen und des landwirtschaftlichen Einkommens als der Klimawandel spielt, bleibt letzterer für die Untersuchungsregion nicht ohne Folgen. Unabhängig vom gewählten Preisszenario, führt der Klimawandel zu einem starken Anstieg der landwirtschaftlichen Wassernachfrage in der Broye. Interessanterweise ist diese nicht auf eine Ausdehnung der bewässerten Fläche, sondern nur auf einen erhöhten Wasserbedarf im Anbau von Kartoffeln und Zuckerrüben zurückzuführen. Für Winterkulturen, wie z.B. Winterweizen oder Wintergerste, lohnt sich die Bewässerung von einem ökonomischen Standpunkt aus auch unter zukünftigen Klimaszenarien nicht.

Schlussendlich wurden die Wirkungen verschiedener Massnahmen in der lokalen Wasserpolitik simuliert, um die unter Klimawandel erhöhte landwirtschaftliche Wassernachfrage zu reduzieren. Diesbezüglich zeigen unsere Resultate, dass die benötigte Wassermenge des modellierten Betriebes sowohl unter der Annahme eines variablen Wasserpreises, wie auch unter der Annahme einer Kontingentierung der betrieblich verwendbaren Wassermenge stark abnimmt. Der negative Einfluss dieser Massnahmen auf das landwirtschaftliche Einkommen ist dagegen eher gering, da das Modell Anpassungen im Betriebsmanagement (z.B. Kulturwahl, Flächenallokation, etc.) zulässt.

Zusammenfassend lässt sich daher sagen, dass negative Klimawandeleffekte im Ackerbau im Broye Einzugsgebiet weitgehend durch Anpassungsmassnahmen minimiert werden

können. Allerdings bringen solche Anpassungsmassnahmen eine starke Steigerung der landwirtschaftlichen Wassernachfrage mit sich. Geht man von der Annahme aus, dass keine neuen Wasserressourcen für Bewässerungszwecke erschlossen werden, sind Anpassungen der Wasserpolitik in der Broye, um häufige Wasserknappheit in den Flüssen zu vermeiden, in der nahen Zukunft unumgänglich.

Content

1 Introduction

In Switzerland, pronounced changes in climate conditions have been observed throughout the 20th century. While the annual average temperature of the northern hemisphere has generally increased from 1959 to 2009 by about 1.1°C, a warming trend of 1.75°C has been found for Switzerland in the same period (Ceppi et al., 2012). In line with this, further significant temperature increases of 0.9-1.4°C (depending upon region and season) are expected for Switzerland until 2030 (Fischer et al., 2012). With regard to precipitation, the predictions are subject to larger uncertainties and show only towards the end of the 21th century significant signals for drier summer and likely increases in winter precipitation for southern Switzerland (Fischer et al., 2012).

The vulnerability of different systems to these expected changes largely depends on a system's actual exposure to climate conditions, its sensitivity to fluctuations thereof and its adaptive capacity (McCarthy et al., 2001). Agricultural systems, in particular, are inherently sensitive to global warming (Adams et al., 1990) as biophysical processes in agroecosystems are strongly affected by environmental conditions. The heat wave in 2003, for instance, decreased the net primary production of ecosystems over Europe by about 30% (Ciais et al., 2005). Not surprisingly, drought-related losses of up to 500 Million Swiss Francs have been estimated in Swiss agriculture for the year 2003 (Keller and Fuhrer, 2004).

Even though, agricultural systems are very sensitive to climate variations, their vulnerability to global warming can be significantly reduced by adaptation measures (Smit and Skinner, 2002) and already small changes in farmers' specific management strategies (e.g., shift of sowing dates, adjustment of fertilization intensities) can partially mitigate negative climate change impacts on agricultural systems (e.g., Torriani et al., 2007b; Lehmann et al., 2011).

Recently, many studies have been conducted which evaluate climate change impacts on agriculture in Switzerland (e.g., Calanca and Fuhrer, 2005; Torriani et al., 2007a; Torriani et al., 2007b; Finger and Schmid, 2008; Finger et al., 2010; Finger et al., 2011; Holzkamper et al., 2012). However, so far, studies predominantly assessed climate change impacts on Swiss agriculture at the level of single crops with only minor emphasis on adaptation possibilities at the farm level. Although providing valuable information for agricultural stakeholders, single crop studies tend to overestimate negative climate change impacts, since they do not consider potential measures for adaptation, such as changes in the cultivation of land and manpower put into the cultivation of different crops. Simple to be

implemented, not requiring large investments and generally decreasing overall damage at a high efficiency, it is however exactly these adjustments at the level of individual farm management, which play a key role in the determination of the influence of climate change on local cropping systems.

1.1 Overall objectives

This thesis aims to contribute to a better understanding of how climate change impacts on arable cropping systems in the Broye catchment, western Switzerland[1]. The Broye catchment has been chosen as study region because is an important arable cropping area in Switzerland. Furthermore, the region already faces water scarcity in hot and dry late spring and summer months requiring irrigation as a common management practice. In the next decades, irrigation can be expected to generally gain in importance in Swiss agriculture (Fuhrer and Jasper, 2009) and conflicts in water utilization, in particular in the Broye catchment, will be inevitable. Concretely, the thesis addresses the following research questions:

1. *How does climate change impact on the profitability and on production risks of cropping systems in the Broye catchment?*
2. *How does climate change influence optimal agricultural management decisions at single crop level as well as for arable whole farm systems?*
3. *What is the sensitivity of these optimal management decisions to lower agricultural output prices as expected under an ongoing liberalization of agricultural markets in Switzerland?*
4. *How much does irrigation in the study region gain in importance under warmer and drier climate conditions?*
5. *Which water policies are suitable to reduce the region's water demand under current and future expected climate conditions?*

To address the questions raised above, two different bioeconomic models were developed. The first model, operates at field scale and can be used for studies at the single crop level. The second model runs at farm scale and simulates whole farm systems. Both models have in common that they combine the mechanistic crop growth model CropSyst (Stöckle et al., 2003) with an economic decision model and use a genetic algorithm as optimization

[1] Although the thesis' principal focus lies in the Broye catchment, the studies presented in Chapter 4 and Chapter 5 refer also to the Greifensee catchment.

technique. Nevertheless, the two models differ markedly in the decision variables considered. While the whole farm model optimizes crop acreages and each crop's nitrogen and fertilization intensity, the single crop model takes besides nitrogen fertilization and irrigation intensity also different strategies with regard to the timing and allocation of nitrogen fertilization and irrigation into account.

1.2 Structure of the thesis

This thesis can be divided into three main parts. The first part provides background information on the starting position and on the methodological basis used in the thesis' modeling framework. The first subchapter of Chapter 2 presents a review summarizing state-of-the-art research in the field of climate change impacts on agricultural systems and potential adaptation measures. Applications of mechanistic crop models in climate change impact assessments as well as their strengths and limitations are discussed in the proceeding subchapter. Finally, Chapter 2 is completed by an overview of genetic algorithms and their applications in the agricultural research field. Since this thesis has been performed in the framework of the National Research Program 61 (NRP61) ('Sustainable Water Use') within the AGWAM[2] project, Chapter 3 gives an overview of AWGAM and presents its overall research aims. Furthermore, an overview of the two AGWAM study region with a particular focus on the Broye catchment is provided.

The second part of the thesis consists of five self-contained articles. The first article, presented in Chapter 4, examines the technical question of the required minimum in sample size of crop model runs, in order to obtain robust estimations on statistical moments of crop yields. In the second article (Chapter 5), the single crop model is developed and used to optimize management decisions in winter wheat and grain maize production at two different study sites within the Greifensee and Broye catchment, respectively, considering current and future climate conditions. In the third article (Chapter 6), the single crop model developed in Chapter 5 is extended and used to investigate the effects of different water policy schemes on the profitability and water consumption in potato cultivation in the Broye catchment under current climate conditions. The fourth article (Chapter 7) presents the bioeconomic whole farm model, applying it to optimize an arable farm's management decisions under different climate and water policy scenarios. Finally, the fifth article (Chapter 8) conducts a comprehensive

[2] AGWAM = Water Demand in Swiss Agriculture, and Sustainable Adaptive Options for Land and Water Management to Mitigate Impacts of Climate Change.

validation of the whole farm model presented in Chapter 7 comparing modeling results with the real-world situation. Furthermore, the whole farm model is used in Chapter 8 to simulate the effects of different climate as well as agricultural market scenarios.

Last but not least, the thesis' last part (Chapter 9) summarizes the overall results of the five articles and discusses them in the context of the research questions of this thesis as well as in the context of the AGWAM research project. In an outlook, implications for local policy and suggestions for future research are derived based on the thesis' findings.

2 Background

2.1 Climate change and agriculture

The agricultural sector is highly vulnerable to changes in average climate conditions and climate variability. Climate conditions have direct and indirect impacts on all three crop production levels (see Figure 2.1). Solar radiation and temperature are growth defining factors, which directly determine potential crop growth and potential crop yield. The availability of crop water (i.e., precipitation) is one growth limiting factor, which causes, when supply is limited, a decline in the rate of plant growth and crop yield. Finally, prevailing climate conditions during a crop's vegetation period affect crop growth and yields indirectly, through their impact on the distribution and spread of biotic factors, such as plant pests, diseases, weeds, and pollutants.

Furthermore, changes in the concentration of atmospheric CO_2 impact directly on the potential crop yield levels, since CO_2 is a substrate required for photosynthesis. Although it is expected, for most C3 crops, that a higher atmospheric CO_2 concentration will enhance growth, and thus increase yields (Kimball, 1983; Cure and Acock, 1986; Kimball et al., 2002; Leakey et al., 2009), its quantification is still highly uncertain (Long et al., 2006; Körner et al., 2007; Tubiello et al., 2007).

In recent years, a wide range of different studies have been conducted assessing climate change effects on agricultural systems at different geographic scales. The principal results of some of them are summarized in the following sections, in order to give some insights into understanding climate change effects on agricultural systems on a global and regional scale, and in particular for Switzerland.

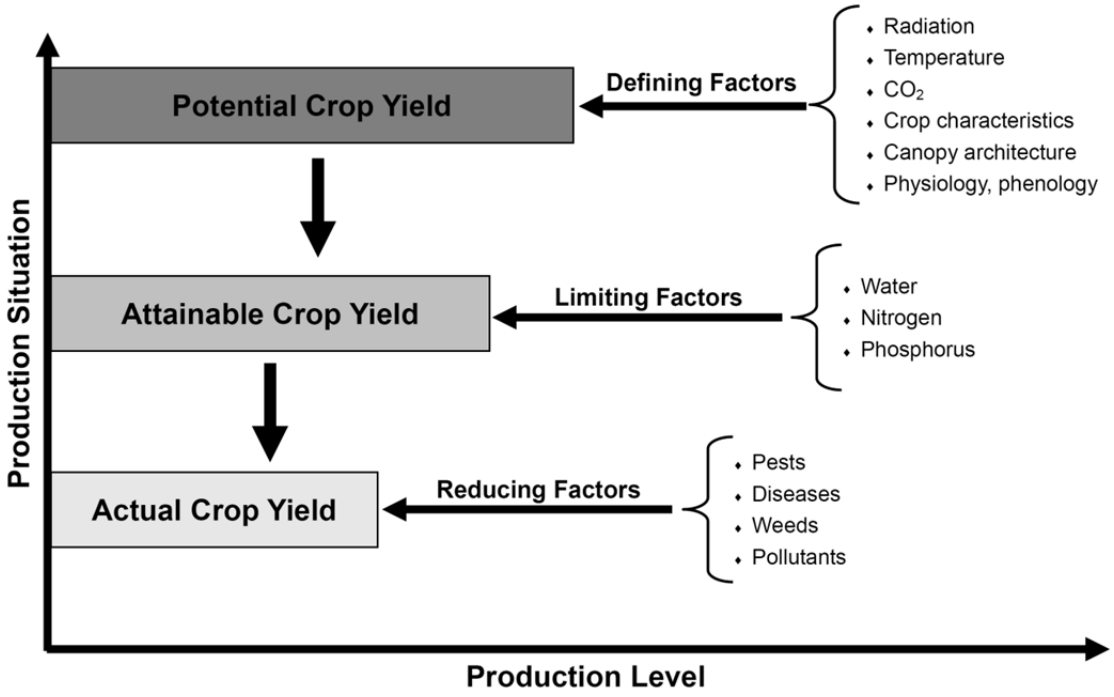

Figure 2.1: Crop production levels (modified from Rabbinge, 1993).

Parry et al. (2004) analyzed the consequences of climate change and linked socio-economic scenarios on global crop production, crop yield levels, and the risk of hunger, using crop growth simulation models and a model of the world food-trade system. Their results show that projected changes in climate conditions are expected to result in a slight decrease of world crop yields, even taking into account the directly beneficial effects of an increase in atmospheric CO_2 concentration and farm level adaptations. If only climate change effects are considered (i.e., not considering beneficial CO_2 fertilization), Parry et al. (2004) expected world crop yields to decrease by 9% to 22%, depending on the considered emission scenario. Furthermore, they found that regional differences in crop production were likely to grow under climate change, leading to substantial increases in crop prices and the risk of hunger amongst poorer nations.

For Europe, the expected impacts of climate change on agricultural systems are heterogeneous. In general, northern Europe may benefit from climate change through the expansion of suitable areas for crop cultivation, higher crop productivity, and the potential introduction of new crop-species and varieties (Carter et al., 1996; Olesen and Bindi, 2002; Lavalle et al., 2009; Iglesias et al., 2012). In southern Europe, however, the disadvantages of global warming are found to predominate (Olesen and Bindi, 2002; Iglesias et al., 2012). Besides lower crop yield levels, and higher yield variability caused by the likely increases in

water shortages and extreme weather events, southern Europe is also expected to suffer from a reduction in suitable areas for traditional crops (Olesen and Bindi, 2002). Furthermore, Iglesias et al. (2012) show that the crop productivity of wheat, maize, and soybeans will decrease in Mediterranean regions under all of their applied climate change scenarios. This is caused by a shortening of the growing period, with subsequent negative effects on grain filling[3].

In recent years, a large number of studies assessing climate change impacts on agricultural systems have also been performed for Switzerland. In the remainder of this subchapter, some of these studies are briefly discussed.

Calanca and Holzkämper (2010) analyzed climate change impacts on agrometeorological indices in the Swiss Plateau using homogenized data series for temperature and precipitation, spanning the period 1864-2009, and climate scenarios from the European research project ENSEMBLES (Hewitt, 2005). They show that the vegetation period in the Swiss Plateau will be extended by about 40 days by 2050, when compared with the reference period in the 1970s. Furthermore, their results indicate that the risk of droughts is not necessarily increased for the same time horizon, since the reductions in summer precipitation in the ENSEMBLES projections are rather small. Nevertheless, Calanca and Holzkämper (2010) point out that the climate scenarios they used in their study are fraught with a high degree of uncertainty.

Despite these rather beneficial climate change impacts on the agrometeorological production conditions in the Swiss Plateau, Torriani et al. (2007b) found, using the crop growth model CropSyst, consistently negative effects on maize and canola yield levels for the time window 2071-2100. For winter wheat, the assumed elevated atmospheric CO_2 concentrations compensate for the negative effects of higher temperatures and decreased precipitation, resulting in higher yield levels. Besides significant changes of average crop yield levels, the study by Torriani et al. (2007b) also indicates higher production risks in grain maize and canola cultivation (i.e., coefficient of yield variation), and decreased yield variability in winter wheat production under climate change.

Finger and Schmid (2008) analyzed climate change impacts on Swiss grain maize and winter wheat production using a bioeconomic modeling approach. Their approach relies on crop yield simulations performed with the crop growth model CropSyst, which are

[3] Note that the approach of Iglesias et al. (2012) accounted for direct, positive CO_2 effects on crop yields and adjustments in sowing dates, nitrogen fertilization intensity, and irrigation, but not for restrictions in the application of nitrogen fertilizer and water availability. Thus, the results described by Iglesias et al. (2012) should be considered rather optimistic from a production point of view.

integrated into an economic decision model. In doing so, their modeling approach is able to account for adaptation options with regard to sowing dates, as well as fertilization and irrigation strategies. Their study shows that such adaptation measures are very sensitive to the climate scenarios employed. Furthermore, yield levels of grain maize and winter wheat are expected to increase between 5% and 17% under climate change, while the yield variability of both crops decreases if the above mentioned adaptation measures are taken into account.

Using empirical crop yield data from farms located in the Swiss Plateau[4], Lehmann (2010) estimated crop-specific regression models to explain regional crop yield levels using regional weather, management, and soil data as explanatory variables. In addition, generated weather data, as expected for the period 2036-2064, was applied to these developed regression models in order to make projections of climate change effects on average regional crop yield levels and crop yield variability. The results of this study show that climate change will decrease average yield levels for wheat and barley in all the studied regions by up to 10%. In contrast, sugar beet tends to benefit in almost all parts of the Swiss Plateau presumably due to the changes in the yearly temperature and precipitation regimes. For potato production, the impact of climate change depends upon the region considered. In the central part of the Swiss Plateau, potato growth benefits from climate change, whilst, in contrast, reductions in yield levels of up to 8% are found in the western part of Switzerland. Regarding climate change effects on crop yield variability, Lehmann (2010) found that the assumed changes in climate conditions will *increase* the yield variability of both cereals in almost all regions, while significant *decreases* in yield variability are found for potato and sugar beet production in most regions.

A similar approach has been used by Flückiger and Rieder (1997). They analyzed relations between wheat, barley, potato, and maize yields at farm scale, and monthly weather variables, by means of regression models. As in the study of Lehmann (2010), these regression models were used to make projections of the impact of climate change on the productivity of the considered crops. In addition to the empirical crop yield weather relations, Flückiger and Rieder (1997) also assumed a crop-specific beneficial CO_2 fertilization effect[5]. Their results showed that the assumed increases in barley and maize yield levels due to higher atmospheric CO_2 concentrations, together with the extended

[4] Lehmann (2010) used crop yield data from the Farm Accountancy Data Network (FADN) (Mouron and Schmid, 2011).

[5] Flückiger and Rieder (1995) assumed an increase in crop yield levels due to a doubled CO_2 concentration of 30% for wheat, barley, and potatoes, and of 15% for maize.

vegetation period, offset the negative effects of higher temperatures. In the case of wheat and potatoes, taking into account a beneficial CO_2 fertilization effect even leads to an *increase* in average crop yield levels of 12% and 24%, respectively. Nevertheless, Flückiger and Rieder (1997) concluded that it is market liberalization, and not climate change, that will be the major driver of future changes in Swiss agriculture.

Besides the impact of climate change on crop productivity, the effects of global warming on grassland systems are also of particular importance in Swiss agriculture. Temporary and permanent grassland cover around 71% of the total agricultural surface in Switzerland (BfS, 2012), providing most of the required feeding stuff in dairy and meat production, and are thus the backbone of Swiss agriculture (Calanca and Fuhrer, 2005). Using a simple model of grass growth, Calanca and Fuhrer (2005) analyzed grassland production and its economic value under projected climate change scenarios. Assuming rather moderate climate change signals, they concluded that grassland production in Switzerland will benefit from elevated atmospheric CO_2 concentrations and more favorable temperature and radiation conditions, resulting in an increase in total grassland production of about 50%. Nevertheless, under more pronounced changes in thermal and hydrological conditions, grassland production in Switzerland will become increasingly water limited, and irrigation facilities will be required in order to meet increased water requirements.

Finger et al. (2010) used a bioeconomic model, which accounts for changes in nitrogen fertilization management, in order to estimate climate change impacts on grassland production in the Swiss Plateau. Their study indicates that grassland yield levels will increase under projected climate change *only* if the benefits of an elevated atmospheric CO_2 concentration are taken into account. Without considering the beneficial CO_2 fertilization effect, grassland yields are expected to decrease under climate change. Furthermore, they found that, irrespective of the CO_2 fertilization effect, grassland yields will become more variable under the assumed climate change projections.

Based on the review of relevant literature presented above, the following conclusions can be drawn. First, climate change effects on agricultural systems are site- and crop-specific. Second, the design of climate scenarios including assumptions about beneficial CO_2 fertilization effects are critical input parameters in studies of the impact of climate change on agricultural systems. And finally, climate change effects on agricultural productivity are most often quantified by model based approaches[6].

[6] Note that, in contrast to field trials, crop growth models easily allow the simulation of plant growth and yields under a wide range of different climate scenarios.

2.2 Adaptation to climate change

Most quantitative studies that address the vulnerability of agricultural systems to climate change focus on exposure and sensitivity, while adaptation strategies are often simplified (Reidsma et al., 2007). Nevertheless, adaptation will be one of the key factors that shapes the severity of climate change on agricultural productivity (Lobell et al., 2008). Several studies show that small and relatively inexpensive changes, such as shifting planting dates (e.g., Iglesias and Minguez, 1997; Torriani et al., 2007b), adjustments in fertilization and irrigation intensities (e.g., Finger and Schmid, 2008; Meza and Silva, 2009; Lehmann et al., 2011; Ventrella et al., 2012), alternative tillage practices (e.g., Olesen et al., 2011) or switching to other crops (e.g., Kurukulasuriya and Mendelsohn, 2008) may moderate the negative impact of climate change on agricultural systems. Furthermore, even larger benefits can be expected from more costly adaptation measures, including the development of new crop varieties, and the expansion of irrigation (Rosenzweig and Parry, 1994).

The success of adaptation measures depends, in agriculture, not only on the climate stimuli (to which adjustments are made), but also on the considered farm type, location, and the political and economic framework (Bryant et al., 2000). Following Smit and Skinner (2002), adaptation strategies in agriculture can be grouped into four different categories: (1) technological developments (e.g., the development of new crop varieties or new irrigation systems); (2) government programs and insurance (e.g., new crop insurance or government income stabilization programs); (3) farm production practices (e.g., crop substitution, production intensification, or crop mix); and (4) the financial management of farms (e.g., crop insurance, crop shares, and futures).

Adaptation responses can also be classified according to their intent. Autonomous responses are a regular part of ongoing management, and occur as a response without the conscious decision of the agent (Bryant et al., 2000; Reilly and Schimmelpfennig, 2000). On the other hand, planned adaptations are taken on the basis of the conscious decision of farmers or the public agency, based on the awareness that conditions are about to change or have changed. Finally, adaptation responses can also be categorized along another dimension, i.e., tactical versus strategic decisions (Smit et al., 1996). Strategic adaptation decisions are made based on market, climate, and other signals over multiple years (Kandlikar and Risbey, 2000), and typically involve changes in farm activities or investments in new production technologies (e.g., irrigation systems). Tactical decisions are made on a local scale, based on short term weather signals (Kandlikar and Risbey, 2000), and essentially cover management decisions such as the timing of planting, harvesting, and input use.

In this thesis, tactical and strategic adaptation strategies of farm production practices are taken into account. In particular, we consider adaptation strategies with regard to crop choice, crop land allocation, nitrogen fertilization, and irrigation. Progresses in agricultural technologies (e.g., new cultivars or more efficient pesticides) are not considered. Although technological development will have a larger impact on crop yield levels and agricultural productivity than climate change (Ewert et al., 2005), its interaction with other climate change adaptations are difficult to project (Tubiello et al., 2000).

2.3 Crop models

Mechanistic crop models[7] are mathematical models that describe crop growth and development, and their interaction with soil and the atmosphere (Wallach, 2006). Therefore, crop growth models can be seen as a set of differential or difference equations, which describe the dynamics of a system being composed of the crop, soil, and the atmosphere (Wallach, 2006; Dumont et al., 2012). In general, crop models operate with a time interval of one day, and require daily weather data as input (Nonhebel, 1994). Besides weather data, information on the initial field conditions (e.g., soil chemistry and hydraulics), modeled crop (cultivar characteristics) and field management (e.g., fertilization and irrigation) are needed as input in crop growth models.

During the early stages of crop modeling, it was thought that crop models could completely substitute field experiments (Sinclair and Seligman, 1996). However, this has proven not to be the case, since, at best, crop models should be taken as supplements to field trials, which help to identify and explain processes and parameters that are especially critical for the performance of crop growth systems (Soltani and Sinclair, 2012). However, even though crop growth models cannot produce all the answers to crop production problems, their application potential – when they are reasonably constructed – is great. For instance, crop growth models can be used as decision-support systems to help farmers: They are employed to determine optimal sowing windows (e.g., Olesen et al., 2000; Heng et al., 2007; Bassu et al., 2009) or to evaluate the effects of different nitrogen and irrigation intensities on crop yields and profits (e.g., Rinaldi, 2004; Benli et al., 2007; Singh et al., 2008; He et al., 2012; Ventrella et al., 2012). Crop models can also be useful for the identification and understanding of traits for genetic improvement. This is especially so for complex traits such as tolerance to drought, for which crop models provide assistance in understanding genotype-environment interactions (Chapman et al., 2002; Sinclair et al.,

[7] Also the terms process-based, biophysical and crop growth simulation models are frequently used.

2005; Sinclair et al., 2010). In the past few years, they have also been used to successfully evaluate the agricultural potential of different geographic regions. More specifically, crop growth models can be used to quantify and explain a region's yield gap (the difference between attainable and actual yield) (Affholder et al., 2003; Wang et al., 2011). Finally, crop models are important tools in estimating the environmental impact of different agricultural production systems, especially by estimating the impacts of different crop management practices and climate conditions on nitrate leaching (Dueri et al., 2007; Jego et al., 2008; Constantin et al., 2011) and soil erosion (Wang et al., 2008).

In recent years, crop growth models have also been intensively used to assess the effects of climate change on agricultural systems (see White et al., 2011, for an overview). In contrast to climate change impact studies based on regression models, which rely on observed empirical data, crop growth models can be used to make projections of crop growth and crop yields under environmental conditions that are beyond the observed range. Additionally, process-based crop models easily allow to assess different management options (fertilization, irrigation, soil cultivation, etc.) not only under current environmental conditions, but under future ones as well. However, the main weakness of crop models is their inability to simulate adaptations in farm management that depends on the prevailing market, policy, and weather conditions (Risbey et al., 1999).

For this thesis, the crop growth model CropSyst (Stöckle et al., 2003) is used. CropSyst is a multi-year, multi-crop cropping system, which operates on a daily time scale (Stöckle et al., 2003). It was designed to draw from the conceptual strengths of EPIC (Williams et al., 1989), but also includes a more process oriented approach to the simulation of crop growth and its interaction with management and the surrounding environment. Since CropSyst can be used to simulate water and nitrogen limited yields, a wide range of different management options, such as nitrogen fertilization, irrigation, and soil cultivation can be applied. Evaluations of CropSyst have shown that the model is suitable for the simulation of cropping systems in a variety of conditions, including different locations, soil types, crops, and management options (see Stöckle et al., 2003, for an overview). Nevertheless, a proper site-specific calibration of CropSyst requires highly detailed information on the initial soil conditions and modeled cultivar, which it is not always available, and is furthermore confounded by significant spatial variability under typical field situations (Stöckle et al., 2003).

For this thesis, we use a site-specific CropSyst calibration performed by (Klein et al., 2012). This CropSyst calibration is based on local yield records from the Swiss Farm Accountancy Data Network (FADN) (Mouron and Schmid, 2011) and therefore has an advantage in that CropSyst was calibrated against farm yield observations and not *only* against yield records

from field trials, which might not be representative of the real-world situation. Furthermore, the validation of this calibration set-up against data from a long term field trial, which contained detailed information on fertilizer applications, showed good agreement (Klein et al., 2012).

2.4 Bioeconomic modeling

As mentioned in Chapter 2.3, crop models cannot directly account for adaptation measures likely to be taken by farmers under changing environmental and socio-economic conditions. Thus, the neglect of such potential adjustments in crop management options can result in an overestimation of the negative effects of climate change on agricultural systems. In this thesis, we overcome this drawback by using a bioeconomic modeling approach that links the biophysical crop growth model CropSyst with an economic decision model.

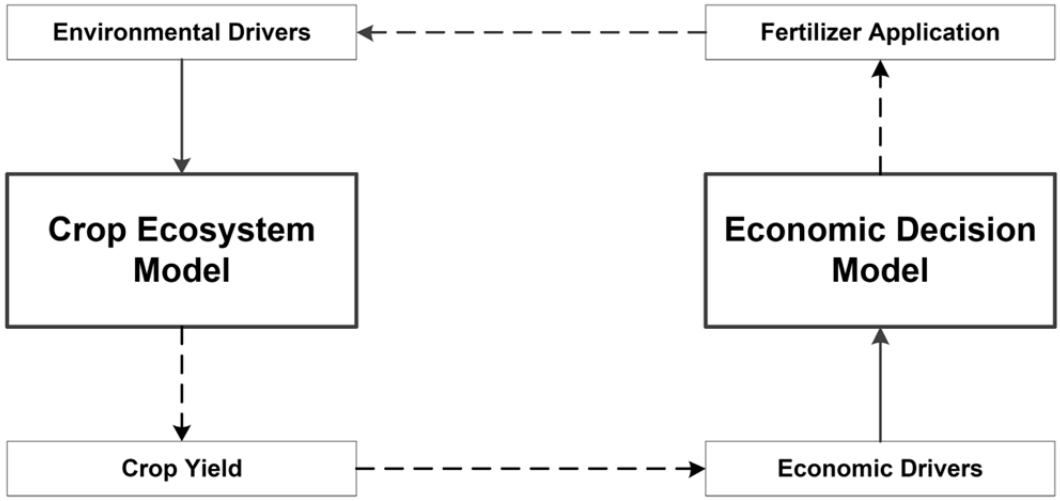

Figure 2.2: Simplified bioeconomic model. Dotted connectors represent feedback from system states to drivers in the coupled model, dashed connectors represent feedback between processes within the bioeconomic model (modified from Antle et al., 2001).

A bioeconomic model is generally known as a link between models from different disciplines to provide multi-scaled and multi-disciplinary answers to a given problem (Flichman et al., 2011). In agriculture, a bioeconomic model is defined as a model that links formulations describing farmers' resource management decisions to formulations that illustrate current and alternative production possibilities (in terms of required inputs) in order to achieve certain outputs and associated externalities (Janssen and van Ittersum, 2007). Figure 2.2 describes a typical simplified agricultural bioeconomic model. The

economic decision model determines the fertilization intensity as a function of economic drivers and crop yields, while the crop yields in the ecosystem model are defined as a function of exogenous environmental drivers (e.g., soil or climate) and the intensity of fertilization (Antle et al., 2001). The bioeconomic model presented in Figure 2.2 can be used, for instance, to optimize the intensity of fertilization with respect to a given objective function criterion (e.g., agricultural income or farmer's utility).

Following Janssen and van Ittersum (2007), bioeconomic modeling approaches have the following advantages in respect to other methods: (1) they are based on constrained optimization procedures (e.g., limited farm resources), and thereby seem to better match the reality of farmers; (2) bioeconomic models can consider many activities, restrictions, and new production techniques simultaneously (Weersink et al., 2002); (3) the effects of changing input parameters (e.g., prices and climate scenarios) can be easily assessed through sensitivity analysis (Wossink and Renkema, 1994); and (4) they can be used for both short term and long term explorations (van Ittersum et al., 1998). Taking these advantages into consideration, bioeconomic models are very appropriate modeling tools to assess the impact of climate change on agricultural systems.

In this thesis, we use two different bioeconomic models. The first model focuses on the field scale and takes into account a wide range of crop-specific agronomic management decisions with regard to nitrogen fertilization and irrigation. This model is applied to winter wheat and grain maize cultivation in Chapter 5 as well as to potato production in Chapter 6. The second model focuses on the farm scale. The development and different applications of this model are described in Chapter 7 and Chapter 8. The whole farm model developed in this thesis considers six different crops (winter wheat, winter barley, winter rapeseed, grain maize, potatoes, and sugar beets) and optimizes management decision variables with regard to crop choice, crop land allocation, and crop-specific nitrogen fertilization and irrigation strategies. Since the complexity of the farm scale model is much higher than in the crop-specific field scale model, compromises with respect to the number of crop-specific agronomic decision variables (i.e., nitrogen fertilization and irrigation strategy) had to be made.

Nevertheless, *both* models developed in this thesis are based on a mechanistic normative modeling approach. Mechanistic models rely on existing knowledge and theory (Austin et al., 1998). In contrast to empirical models, which try to find relationships in the observed data (Austin et al., 1998), mechanistic models are suitable for extrapolations (Antle et al., 2001). The term 'normative' refers to the fact that both developed models are based on a normative mathematical programming (NMP) approach, which optimizes the decision variables, while maximizing the objective set (Hazell and Norton, 1986). Normative

mathematical optimization approaches have the advantage that they do not have to be calibrated to historical data, and basic knowledge of the system is sufficient for constructing the model (Buysse et al., 2007). However, since NMP approaches are not calibrated to the real-world situation, they do not necessarily guarantee that the observed or reference data is reproduced. This is in contrast to positive mathematical modeling approaches, in which some parameters are adjusted to be able to reproduce exactly a given reference situation (Buysse et al., 2007).

2.5 Genetic algorithms

Most studies using bioeconomic field or farm scale models are based on linear programming (see Janssen and van Ittersum, 2007, for an overview). However, linear programming approaches can only be used under the assumption that the farm managers have perfect knowledge, decisions are made in a risk-neutral environment, and that the market is perfectly competitive appropriate (El-Nazer, 1984). In addition, linear programming techniques are limited to linear objective functions and constraints. Thus, if stochastic weather and price data are incorporated into the modeling approach, and risk averse decision makers are assumed, other programming techniques are required. In order to overcome these limitations, we use, for this thesis, a genetic algorithm (GA) as optimization technique.

GAs belong to the class of evolutionary algorithms and are a heuristic optimization technique. They were originally developed by Holland (1975), and are based on the biological concept of genetic reproduction by mimicking the natural selection processes of evolution (Radcliffe and Wilson, 1990). In contrast to linear optimization techniques, GAs can handle any kind of objective function or constraint defined in the discrete, continuous, or mixed search space (Gen and Cheng, 2000). Furthermore, the incorporation of stochastic variables into the optimization model is possible using GAs.

The following three main characteristics can be assigned to GAs (Yu and Gen, 2010):

- *GAs are population-based:* GAs maintain a group of individuals (=potential solutions) called a population, to optimize the problem in a parallel way.
- *GAs are fitness-oriented*: Every individual is represented by its code, and its performance is evaluated by its fitness value. Individuals with better fitness values are preferred.
- *GAs are variation-driven*: Individuals undergo a number of variation operations (e.g., mutation, crossover, or recombination) to mimic genetic changes.

2.5.1 Fundamentals of genetic algorithms

Within a GA, decision variables are most commonly coded as binary strings on a chromosome (=individual). A chromosome comprises all the decision variables, called genes, of an optimization problem and stands for a potential solution to the optimization problem (Figure 2.3). The number of digits assigned to a gene determines the numerical accuracy of a decision variable.

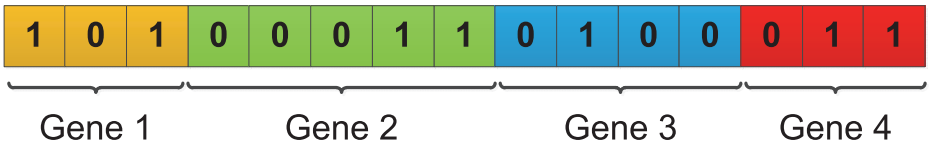

Figure 2.3: Schematic structure of a binary chromosome.

The optimization process in GAs is presented in Figure 2.4. As a first step, an initial population comprising different individuals (=chromosomes) is randomly generated. Next, the feasibility of each solution is examined. If a solution is feasible, its fitness can directly be evaluated. If a solution is not feasible (i.e., the solution violates the constraints), a penalty function is used which decreases the solution's fitness value. In other words, GAs transform a constrained problem into an unconstrained problem by penalizing solutions that violate the implemented constraints. Finally, a new population (i.e., a new generation) of potential solutions evolves by performing genetic operations such as reproduction, crossover, and mutation on genes in the current population, and placing the resulting chromosomes into the succeeding population. These processes are repeated until the optimization converges to an optimal solution.

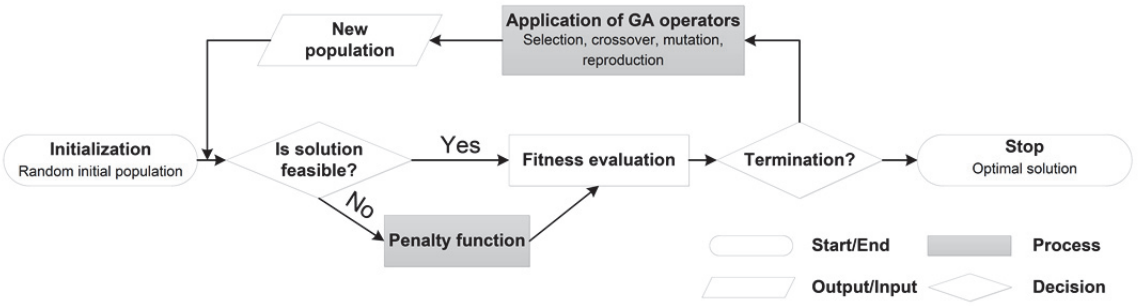

Figure 2.4: Optimization procedure of a genetic algorithm.

Reproduction involves the selection of two parent chromosomes from a current population. The higher the fitness value of an individual, the higher the probability that it will be selected for reproduction (Lee and Takagi, 1993). After the selection of the parent chromosomes, crossovers are performed according to the implemented crossover probability (Lee and Takagi, 1993). If a crossover occurs, parent genes are changed after the crossover point, resulting in modified offspring chromosomes (see Figure 2.5). Besides crossovers, chromosomes can also be modified by mutation. Each bit has a certain probability ('mutation probability') that it will be flipped (see Figure 2.5), which changes the chromosome's binary code.

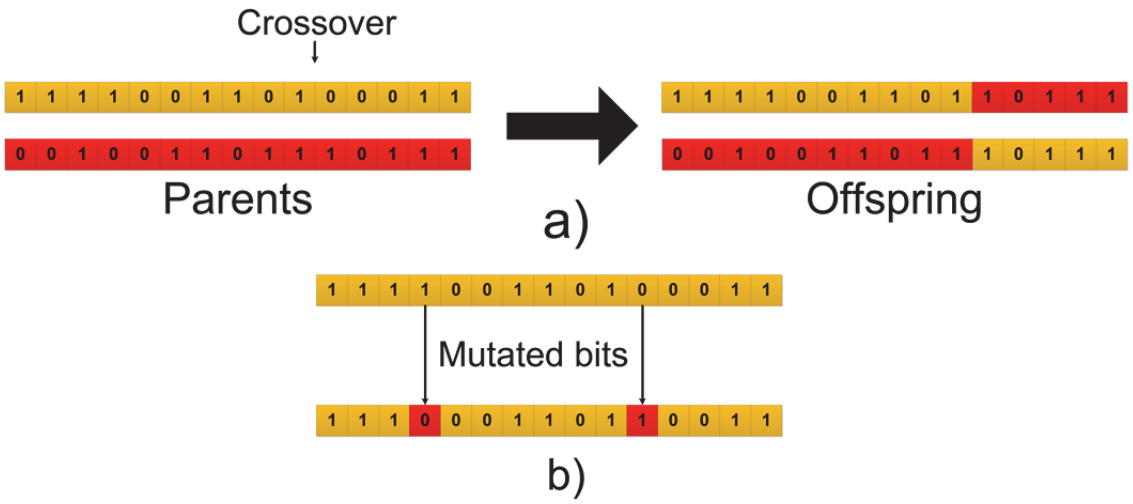

Figure 2.5: Genetic operations: (a) crossover, and (b) mutation.

2.5.2 Advantages and limitations of genetic algorithms

One of the most important advantages of GAs lies in the fact that the algorithm and its implementation are intrinsically simple (Chacon et al., 1998). As mentioned above, GAs can

handle any kind of objective function and constraint defined in the discrete, continuous, or mixed search space (Gen and Cheng, 2000). Furthermore, GAs are known to perform robustly if the fitness function is noisy (Mitchell, 1998). Compared with other weaker optimization methods (e.g., random search), GAs are expected to be superior if the search space is large and cannot be searched exhaustively (Mitchell, 1998). Furthermore, due to parallelism, GAs are well suited to solve problems where the space of all potential solutions is too huge to search exhaustively in any reasonable amount of time (Bajpai and Kumar, 2010). In addition, the use of parallelism enables GAs to modify many parameters simultaneously, producing multiple and equally good solutions to the same problem (Bajpai and Kumar, 2010).

In spite of these advantages, GAs also have some limitations. First, it is important to keep in mind that since GAs are a heuristic optimization method there is no absolute guarantee that the global optimum will be reached in an appropriate amount of time. Additionally, it has been shown that the performance of binary GAs is satisfactory only for small and moderate sized problems. For high dimensional problems, in which a higher degree of precision is required, binary GAs require huge computational time and memory (Goldberg, 1991). This problem can be overcome by using real coded GAs[8], which have now been established as superior to binary coded GAs for continuous optimization problems (Janikow and Michalewicz, 1991).

2.5.3 Applications of genetic algorithms on agricultural systems

During the last two decades, GAs have been applied in many disciplines, including applications in the agricultural research field. Cacho and Simmons (1999) used a binary GA to optimize a farm portfolio. They concluded that GAs have some features which are very attractive in the agricultural economics research field. On the one hand, the genetic memory in GAs is an improvement on the treatment of priors in certainty equivalent models. On the other, the GA model used in their study allowed the modeling of risk responses over time.

Musshoff and Hirschauer (2009) developed a methodological hybrid consisting of GA and Monte-Carlo simulations. This hybrid approach was applied to the production-planning problem of a German arable crop farm. They found that the GA ensured the optimization procedure remains applicable, even in the case of complex stochastic information. Furthermore, the hybrid approach developed was able to improve considerably farm program decisions.

[8] In contrast to binary GAs, the genes in real coded GAs are coded as real variables.

Mayer et al. (1996) compared the performance of different heuristic optimization techniques (i.e., hill climbing, direct search, GAs, and simulated annealing) using a whole farm dairy model. Their whole farm model considered seventeen different decision variables with regard to pasture, forage, and dairy cow management, applying the farm gross margin as an objective function. The results of their study showed that the performance of the GA and the simulated annealing technique was clearly higher than the performance of the hill climbing and direct search optimization approaches.

Ortega Álvarez et al. (2004) applied a GA and the MOPECO[9] model to determine an optimum cropping pattern and irrigation strategy, using an optimization criteria based on the expected farm profit and the economic risk associated with annual climatic variability. In their work, the use of the GA was necessary because the relations between the decision variables (e.g., irrigation depth) and the objective value were non-linear and very complex.

Furthermore, GAs have also recently been employed in several studies for parameter estimation of crop models (Pabico et al., 1999; Bulatewicz et al., 2009; Dai et al., 2009; Klein et al., 2012).

[9] The MOPECO model is a tool for identifying optimal irrigation management strategies and production plans (Ortega Álvarez et al. 2004).

3 AGWAM and study region

3.1 The NRP 61 project AGWAM

This PhD thesis is embedded in the NRP 61[10] project AGWAM. The principal objective of AGWAM is to develop sustainable strategies for agricultural land use and farm management in order to mitigate the negative impacts of climate change on the agricultural water demand of two study regions, located in Switzerland, around the year 2050 (Fuhrer et al., 2009). Specifically, the AGWAM project aims to answer the following three research questions:

1. *What is the water consumption by agriculture in two selected regions (catchments) under present and future conditions (considering climate, economy and agricultural policy), and how large is the risk to agricultural production due to reduced water availability?*
2. *How can we optimize strategies for water conservation in agricultural land use (forage, crop and livestock production) at the regional (catchment) scale, and at the scale of individual farms, and what are the environmental impacts of such strategies?*
3. *What recommendations for management and policy measures can be made to implement sustainable water use in Swiss agriculture considering a range of possible climate change scenarios?*

In order to answer these research questions, the AGWAM project is divided into five work-packages (WP) (see Figure 3.1). WP1 develops scenarios of economic, political, and climatic changes to 2050. In WP2, spatial optimization routines are developed, which are then used to maximize agricultural productivity, while minimizing management-related environmental impacts such as water consumption and erosion. WP3, in which this thesis is embedded, builds a farm scale model and uses it to optimize farmers' management decisions under different climate and socio-economic scenarios. In WP4, the environmental impacts of the optimal land use schemes identified in WP2, and optimal management decisions at farm scale developed in WP3, are assessed using a Life Cycle Assessment (LCA) approach. Finally, in WP5, results from WP2, WP3, and WP4 are

[10] The National Research Programme 61 'Sustainable Water Management' (NRP 61) develops scientific foundations and methods for the sustainable management of water resources in Switzerland (NRP61, 2008).

amalgamated in order to derive recommendations for sustainable adaptation strategies at the spatial (regional) and farm scale (Fuhrer et al., 2009).

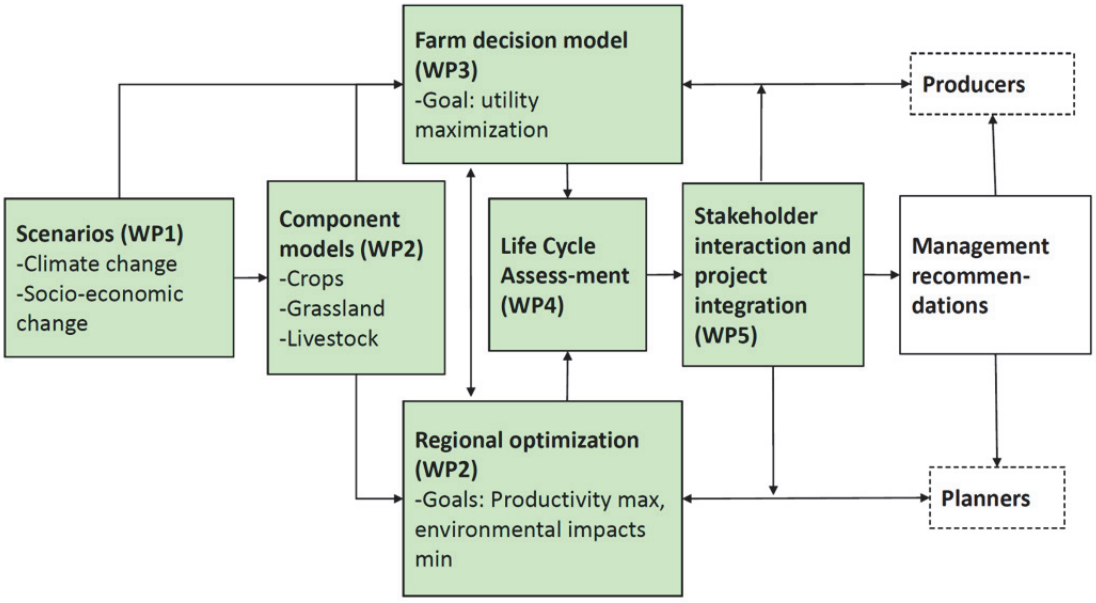

Figure 3.1 Overview of the AGWAM project (Fuhrer et al., 2009).

As mentioned above, AGWAM focuses on two contrasting study regions in Switzerland: the Broye and the Greifensee catchment (Figure 3.2). Since the studies of this thesis are primarily concerned with the Broye catchment[11], this region is presented in more detail in the next subchapter.

[11] Note that the study presented in Chapter 4 and Chapter 5 is not only about climate change impacts in the Broye but also in the Greifensee catchment.

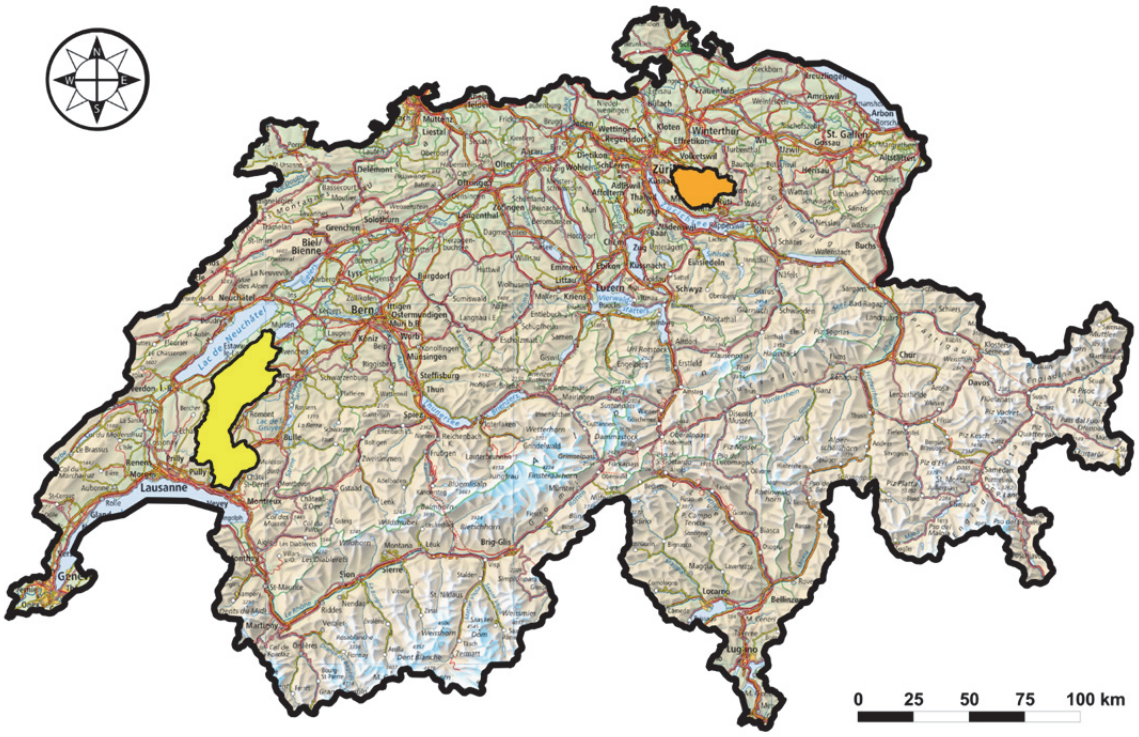

Figure 3.2: Location of Broye (yellow area) and Greifensee (orange area) catchment. *Source: Swisstopo.*

3.2 The Broye catchment

The Broye catchment is located in western Switzerland in the canton of Fribourg and Vaud, and covers a total area of 598 km^2. The catchment's principal river, the Broye, originates in the Prealps in the canton of Fribourg in Semsales, and flows through Moudon and Payerne before reaching the lake of Morat, about 40 km to the north of its source (see Figure 3.3). The average annual discharge of the Broye at Payerne amounts to 8.9 m^3·s^{-1}, and its highest discharges can be observed at the end of July (Hari et al., 2006).

Agriculture plays an important role in the Broye catchment, and more than 70% of the region is used for agriculture. The northern plain of the region is dominated by arable farms with few livestock, while mixed farms with dairy or beef cattle, as well as crop production, prevail in the region's hilly southern part (BLW, 2010). In 2009, about 40% of the region's total agricultural surface was covered by permanent grasslands (BLW, 2010). Cereals made up about 22%, and temporary grassland about 17%, of the total agricultural area (BLW, 2010). Furthermore, it is important to point out that potato and sugar beet production have a relatively high importance in Broye, when compared with rest of Switzerland. The average total share of these two tuber crops make up more than 5.7% of

the region's agricultural surface (BLW, 2010)[12]. In terms of livestock, in 2009 the region's farmers held over 30,000 dairy cows; other livestock types (swine, poultry, small ruminants etc.) are of minor importance (BLW, 2010).

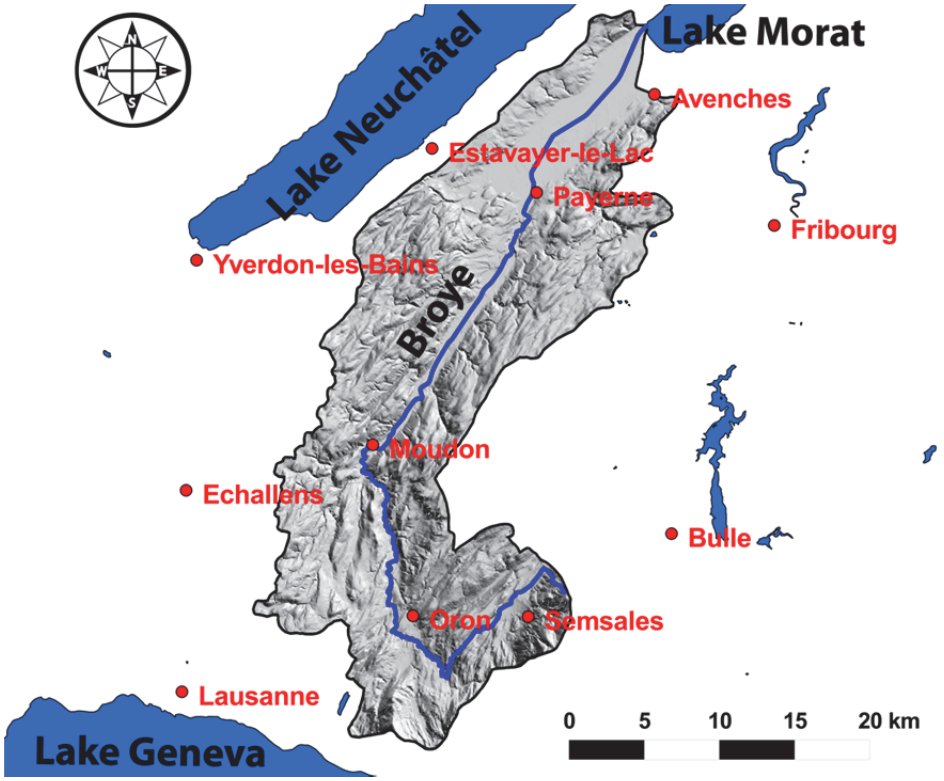

Figure 3.3: Broye catchment. *Source: Swisstopo.*

Climate conditions in the north of the Broye region differ substantially from those in the south. At Payerne, the annual average precipitation is about 885 mm. At Moudon, however it amounts to 1108 mm, and at Semsales to 1546 mm per year (Brun, 2010). Thus, a decreasing gradient in the annual irrigation amount from north to south can be observed in the Broye catchment. Differences in temperature regimes between different sites within the Broye region can be explained mainly by the altitude of those different sites. At lower sites (i.e., in the northern part of the region), the annual temperature profile is comparable with other sites located in the Swiss Plateau (Brun, 2010).

The dry climate conditions in the northern parts, and the relatively large crop shares of high value crops (e.g., potatoes and sugar beets), have promoted irrigation as a management option in the arable agriculture of the Broye catchment. Currently, about

[12] Note that in 2011, the average share of potatoes and sugar beets amounted to 1.0% and 1.8%, respectively, of the total agricultural land in Switzerland (BfS, 2012).

1,377 hectares in the region are under irrigation (Robra and Mastrullo, 2011). The most important irrigated crop is potato, which makes up about 40% of the total irrigated land (Robra and Mastrullo, 2011). Besides potatoes, 50% of the total irrigated surface is used for maize, tobacco, and sugar beet production (Robra and Mastrullo, 2011).

Due to increasing quality demands from the food processing industry, decreasing spring and summer precipitation, and higher temperatures during the vegetation period, agricultural water demand has increased in the Broye catchment in recent years (Mühlberger de Preux, 2008). Since water that is destined for irrigation is almost exclusively withdrawn from the region's rivers, surface water bodies in the Broye catchment repeatedly suffer low water levels in the summer months.

In the future, the agricultural water demand in the Broye catchment will further increase due to climate change. Because the easily usable sources for irrigation in the region (i.e., from rivers) are already almost exhausted, changes in the prevailing agricultural production schemes, and in the region's water policies, are necessary.

4 Sample size requirements for assessing statistical moments of simulated crop yield distributions[13]

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ABSTRACT

Mechanistic crop growth models are becoming increasingly important in agricultural research and are extensively used in climate change impact assessments. In such studies, statistics of crop yields are usually evaluated without the explicit consideration of sample size requirements. The purpose of this paper was to identify minimum sample sizes for the estimation of average, standard deviation and skewness of maize and winterwheat yields based on simulations carried out under a range of climate and soil conditions. Our results indicate that 15 years of simulated crop yields are sufficient to estimate average crop yields with a relative error of less than 10% at 95% confidence. Regarding standard deviation and skewness, sample size requirements depend on the degree of symmetry of the underlying population's distribution. For symmetric distributions, samples of 200 and 1500 yield observations are needed to estimate the crop yields' standard deviation and skewness coefficient, respectively. Higher degrees of asymmetry increase the sample size requirements relative to the estimation of the standard deviation, while at the same time the sample size requirements relative to the skewness coefficient are decreased.

KEYWORDS

CROP YIELD DISTRIBUTIONS; STATISTICAL MOMENTS; SAMPLE SIZES REQUIREMENTS; CROP MODELS; STOCHASTIC WEATHER GENERATOR; CLIMATE CHANGE

[13] Lehmann, N., Finger, R., Klein, T., Calanca, P. (2013). , *Agriculture (MDPI)* 3(2), 210-220.

4.1 Introduction

Mechanistic crop growth models are of high importance in agricultural research. They offer a cost-effective tool for simulating plant growth under a wide range of management options and environmental conditions (Jalota et al., 2007). The field of application of crop models is wide: For instance, new management technologies can be tested in quasi-field trials and agro-environmental problems can be addressed at field-, farm- or watershed-level (Hoogenboom, 2000). Crop growth simulation models can also be used to identify critical traits with respect to survival rates and yield levels (e.g. Sinclair et al., 2005; Sinclair et al., 2010). They are further extensively employed for climate change (CC) impact assessments (e.g. Tubiello et al., 2000; Donatelli et al., 2002; Challinor et al., 2004; Torriani et al., 2007b; Finger et al., 2010; Finger et al., 2011), in which the goal is often to derive crop yield distributions for varying climate conditions and management options, in particular with respect to irrigation, fertilization intensity or soil cultivation (e.g. Tubiello et al., 2000; Finger et al., 2011; Ventrella et al., 2012; Lehmann et al., 2013).

Optimal crop- and site-specific management patterns highly depend on the prevailing climate conditions. Reliable information concerning the distribution of yields can thus be obtained only from simulations spanning a sufficiently large number of years (Jame and Cutforth, 1996). In principle this is not a problem, in particular if climate records are developed with the help of stochastic weather generators (Apipattanavis et al., 2010). In practice, however, the computational burden can easily become a critical issue. For instance, the simulation of crop growth during a single vegetation period with the crop model CropSyst requires about 7 seconds on a common PC (Intel Pentium Core(TM) i5 at 3.33GHz). Thus, the decision to run one hundred or one million simulations is not without consequences. Computational constraints are even more relevant if crop models are applied in a spatially explicit setup (e.g. Liu et al., 2007) or if a large number of management options is optimized simultaneously by heuristic optimization techniques (e.g. Royce et al., 2001; Lehmann et al., 2013).

The choice of an adequate sample size is a well-known problem in statistics (Cochran, 1977; Noether, 1987; Adcock, 1997) and is crucial for the analysis of yield distributions. Yet, it has never been addressed in a systematic way in agronomic studies and climate change impact assessments. A review of the existing literature indicates a wide range of assumptions made at this stage. For instance, Marco et al. (2009) consider yield records extending over 100 years to derive information on mean and standard deviation of crop yields, whereas Tingem et al. (2009) rely on 50-year records to simulate mean yield levels. Next, Thornton et al. (2009) use 30 repetitions to estimate the first two statistical moments, while only 25 runs are used by Finger and Calanca (2011) to estimate also

skewness. Finally, Kapphan et al. (2012) use 1000 crop yield simulations in order to estimate climate-related risks and to design optimal crop yield insurance contracts.

Under the assumption that samples are normally distributed, statistical theory provides solutions regarding the sample size requirements for the estimation of both the mean as well as the standard deviation. In the former case, the minimum sample size n_μ necessary to obtain an estimate with an maximum absolute error of d at a confidence level α can be given following Cochran's sample size formula (Cochran, 1977):

$$n_\mu > \left(\frac{z_{\alpha/2}}{d}\right)^2 \cdot \sigma^2 \tag{4.1}$$

where $z_{\alpha/2}$ is the upper $(1-\alpha/2)$ quantile of the standard normal distribution and σ^2 is the population variance. Regarding standard deviation, the minimum sample size n_s to obtain an estimate with the relative error d_s can be determined from the method of Thompson and Endriss (1961):

$$n_s \approx 1 + 0.5 \cdot \left(\frac{z_{\alpha/2}}{d_s}\right)^2 \text{ with } d_s = \frac{|s-\sigma|}{\sigma} \tag{4.2}$$

where s is the sample standard deviation, which represents an unbiased estimate for the underlying population statistics σ.

Distributions of crop yields, however, does only seldom follow the normal distribution (Harri et al., 2009). Furthermore, Equations 4.1 and 4.2 do not provide guidance concerning the sample size requirements relative to the estimation of higher statistical moments, in particular skewness, which is of great importance for many applications in agricultural economics (Groom et al., 2008).

Against this background, the aim of this study was to investigate sample size requirements for the estimation of the first three statistical moments of crop yield distributions. The analysis is based on a large simulation experiment conducted with the crop growth model CropSyst (Stöckle et al., 2003). Given the fact that yield distributions may vary considerably in shape depending on crop, climate and soil characteristics, we set up our simulation study as a combinatory experiment with two crops, viz. winterwheat (*Triticum aestivum L.*) and maize (*Zea mays L.*), two sites at the Swiss Plateau, viz. Payerne and Uster, and two climate scenarios, viz. a baseline scenario reflecting current climatic conditions and a future scenario characterized by markedly higher temperature and reduced summer precipitation amounts.

4.2 Methods

CropSyst is a deterministic, process-based crop growth model, which simulates crop growth at a daily time scale (Stöckle et al., 2003). In order to drive the biological and environmental processes, CropSyst requires daily weather data along with the specification of soil and crop characteristics (Stöckle et al., 2003).

In our study CropSyst was used to simulate crop yields at Payerne (6°57' E, 46°49' N, 490 m a.s.l.) and Uster (8°42' E, 47°21' N, 440 m a.s.l). Payerne is located in western Switzerland and has relatively low annual precipitation (885 mm per year). Uster lies in the northeastern part of Switzerland and is characterized by more humid conditions (1183 mm precipitation per year). We employ soil properties following Lehmann et al. (2013), with fractions of sand, clay and silt of 62%, 12% and 26% at Payerne and 66%, 12% and 22% at Uster.

The crops considered for our analysis are grain maize, a warm season crop being particularly sensitive to drought at flowering (Richards, 1996), and winterwheat, a cool season crop being prone to excess temperature (Delcourt and van Kooten, 1995), which is sown in autumn and harvested in summer. Site specific crop parameters for maize and winterwheat were obtained from results of the calibration exercise described in Klein et al. (2012). Following (Lehmann et al., 2013), the sowing date of winterwheat was fixed at 10 October whereas grain maize was sown when the 5-day average air temperature exceeded 10°C. Furthermore, standard nitrogen fertilization amounts of 140 $kg \cdot ha^{-1}$ and 110 $kg \cdot ha^{-1}$ were assumed for winterwheat and maize, respectively (Amaudruz et al., 2011). In addition, identical initial soil conditions with respect to the concentrations of organic matter and nitrogen were used in each year in order to avoid distortions due to dynamic effects in soil nutrient availability. Thus, all variations in simulated crop yields were only due to differences in weather conditions. Effects of elevated CO_2 concentrations on crop growth were not taken into account, because its quantification is still highly uncertain (Körner et al., 2007).

1500 years of synthetic daily weather data was generated consistently with observations for the reference period of 1981-2009 (*Baseline*) as well as for a climate change (*CC*) scenario valid for 2036-2065 using the stochastic weather generator LARS-WG (Semenov and Barrow, 1997; Semenov et al., 1998). As detailed in (Lehmann et al., 2013), the *CC* scenario was specified according to simulations performed with the ETHZ-CLM regional climate model (Jaeger et al., 2008) in the context of the ENSEMBLES experiment (van der Linden, 2009) assuming a A1B emission pathway (Nakićenović and Swart, 2000). The scenario projects increases in monthly average temperatures between 2.0°C in winter and

4.0°C in summer months. Regarding average precipitation, only in summer months significant changes of up to -30% are found. Given the underlying assumption in LARS-WG (Semenov and Barrow, 1997; Semenov et al., 1998), the simulated data can be considered as representing 1500 independent realizations of annual weather states.

For each combination of crop × location × scenario, the synthetic weather data was used as input to CropSyst for the simulation of 1500 crop yields. These were assumed to represent the underlying yield population, with corresponding statistical moments denoted as μ_{ref} (mean yield), σ_{ref} (standard deviation of crop yields) and γ_{ref} (skewness of crop yields). In order to analyze the effect of different sample sizes on the robustness and accuracy of the estimated statistical moments and to determine minimum sample size requirements, the following procedure was implemented:

1.) 5000 samples of crop yields were drawn without replacement from the population for sample sizes i =5,10,15,...,1500..

2.) For each sample size i and realization j, mean ($\hat{\mu}_{ij}$), standard deviation ($\hat{\sigma}_{ij}$) and skewness ($\hat{\gamma}_{ij}$) were estimated based on the drawn sample.

3.) Relative deviations of the individual estimates from their reference values were computed for all moments as:

$$\Delta_{\hat{\mu}_{ji}} = \left| \frac{\hat{\mu}_{ji} - \mu_{ref}}{\mu_{ref}} \right| \tag{4.3}$$

with analogous equations for the standard deviation and the skewness. Here, $\Delta_{\hat{\mu}_{ij}}$ is the relative difference of the mean yield $\hat{\mu}_{ij}$ in the sample j =1,2,3,...,5000 of size i =5,10,15,...,1500 from the population's mean yield μ_{ref}.

4.) Finally, upper 95%-quantiles for the distributions of $\Delta_{\hat{\mu}_{ij}}$, $\Delta_{\hat{\sigma}_{ij}}$ and $\Delta_{\hat{\gamma}_{ij}}$ were computed for each sample size i. This measure can be used to determine the minimum sample size leading for 95% of all 5000 samples to a relative error smaller than a pre-defined level Δ = 5, 10, 15 and 25%. The 95%-quantile has been chosen because it represents a robust measure and can directly be compared with the 95%-confidence interval usually applied in conjunction with Equations 4.1 and 4.2.

4.3 Results

Figure 4.1 shows the distributions of the simulated 1500 crop yields for all considered simulation settings. The corresponding statistical moments are presented in Table 4.1. Since winterwheat is already harvested in early summer, it is less exposed to summer droughts and exhibits a narrower yield distribution than grain maize. Figure 4.1 further suggests a smaller spread of yields at Uster than at Payerne owing to the relatively more humid climate conditions at the former location. Average yield levels are reduced for both crops and at both locations under *CC*. The null hypothesis of normality is rejected by a Kolmogorov-Smirnov test for all scenarios except for grain maize at Payerne and winterwheat at Uster both simulated under *CC* climate conditions.

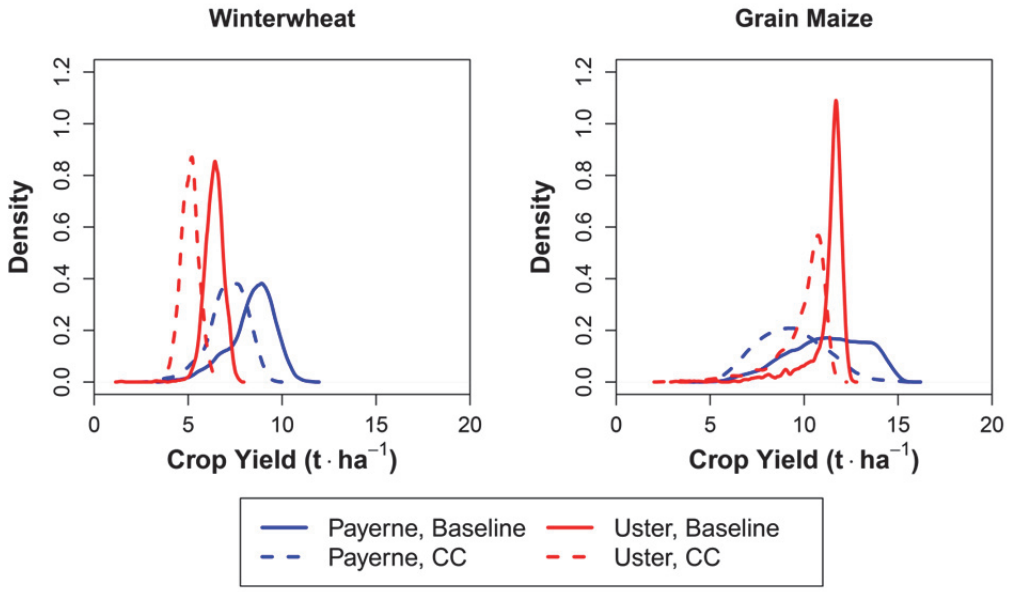

Figure 4.1: Simulated crop yield distributions.

Figure 4.2 shows the relationship between the number of considered weather years and the 95%-quantile of the relative errors of the estimated statistical moments at the example of the winterwheat simulation at Payerne under *Baseline* climate conditions. In all circumstances, relative errors of moment estimates computed according to Equation 4.3 decrease with increasing sample size. As expected from statistical considerations, relative errors of mean yields are smaller than relative errors of estimated standard deviations, which in turn are smaller that relative errors of skewness coefficients. Overall, the results in Figure 4.2 suggest that while about 10 samples are sufficient to estimate average yields with a relative error of less than 10% at 95% certainty, considerably larger samples are needed to estimate higher order moments at the same level of accuracy.

Table 4.1: Statistical moments of simulated yield distributions.

	Payerne			
	Winterwheat Baseline	*Winterwheat CC*	*Maize Baseline*	*Maize CC*
Mean yield μ_{ref} (t·ha^{-1})	8.393	7.109	11.221	9.318
Standard deviation σ_{ref} (t·ha^{-1})	1.212	1.050	2.027	1.761
Coefficient of variation	14.4%	14.8%	18.1%	18.9%
Skewness γ_{ref}	−0.755	−0.655	−0.345	0.270
	Uster			
	Winterwheat Baseline	*Winterwheat CC*	*Maize Baseline*	*Maize CC*
Mean yield μ_{ref} (t·ha^{-1})	6.375	5.086	11.261	9.881
Standard deviation σ_{ref} (t·ha^{-1})	0.515	0.469	1.066	1.386
Coefficient of variation	8.1%	9.2%	9.5%	14.0%
Skewness γ_{ref}	−1.220	−0.050	−2.892	−1.890

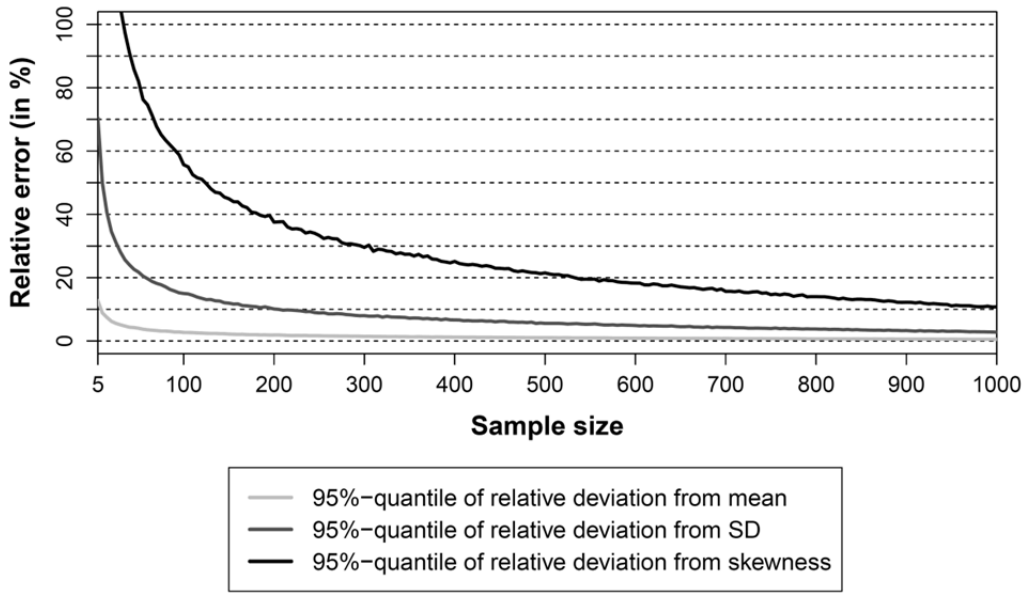

Figure 4.2: Relative error of estimated statistical moments as a function of sample size. Simulations of winterwheat yields at Payerne under *Baseline* climate conditions.

Sample size requirements to obtain moments estimates with a relative accuracy of better than 25%, 15%, 10% and 5% at 95% confidence are summarized in Tables 4.2 and 4.3. These figures suggest that a sample size of 15 observations is for all scenarios sufficient to obtain estimates of the mean yield with a relative error of less than 10%. With respect to mean yield estimations, differences in sample size requirements between the two sites reflect the overall smaller coefficients of variation at Uster than at Payerne.

Much larger sample sizes are required in order to obtain reliable estimates of crop yields' standard deviations, with substantial differences depending on scenario. For instance, 670 observations are required to estimate the standard deviation of maize yields in the

Baseline scenario at Uster to within 10% of the reference at 95% certainty. Conversely, already 120 observations are sufficient to estimate the standard deviation of maize yields at Payerne with the same accuracy and certainty level.

Table 4.2: Minimum sample sizes for different relative errors at Payerne.

	Winterwheat Baseline			*Winterwheat CC*			*Maize Baseline*			*Maize CC*		
Relative Error [a,b]	μ	σ	γ	μ	σ	γ	μ	σ	γ	μ	σ	γ
<25%	5	40	390	5	40	535	5	25	710	5	30	1020
<15%	5	100	750	5	105	900	10	60	1060	10	75	1280
<10%	10	205	1040	10	210	1155	15	120	1275	15	145	1400
<5%	35	580	1355	35	585	1405	50	400	1440	55	450	1475

[a] All values shown in Table 4.2 correspond to the 95%-quantile.

[b] μ = mean yield; σ = standard deviation of yields; γ = skewness of yields

Table 4.3: Minimum sample sizes for different relative errors at Uster.

	Winterwheat Baseline			*Winterwheat CC*			*Maize Baseline*			*Maize CC*		
Relative Error [a,b]	μ	σ	γ	μ	σ	γ	μ	σ	γ	μ	σ	γ
<25%	5	135	1430	5	35	1485	5	165	315	5	90	190
<15%	5	310	1430	5	85	1495	5	395	665	5	225	440
<10%	5	525	1430	5	170	1500	5	670	965	10	425	715
<5%	15	1040	1475	15	505	1500	15	1145	1330	30	915	1180

[a] All values shown in Table 4.3 correspond to the 95%-quantile.

[b] μ = mean yield; σ = standard deviation of yields; γ = skewness of yields

Concerning skewness, sample size requirements are even larger and can vary substantially depending on crop, site and scenario. With the exception of maize at Uster, the results indicate that more than 1000 samples are needed to estimate the skewness coefficient with a relative accuracy of less than 10% with 95% certainty.

While it is difficult to discern more specific patterns in Tables 4.2 and 4.3, concerning the estimation of the standard deviation and the skewness coefficient there are systematic tendencies that appear when plotting minimum sample size requirements against reference values of the skewness coefficient (Figure 4.3). Within the examined range of reference values, the minimum sample size relative to the estimation of the standard deviation increases with the degree of asymmetry. As opposed to this, minimum sample sizes for the estimation of the skewness decrease with increasing degree of asymmetry. This latter feature, however, can be explained by the fact that in the limit of a symmetric

distribution the skewness coefficient is equal to zero, and therefore relative errors are in principle always infinitely large.

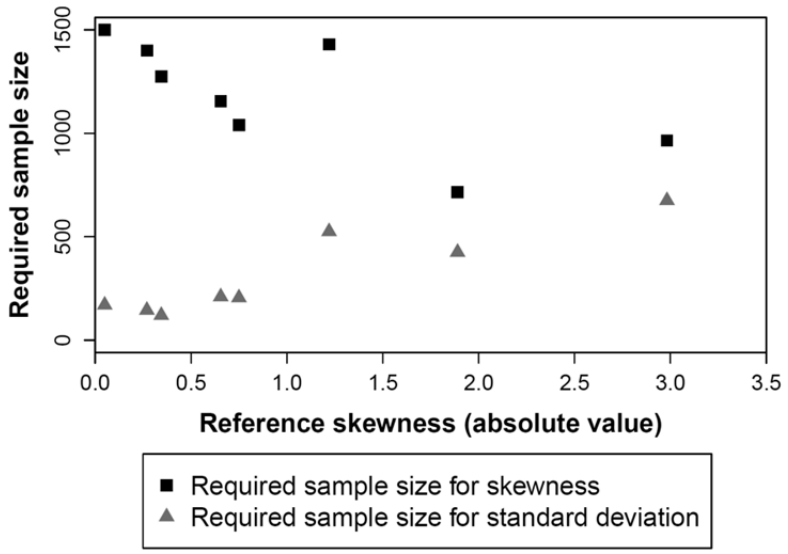

Figure 4.3: Relationship between sample size required for the estimation of standard deviation (triangles) and skewness (squares) and absolute values of the reference skewness. Required sample sizes refer to relative errors of less than 10% at 95% certainty.

Returning to the estimation of mean yields, we notice that minimum sample sizes listed in Tables 4.2 and 4.3 are always very close to the values obtained from applying Cochran's sample size formula (Equation 4.1), in spite of the fact that only in two scenarios simulated crop yield distributions follow normality.

Lower agreement is found between our empirical estimates and the theoretical derived minimum sample sizes for estimating standard deviations obtained from Equation 4.2. For a relative error of 10% at 95% confidence, the latter results for all scenarios in a minimum sample size of 194 observations. At Payerne this figure lies within the range of the empirical data. On the other hand, with the exception of winterwheat yields simulated under the *CC* scenario, the method of Thompson and Endriss (1961) largely underestimates the required sample size at Uster.

4.4 Discussion and conclusions

In our analysis we addressed the evaluation of the minimum sample size required to estimate mean and higher statistical moments of crop yield distributions with given accuracy and confidence. While the sample size required to estimate mean yields did not show large differences across the range of combinations of crop ×× location ×× scenario,

the required sample sizes for higher statistical moments was found to be extremely sensitive to the characteristics of the population from which the samples are drawn. More specifically, our results indicate that the minimum sample size required for estimating the standard deviation and skewness can be related to the degree of asymmetry of the underlying distribution, at least for the range of skewness coefficients implied by our simulations.

Relatively to the eight simulation setups considered in this study, the following conclusions can be drawn:

- A sample size of 15 yield observations is sufficient to obtain estimates of mean yields with a relative error of less than 10% at 95% confidence.
- 200 realizations are in general sufficient to obtain estimates of the standard deviation of crop yields with a relative accuracy of better than 10%. The sample size should be increased to roughly 500 when it can be assumed that the crop yield distribution is strongly skewed (absolute skewness value > 1).
- At least 1000 realizations are needed in most cases to reliably characterize the skewness of the distribution. When a high degree of symmetry is suggested by the available information, much larger samples are needed. This implies that in the absence of prior information, risk analyses should always be based on very large sample sizes.
- In practice, simulating 1000 or more years of crop yields may not always be feasible. In these cases compromises between the computation time and the accuracy of the estimated statistical moments have to be made. For instance, the required sample size is reduced by a factor of about 5 with respect to the estimation of the standard deviation, if the allowable relative estimation error is increased from 10% to 25%. This can be meaningful in studies aiming at optimizing crop management (e.g. Royce et al., 2001; Lehmann et al., 2013) or in studies simulating crop yields in a spatially explicit manner (e.g. Liu et al., 2007).

Concerning the estimation of mean yields, we noticed that Cochran's formula (Equation 4.1, Cochran, 1977) provides a reliable starting point for the determination of the required sample size, in spite of the fact the assumption of normality does usually not apply to crop yields. A further drawback of Equation 4.1 is that in principle knowledge of the population standard deviation σ is needed, whereas in practice only the sample standard deviation s is available. This difficulty can be overcome by considering two-stage sampling procedures (Stein, 1945; Desu and Raghavarao, 1990). Although preliminary tests using Stein's two-stage sampling procedure conducted with our data suggest that there is no necessity for taking a second sample if more than 5 observations are already considered

in the first step, double sampling is simple enough to be implemented in impact assessments.

This kind of drawback is not found with the method of Thompson and Endriss (1961), since it depends only on the choice of the relative accuracy and confidence level. However, our results suggest that its outcomes tend to largely underestimate sample size requirements, in particular when the distributions are narrow and the coefficients of variation are low.

Despite the fact that we considered two different crops, two sites and two climate scenarios, our study cannot have the pretension of being exhaustive and further work is needed to develop general rules. Future research should consider other crop types and extend the analysis to geographic areas characterized by more extreme conditions than examined in this study. Furthermore, analyses of simulated crop yields should be complemented with more theoretical studies referring to standard distributions other than the normal one. Insights could be gained, e.g. from consideration of the beta distribution. Apart from the fact that it has been shown suitable for describing crop yields (Tran et al., 2013), the beta distribution is flexible enough to mimic distributions with various degree of asymmetry and spread. Moreover, exact formulas are available for evaluating the statistical moments of interest in impact assessments.

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5 Adapting crop management practices to climate change: Modeling optimal solutions at the field scale[14]

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ABSTRACT

Climate change will alter the environmental conditions for crop growth and require adjustments in management practices at the field scale. In this paper, we analyzed the impacts of two different climate change scenarios on optimal field management practices in winterwheat and grain maize production with case studies from Switzerland. Management options included nitrogen fertilization (amount, timing and allocation) as well as irrigation. Optimal solutions that maximize the farmer's utility were sought with the help of a bioeconomic modeling system that integrated the process-based crop growth model CropSyst into an economic decision model. The latter accounted not only for the crop-specific average profit margins, but also for production risks, reflecting the utility (expressed as the certainty equivalent) of a risk-averse farmer's management decisions at field scale. In view of the non-linearity and complexity of the problem, we used a genetic algorithm as optimization technique. For grain maize, our results showed that climate change will foster the use of irrigation, not only at sites prone to water limitation already under current climatic conditions, but more in general for climate change scenarios projecting a substantial decrease in summer precipitation. For winterwheat, irrigation was never identified as an optimal management option. For both crops and sites, climate change reduced the optimum nitrogen fertilization amount and decreased for winterwheat the number of fertilization applications. In all cases, the farmer's certainty equivalent decreased between 7% and 25% under climate change, implying negative impacts on winterwheat and grain maize production even under the assumption of an adjustment of the optimum management practices.

KEYWORDS

BIOECONOMIC MODEL; CLIMATE CHANGE; FARM ADAPTATION; GENETIC ALGORITHM

[14] Lehmann, N., Finger, R., Klein, T., Calanca, P., Walter, A. (2013). Adapting crop management practices to climate change: Modeling optimal solutions at the field scale. *Agricultural Systems* 117, 55-65.

5.1 Introduction

Recent climate trends had negative impacts on global yield levels of the six most widely grown crops (wheat, rice, maize, soybeans, barley and sorghum (Lobell and Field, 2007). Even taking beneficial direct effects of CO2 fertilization and adaptation measures into account, projected changes in global climate conditions over the coming decades are expected to further decrease world crop yields at the global scale (Parry et al., 2004). At a regional scale, however, climate change (CC) impacts are likely to lead to more heterogeneous results. For instance, while in Northern Europe moderate changes in climatic conditions are projected to have positive effects on agricultural systems, in Southern Europe, agriculture is very likely to suffer from global warming (Olesen and Bindi, 2002).

To abate the negative impacts of CC, the adaptation of agricultural practices will play a decisive role (Lobell et al., 2008). Agricultural production can benefit already from small changes at the tactical level, e.g. adjustments in sowing dates and fertilization intensity, as shown by Torriani et al. (2007b) and Lehmann et al. (2011). More effective results, however, are likely to require measures that either are costly, as in the case of irrigation (Rosenzweig and Parry, 1994), or can be implemented only slowly, as in the case of breeding of drought-tolerant cultivars (Campos et al., 2004; Araus et al., 2008). Furthermore, it is clear that the consideration of economic constraints is necessary for assessing the potential for adaptation and inform stakeholders and policy makers (Kaufmann and Snell, 1997).

In this context, the use of bioeconomic models linking crop growth models with economic decision models has been suggested in various studies as a way forward toward integrated assessments (e.g. Challinor et al., 2009; Reidsma et al., 2010; Finger et al., 2011; Olesen et al., 2011). Process-based crop growth models as stand-alone tools have been extensively used in CC impact studies in agriculture (Haskett et al., 1997; Guerena et al., 2001; Eitzinger et al., 2003; Jones and Thornton, 2003; Torriani et al., 2007a; Torriani et al., 2007b; Finger et al., 2011). The benefits are obvious. Crop models are able to simulate crop growth under climate scenarios that exceed the range of current conditions (Finger and Schmid, 2008) and can thus be used to explore a whole range of alternatives climate or management scenarios (Bellocchi et al., 2006). The drawback, however, is that crop models are not designed to simulate adjustments in farm management in response to economic and political constraints (Risbey et al., 1999). Furthermore, earlier studies assessing the potential benefits of adjustments in agricultural management practices often focused on a narrow subset of management decision options (Torriani et al., 2007b; Gonzalez-Camacho et al., 2008; Finger et al., 2011). However, most crop growth models allow to investigate various aspects of crop management simultaneously. Thus, the full potential

of such models is only tapped when as many different management variables as possible are considered simultaneously under changing environmental or/ and economic scenarios (Royce et al., 2001).

In this study, we developed a bioeconomic modeling system for applications in integrated CC impact and adaptation assessments at field scale. The developed modeling system integrates the crop growth model CropSyst (Stöckle et al., 2003) with an economic decision model that represents the farmer's decision making process. The system operates at the daily scale and is thus suitable to examine tactical adaptation. The model was applied to examine CC impacts on winterwheat (*Triticum spp. L.*) and grain maize (*Zea mays L.*) production at two different study sites in Switzerland. Nitrogen fertilization and irrigation were considered as management options. The analysis of these two factors was motivated by the fact that nitrogen and water inputs control not only average yield levels but also yield variability. Previous assessments (e.g. Finger et al., 2011) have shown that irrigation is expected to gain in importance in crop production in Switzerland under CC even in regions that do not face water scarcity under present climate conditions. Furthermore, the costs of both, nitrogen fertilization and irrigation, make up a large part of the total production costs in winterwheat and grain maize production and are thus highly relevant from an economic perspective. In order to optimize on- farm management decisions related to both production factors, we integrated the crop growth simulation model CropSyst into a complex economic decision model. For our analysis, we relied on an economic decision model that represents a risk-averse decision maker, i.e. a decision maker that cares not only about the long- term average revenue but also bases his decisions on considerations of the income variability. This interest for production risks was motivated by the observation that CC may have particularly large effects on production variability (Torriani et al., 2007b).

5.2 Methodology

5.2.1 Optimization problem

The study's objective was to optimize management decisions in winterwheat and grain maize production under different climate scenarios at two study sites in Switzerland from a risk-averse farmer's perspective (Figure 5.1). Optimal solutions were sought that maximize the farmer's utility in crop production relatively to the certainty equivalent (CE). The CE accounts for both average profit levels and production risks, i.e. profit variability, and can be interpreted as the guaranteed payoff which a risk-averse decision maker views as equally desirable as higher but more uncertain levels of payoffs. For both crops, twelve

management decision variables related to the nitrogen fertilization and irrigation strategy were optimized. The modeling approach is sketched in Figure 5.1.

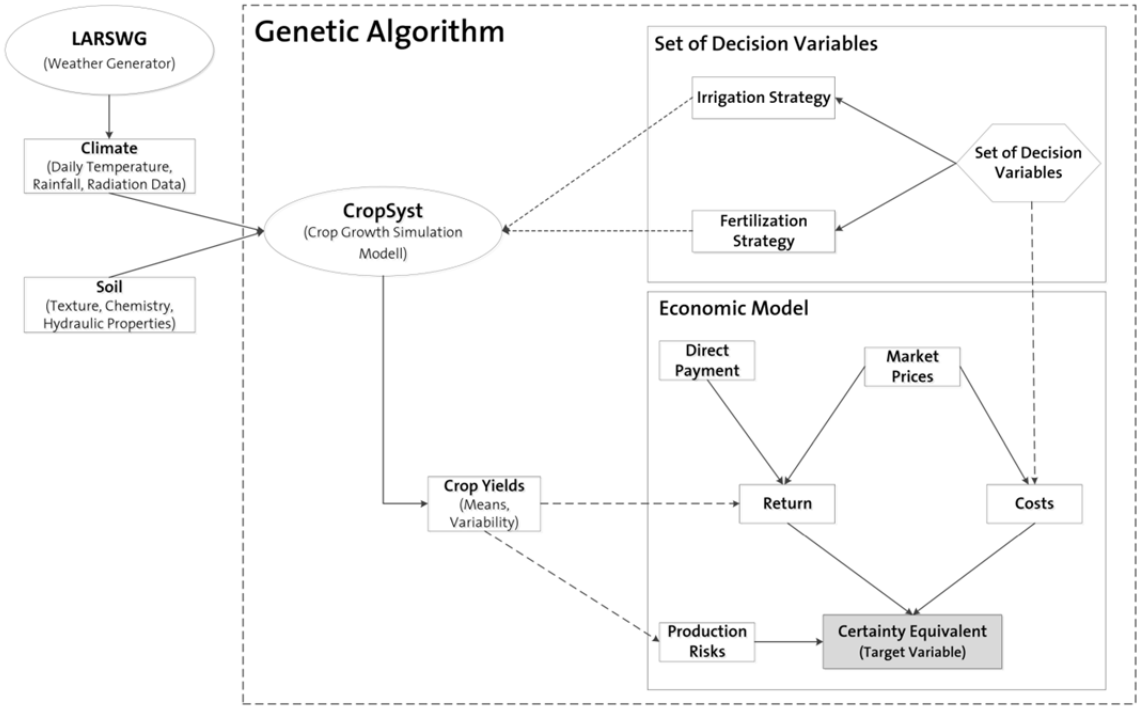

Figure 5.1: Structure of the modeling system used in our study. At each iteration of the genetic algorithm (GA), a set of decision variables is generated for each individual. These decision variables are passed to CropSyst and used to simulate crop yields. Daily weather data needed as input data in CropSyst is generated by the LARS-WG weather generator. The simulated crop yields are further passed to the economic decision model where the farmer's certainty equivalent (CE) (i.e. target variable) is computed. The latter information is fed back into the GA. This procedure is repeated until the CE converges to a maximum value.

The core of the bioeconomic model consists of the crop growth model CropSyst and the economic decision model operating at field scale. Both are embedded in a genetic algorithm (GA) that generates different sets of management decision variables (see upper right part in Figure 5.1). These decision variables are passed to CropSyst where they are used, along with daily weather data and soil information, as input factors for simulating mean and standard deviation of crop yields (see upper center part in Figure 5.1). The simulated crop yields are fed into the economic model in order to compute the return of a specific set of management decisions (see lower right part in Figure 5.1). Under consideration of production risks, the economic returns are finally used along with production costs to evaluate the CE, which is the target variable in the optimization routine. Besides CropSyst and the economic decision model, the modeling suite includes LARS-WG, a stochastic weather generator used for the generation of daily weather data as needed as input for CropSyst.

5.2.2 Study sites and simulation of weather data

Two sites in Switzerland (Figure 5.2) were selected to conduct the case studies. The first site, Payerne, is located in Western Switzerland (cantons of Vaud and Fribourg) within the Broye-Watershed. Water scarcity is frequent at this site already under current climate conditions and irrigation is thus a common management practice (Robra and Mastrullo, 2011). The second site, Uster, lies in the Greifensee-Watershed, which is located in the Northeastern part of Switzerland (canton of Zurich). Compared to Western Switzerland, this region is characterized by more humid weather conditions. Consequently, current crop production in this region is essentially rainfed.

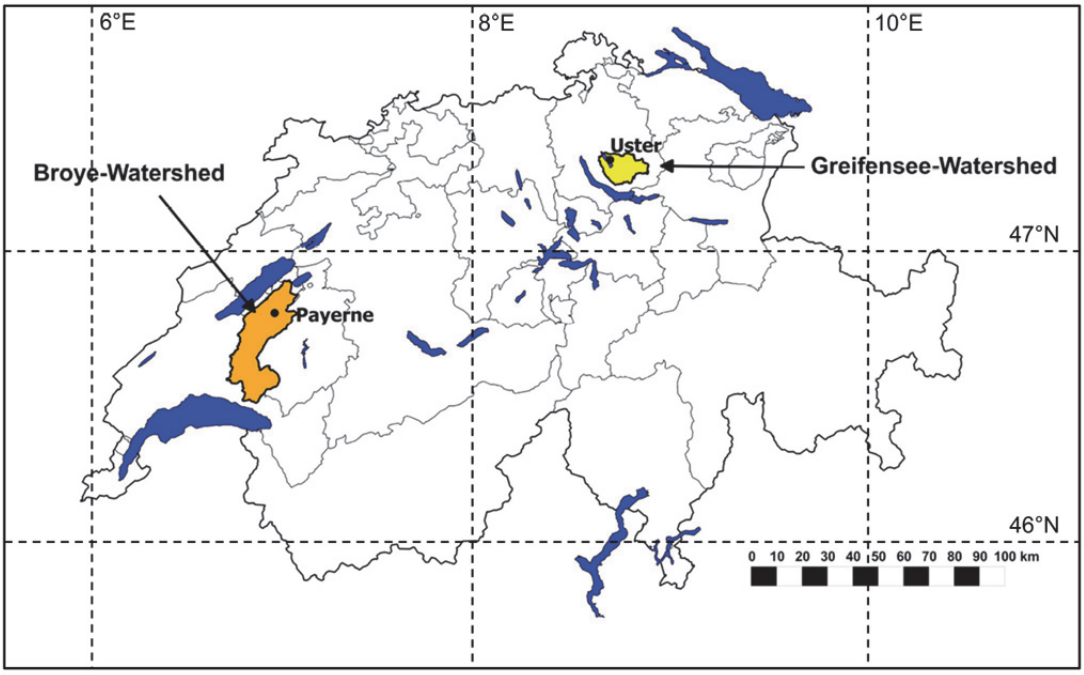

Figure 5.2: Geographic location of the two study sites: Payerne (6°570 E, 46°490 N, 490 m a.s.l.) and Uster (8°420 E, 47°210 N, 440 m a.s.l). Since the meteorological station at Uster measures only precipitation-related variables, representative temperature and solar radiation measurements for the Greifensee were obtained from the record at a nearby climate station (Zurich-Fluntern, 8°340 E, 47°230 N, 555 m a.s.l.).

For both sites, synthetic weather data (daily minimum and maximum temperature, rainfall occurrence and amount and daily total solar radiation) was generated for present and future climatic conditions using the stochastic weather generator LARS-WG (Semenov and Barrow, 1997; Semenov et al., 1998). Local weather observations of two climate stations located at Payerne and Uster, respectively, of the Swiss Meteorological Network spanning the period 1981–2010 were used to calibrate LARS-WG. After calibration, 25 years

of synthetic weather data were generated for both, the Baseline period as well as for two CC scenarios. The latter are valid for the year 2050 and refer to the A1B emission scenario, a path-way envisaging a future world of very rapid economic growth, a global population that peaks in mid-century and declines thereafter, the rapid introduction of new and more efficient technologies and a balanced use of fossil and non-fossil energy sources (Nakicenovic et al., 2000)

Following Semenov (2007), data for the CC scenarios was simulated by specifying changes in monthly mean climate (see Table A.1 in Appendix A). The latter were derived from the outputs of two climate model runs performed in the context of the ENSEMBLES project (van der Linden and Mitchell, 2009). The first was conducted with regional climate models maintained by the Swiss Federal Institute of Technology (ETHZ-CLM scenario), while the second was completed with the regional climate model of the Swedish Meteorological and Hydrological Institute (SMHI-Had scenario). For both runs, boundary conditions were obtained from global simulations with the Hadley Centre global climate model HadCM3. Both scenarios indicate for 2050 a significant temperature increase (see Table A.1 in Appendix A). The ETHZ-CLM scenario is furthermore characterized by a substantial decrease in precipitation during spring and summer. With the SMHI-Had scenario, precipitation is projected to increase in all months except in June at Uster, and to decrease at Payerne in spring and summer months, although less markedly than with the ETHZ-CLM scenario.

5.2.3 CropSyst

Crop growth was simulated with CropSyst (Version 4.13.09), a process-based, multi-crop, multi-year cropping simulation model that addresses biological and environmental above- and below- ground processes of a single land block fragment at the daily scale (Stöckle et al., 2003). CropSyst allows the simulation of a wide range of management options including crop rotation, cultivar selection, irrigation, nitrogen fertilization, tillage operations and residue management.

In recent years, the model has been applied to simulate crop responses to climate for a wide range of environmental conditions (Donatelli et al., 1997; Stöckle et al., 1997; Pannkuk et al., 1998; Sadras and Roget, 2004; Todorovic et al., 2009). Several examples of applications to crop production in Switzerland are also available from literature (Torriani et al., 2007a; Torriani et al., 2007b; Finger and Schmid, 2008; Finger et al., 2011; Lehmann et al., 2011). Moreover, the model has been applied to examine management options in cropping systems. For instance, Garofalo et al. (2009) employed CropSyst to evaluate the effect of faba bean cultivation as a break crop in the continuous durum wheat cropping

system in southern Italy. The model was further used by Bellocchi et al. (2006) to gauge the benefits and drawbacks of different nitrogen fertilization regimes in winterwheat production. In another study, Benli et al. (2007) evaluated CropSyst for its ability to simulate growth, bio- mass, grain yield and evapotranspiration of wheat applying different sowing dates and irrigation strategies. Furthermore, Jalota et al. (2010) assessed the effects of tillage, date of sowing, and irrigation practices on a maize–wheat cropping system using CropSyst as crop growth model. All of these studies conclude that CropSyst is an appropriate model for the evaluation of different management options in cereal cropping systems.

For our analysis crop-specific parameters were specified according to calibration runs performed by Klein et al. (2012). Soil textural characteristics, which are an important input factor in CropSyst, were defined based on information from soil profiles re- corded in close proximity to the two climate stations at Payerne and Uster. The soil profile at Payerne indicates a soil texture with 60% of sand, 11% of clay and 29% of silt. Corresponding percentages at Uster are 66% for sand, 12% for clay and 22% for silt. An initial soil organic carbon concentration of 2.8% for the top soil layer and 2% for the other layers was obtained from the results of a 300 years spin-up run performed by Klein et al. (2012). These values are typical for the Swiss Plateau and within the range of observations presented by Dubois et al. (1999) and Leifeld et al. (2003). More details on soil profiles and initial soil organic carbon conditions are given in Table A.2 in the Appendix A.

5.2.4 Economic model

The economic model adopted for our study maximizes the farmer's certainty equivalent (CE) on his management decisions in the specific cropping system. The CE is defined as shown in Equation 5.1 which formulates the target function of the optimization problem:

$$\max\left(CE\middle|DV_1, DV_2, ..., DV_{12}\right) = E(\pi) - RP \tag{5.1}$$

where DV_i stands for decision variable i (e.g. irrigation strategy, fertilization amount), $E(\pi)$ is the expected profit margin and RP is the risk premium (both expressed in CHF·ha^{-1}).

The risk premium is the amount of money the decision maker is willing to pay to eliminate risk exposure (Di Falco et al., 2007). The decision-maker is risk-averse, risk-neutral and risk-loving if the $RP > 0$, $RP = 0$ or $RP < 0$ (Pratt, 1964). According to Pratt (1964), the risk premium can be approximated by:

$$RP \approx 0.5 \cdot {}^{\gamma}\!/_{E(\pi)} \cdot \sigma_{\pi}^{2} \tag{5.2}$$

where γ is the coefficient of relative risk aversion and σ_{π}^{2} is the variance of the profit margins. Values for γ between 1 and 4 represent typical forms of risk behavior (Gollier, 2004). For this study, we assumed $\gamma = 2$, representing a moderate risk-aversion and implying a decreasing absolute risk aversion (Di Falco and Chavas, 2006).

The profit margin π can be obtained from Equation 5.3:

$$\pi = \rho + DP - c_{fix} - c_{\text{var}} \tag{5.3}$$

where ρ is the revenue, DP are the governmental direct payments, c_{fix} the fixed costs and c_{var} the variable costs (all expressed in CHF·ha^{-1}).

Variable production costs are comprised of charges for fertilizer, water, insurance and capital as well as yield dependent cleaning and drying costs at harvest (Table 5.1). Since in CropSyst only nitrogen fertilization is considered, we coupled the costs of P_2O_5, K_2O and Mg fertilizer to the applied nitrogen amount. Insurance costs were assumed to be proportional to the expected revenue (i.e. premiums are higher for higher production levels). The interest claim was defined as product of the interest rate and the invested capital (fixed costs and variable costs) for an average commitment of 6 months.

The considered fixed costs comprise costs for seeds, plant protection and growth regulation as well as contract work and machinery. Contract work and machinery costs, were specified following AGRIDEA and FIBL (2010). Regarding the price of winter- wheat and maize, we followed the recommendation of AGRIDEA and FIBL (2010) published for the year 2010. In view of the specificities of agricultural markets in Switzerland (i.e. the agricultural markets in Switzerland are characterized by high entry barriers), these prices are higher than found in other European countries.

Table 5.1: Revenue and costs in winterwheat and grain maize production.

Revenue	*Winterwheat*	*Grain maize*
Crop price (CHF · kg^{-1})[a]	0.51	0.365
Direct payment		
Direct payment (CHF · ha^{-1})[a]	1680	1680
Fixed costs		
Seed (CHF · ha^{-1})[a]	218	268
Plant protection (CHF · ha^{-1})[a]	265	220
Plant growth regulant (CHF · ha^{-1})[a]	41	0
Contract work and machinery costs (CHF · ha^{-1})[a]	783	844
Irrigation system costs (CHF · ha^{-1})[b,c]	447.41	447.41
Variable costs		
Nitrogen fertilizer (CHF · kg^{-1} · N^{-1})[a]	1.4	1.4
Other fertilizer costs (CHF · kg^{-1} · N^{-1})[a]	0.72	1.54
Hail insurance (% of Crop Yield Revenue)[a]	2.1	3.6
Cleaning, drying costs (CHF · t^{-1})[a,d]	39.5	71.3
Other costs (CHF · t^{-1})	6.7	0
Variable irrigation costs (CHF · mm^{-1} · ha^{-1})[b]	1.00	1.00
Interest rate (%)[a,e]	3.0	3.0

[a] Source: AGRIDEA and FIBL (2010)

[b] Source: Spörri (2011)

[c] Note that the irrigation system costs disappear if irrigation is not chosen as management option.

[d] Note that the cleaning and drying costs depend on the yield at harvest which have a higher water content than the final yield. The dry matter contents of the winterwheat and grain maize harvest are assumed to be 85.5% and 86%, respectively AGRIDEA and FIBL (2010).

[e] Interest claims have been calculated on the invested capital (fixed costs, fixed irrigation costs and variable costs) for an average commitment of 6 months.

5.2.5 Decision variables

For both crops, we considered twelve different management decision variables, all of them related to nitrogen fertilization and irrigation (Table 5.2). In order to enable feasible computation times to solve the model, we integrated all management variables as discrete values.

Regarding fertilization, we considered for both crops up to 4 applications per year. In the context of standard fertilization procedures, three nitrogen fertilization applications are currently recommended in Switzerland both for winterwheat as well as for grain maize (Flisch et al., 2009). A minimum interval of 20 and 10 days was specified between two consecutive fertilization applications for winterwheat and grain maize, respectively. More frequent applications are not considered, because in this case marginal labor and

machinery costs exceed the benefits. Apart from timing, we also considered a variable fraction of the total nitrogen amount applied with each fertilization event as decision variable (Table 5.2).

Table 5.2: Considered management variables.

Decision Variable	*Management variable*	*Unit*	*Range (min-max)*		*Variable increment*		*Number of Alternatives*	
			Grain maize	*Winter-wheat*	*Grain maize*	*Winter-wheat*	*Grain maize*	*Winter-wheat*
1	Total Nitrogen Amount	$kg \cdot ha^{-1}$	0-250	0-250	10	10	26	26
2	Number of N Fertilization events	-	0-4	0-4	1	1	5	5
3	Percentage of 1st N application	%	0-100	0-100	10	10	11	11
4	Timing of 1st N application	Days after sowing	0-150	120-220	10	5	31	21
5	Amount of 2nd N application	%	0-100	0-100	10	10	11	11
6	Timing of 2nd N application	Days after sowing	10-150	140-220	10	10	29	17
7	Amount of 3rd N application	%	0-100	0-100	10	10	11	11
8	Timing of 3rd N application	Days after sowing	20-150	160-220	10	10	27	13
9	Amount of 4th N application	%	0-100	0-100	10	10	11	11
10	Timing of 4th N application	Days after sowing	30-150	180-220	10	10	25	9
11	Maximum allowable depletion	-	0-1	0-1	0.1	0.1	11	11
12	Irrigation refill point	-	0-1	0-1	0.1	0.1	11	11

Irrigation was simulated using the automatic irrigation option available from CropSyst. Two decision variables were considered in this case. The first was the maximum allowable depletion. This value triggers irrigation as soon as the soil water depletion at 1 m soil depth is larger than this user-defined threshold (Stöckle and Nelson, 2000). The maximum allowable depletion is expressed as percentage of the maximum field water content (e.g. a maximum allowable depletion of 0.6 means that irrigation starts if the soil's water content is 60% smaller than the soil's field capacity). The second decision variable was the refill point, i.e. the relative soil water level up to which water is added during irrigation (Stöckle and Nelson, 2000). In relative units, the refill point also ranges from 0 (permanent wilting point) to 1 (field capacity). Since the two are complementary, the refill point must be specified so as to exceed one minus the maximum allowable depletion.

As a rule, the lower the maximum allowable depletion, the more frequent will be irrigation. In contrast, the refill point determines the intensity (i.e. applied water amount) of each irrigation event. The joint consideration of both variables allowed to mimic deficit irrigation, i.e. the application of water below the optimum evapotranspiration requirements of crops (English, 1990). The purpose of deficit irrigation is to maximize the economic returns rather than physical crop yield levels.

We assumed an irrigation efficiency of 77% corresponding to the irrigation efficiency of sprinkler irrigation systems (Irmak et al., 2011), the most common technique employed in Switzerland (Weber and Schild, 2007). In order to account for hydraulic limitations of the irrigation equipment, a minimum irrigation quantity of 15 mm per irrigation event was specified. Thus, irrigation was delayed if the difference between the refill point and one minus the maximum allowable depletion value was less than this threshold of 15 mm.

In agreement with the current practice, the sowing date of winterwheat was fixed for all climate settings (Baseline and CC scenarios) to October, 10. For maize, the sowing date was specified depending on temperature. Currently, in Switzerland sowing is recommended when the soil temperature at a depth of 0.05 m exceeds 10°C (AGRIDEA, 2011). An analysis of observed daily mean air and soil temperature at Payerne suggested that this condition is fulfilled when the five-day average mean air temperature also exceeds 10°C Thus, we used the conditional sowing model in CropSyst for maize, whereas maize was sown if the 5-day average air temperature exceeded 10°C.

5.2.6 Genetic algorithms

Due to the discrete nature of the decision variables, the presented optimization problem could be interpreted as a combinatorial problem. In this study, though, the simple evaluation of each feasible solution was not possible because the calculation of all possible combinations would have been too time-consuming. Moreover, the relations between the decision variables and the target variable (CE) could not be represented with analytic functions. Therefore, the optimization problem was solved with the help of a genetic algorithm (GA).

GAs are based on the biological concepts of genetic reproduction and survival of the fittest (Mayer et al., 1999; Aytug et al., 2003). A population of individuals, each representing a possible solution for a given problem, evolves over time by selecting the best individuals in each generation and reproduction. The different decision variables are coded as binary strings of genes on a chromosome (=individual) representing a set of possible decision variables. As in genetics, the term genotype is used in GAs for the set of decision variables represented by one specific chromosome, while the term phenotype refers to the physical

outcome and hence the fitness that is caused by the expression of the decision variables (De Jong, 1992). The fitter the individual, the higher is the chance of being chosen for the reproduction of offspring (Beasley et al., 1993). Thus, a whole new population of possible solutions is produced by selecting the best individuals of the current population and mating them in order to generate a new set of individuals (Beasley et al., 1993). After several generations, the algorithm converges to the best individual which is either a global or a local optimum of the optimization problem (Gen and Cheng, 2000). A GA involves at least the following three types of operators: selection, crossover and mutation (Mitchell, 1998). The selection operator selects the chromosomes based on their fitness value in the current population for reproduction; the crossover operator randomly exchanges subsequences between two selected chromosomes in order to create offspring; and the mutation operator randomly flips some of the bits in a chromosome (Mitchell, 1998).

In contrast to traditional optimization techniques, GAs do not require gradient information and are more likely to find the global optimum (Mahfoud and Mani, 1996). Furthermore, this non-parametric optimization technique avoids the often required intermediate step of statistical coefficient estimation of crop yield-input factor relations (e.g. Finger et al., 2011).

For this work, we used the C++ based GA package Galib (Wall, 1996) and applied a steady-state GA. The steady-state GA uses overlapping populations, whereby at each step the overlap defines the percentage of the current population that is replaced (Wall, 1996). In line with Mayer et al. (2001), we applied the following control parameters to the GA: genome size = 8 bits; population size = 40; proportion of replacement = 0.2; selection routine = roulette wheel; mutation probability = 0.15; crossover probability = 0.5; fitness function = a sigma truncation scaling (Wall, 1996). Furthermore, the convergence criterion stopped the optimization when no improvement of the target variable was observed over 1000 generations. Nevertheless, since even this strict convergence criterion does not guarantee attaining a global optimum, each optimization run was repeated three times using different, randomly generated initial populations. In our case, this led for all scenarios to the same optimal solution. Results from the optimization presented in this paper are thus interpreted as global optima.

Although GA are computationally efficient, the overall setup of our optimization problem was computational intensive, requiring one week on a PC with Intel Pentium Core™ i5 at 3.33 GHz.

5.3 Results

The optimal management schemes for all climate scenarios are presented for both sites and crops in Table 5.3 and Table 5.4.

Table 5.3: Optimal management parameters for winterwheat.

Management variable	*Unit*	*Winter-wheat at Payerne Baseline*	*Winter-wheat at Payerne ETHZ-CLM*	*Winter-wheat at Payerne SMHI-Had*	*Winter-wheat at Uster Baseline*	*Winter-wheat at Uster ETHZ-CLM*	*Winter-wheat at Uster SMHI-Had*
Total N amount	$kg \cdot ha^{-1}$	150	110	120	140	80	110
Number of fertilization events	-	2	1	1	3	1	1
Percentage of 1st N application	%	60	100	100	30	100	100
Timing of 1st N application	Days after sowing	120	140	140	120	140	140
Percentage of 2nd N application	%	40	0	0	30	0	0
Timing of 2nd N application	Days after sowing	140	-	-	140	-	-
Percentage of 3rd N application	%	0	0	0	40	0	0
Timing of 3rd N application	Days after sowing	-	-	-	160	-	-
Percentage of 4th N application	%	0	0	0	0	0	0
Timing of 4th N application	Days after sowing	-	-	-	-	-	-
Mean irrigation amount (standard deviation of irrigation amount)	mm	0	0	0	0	0	0
Maximum allowable depletion	-	1	1	1	1	1	1
Irrigation refill point	-	1	1	1	1	1	1

In spite of contrasting precipitation scenarios, neither in the ETHZ-CLM nor in the SMHI-Had scenario irrigation was identified as an optimum management strategy for winterwheat production. For winterwheat, however, differences in the specification of the CC scenario had a strong impact on fertilization. As a rule, the stronger the increase in temperature and decrease in precipitation, the smaller was the optimal total nitrogen fertilization amount. The results also suggest a single application at mid-May as optimum fertilization strategy under both CC scenarios and for both study sites. This can mainly be explained by the fact that CC shortens the vegetation period of winterwheat at both

locations. At Payerne, for instance, maturity is reached in the ETHZ-CLM scenario one month earlier than in the Baseline scenario.

Table 5.4: Optimal management parameters for grain maize.

Management variable	*Unit*	*Grain maize at Payerne Baseline*	*Grain maize at Payerne ETHZ-CLM*	*Grain maize at Payerne SMHI-Had*	*Grain maize at Uster Baseline*	*Grain maize at Uster ETHZ-CLM*	*Grain maize at Uster SMHI-Had*
Total N amount	$kg \cdot ha^{-1}$	200	160	180	140	120	110
Number of fertilization events	-	4	4	4	4	4	4
Percentage of 1st N application	%	40	40	30	70	50	70
Timing of 1st N application	Days after sowing	10	10	10	10	10	10
Percentage of 2nd N application	%	30	30	40	10	10	10
Timing of 2nd N application	Days after sowing	50	50	60	50	20	50
Percentage of 3rd N application	%	10	10	20	10	30	10
Timing of 3rd N application	Days after sowing	80	70	80	70	50	60
Percentage of 4th N application	%	20	20	10	10	10	10
Timing of 4th N application	Days after sowing	90	90	90	90	80	70
Mean irrigation amount (standard deviation of irrigation amount)	mm	126 (59)	231 (61)	177 (66)	0 (0)	101 (58)	0 (0)
Maximum allowable depletion	-	0.6	0.5	0.6	1	0.6	1
Irrigation refill point	-	0.6	0.6	0.7	1	0.6	1

Regarding grain maize production at Payerne, irrigation was identified as optimum management option for all climate conditions, including the Baseline scenario. A value for the maximum allowable depletion between 0.5-0.6 and a refill point between 0.6-0.7 was found to be optimal for three climate scenarios at Payerne. Nevertheless, since the irrigation demand depended on the season's prevailing climate conditions, the applied average water amount increased under the ETHZ-CLM and the SMHI-Had scenario by 84% and 41%, respectively, relatively to the Baseline scenario.

At Uster, irrigation of grain maize was found to be profitable only under the ETHZ-CLM scenario, whereas irrigation was not required to achieve the maximum CE under the Baseline and the SMHI-Had climate conditions. Under the ETHZ-CLM scenario, a rather extensive irrigation strategy was found to be optimal, with both, a maximum allowable

depletion and a refill point at 0.6. As seen in Table 5.4, this strategy results in an annual irrigation amount of 101 mm.

Regarding fertilization, the optimal nitrogen amounts in grain maize production decreased under the applied CC scenarios, similarly to what has been found in winterwheat production. However, in the case of grain maize CC did not imply changes in the number of fertilizer applications. Nevertheless, CC led to a slightly shorter time span between the first and last nitrogen fertilization event.

The annual profit margins and crop yields for the identified optimal management patterns are shown in Figure 5.3. Under CC, the average profit margin and the average crop yield decreased at both locations and for both crops. Furthermore, CC led to a reduction of the variability of the winterwheat profit margins and yields at Uster. At Payerne, the crop yield variability in winterwheat production increased under the ETHZ-CLM scenario, while the SMHI-Had scenario led to a decrease of the crop yield and profit margin variability.

For grain maize production, the variability in profit margins and crop yields increased at Payerne under both, the ETHZ-CLM and the SMHI-Had scenario. At Uster, irrigation reduced the variability of crop yields and profit margins in grain maize production under the ETHZ-CLM scenario. In contrast, a significant increase in the variability of profit margins and yields was found at this location under the rainfed production conditions identified as optimal under the SMHI-Had scenario.

For both CC scenarios, adjustments in the management practices were not sufficient to maintain farmers' utility (expressed as the CE) at current levels. CC reduced the CE for both crops and at both sites up to 25% relatively to the Baseline scenario (Figure 5.4). The more extreme CC scenario ETHZ-CLM led for both crops and at both locations to a larger reduction in the CE. Furthermore, under both CC scenarios, the relative reductions in the CEs were found to be higher at Uster than at Payerne.

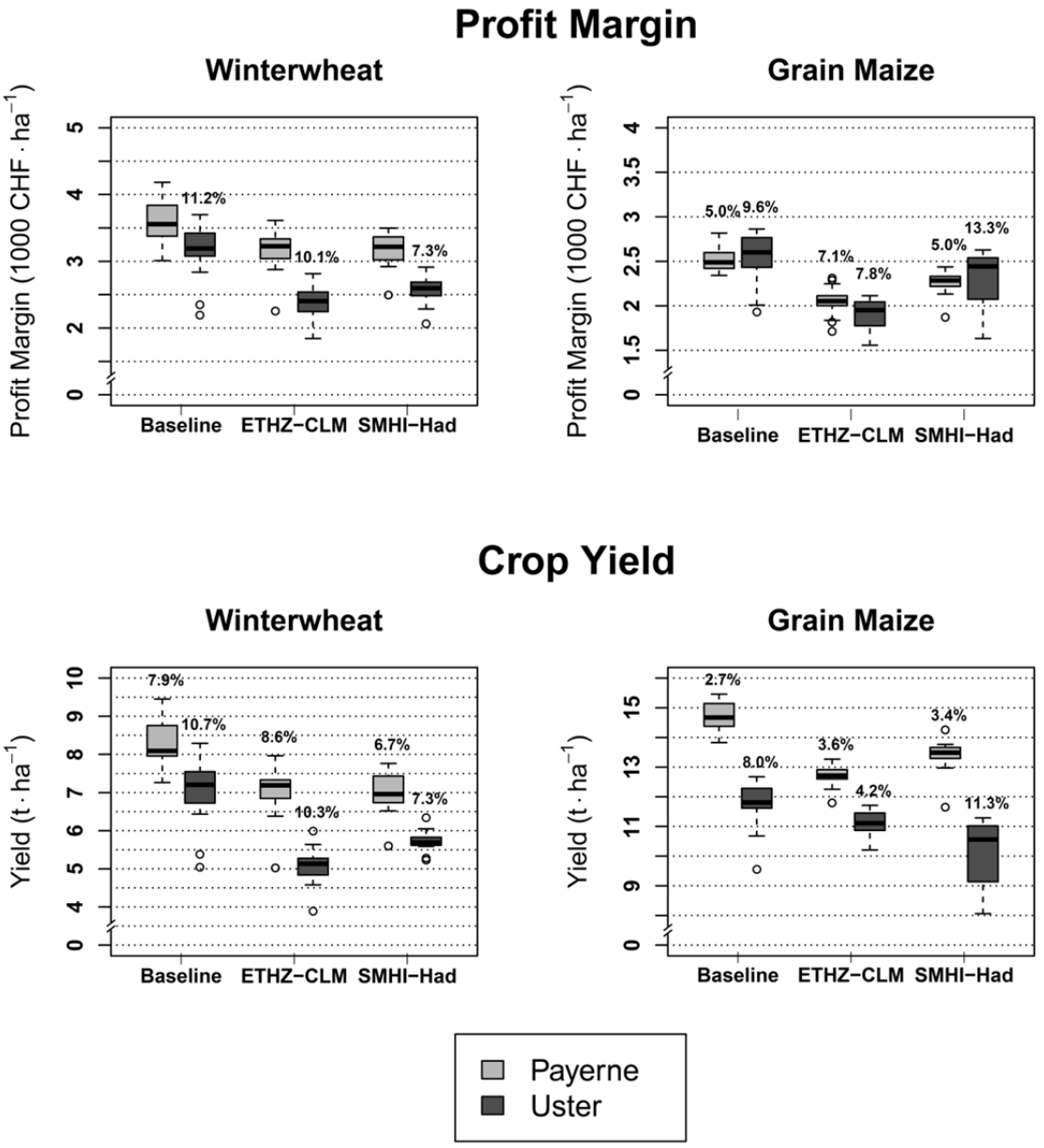

Figure 5.3: Profit margins (upper plots) and crop yields (bottom plots) as obtained for each scenario with optimal management decision. The horizontal line denotes the median. The whiskers extend to a maximum of 1.5 times of the inter-quartile range. The white circles are outliers, which are not included in the range of the whiskers. The numbers above or below the boxplots indicate the coefficient of variation of the profit margins and crop yields. According to an Ansari–Bradley test (Ansari and Bradley, 1960), only the change in crop yield variability of grain maize cultivated at Uster between the Baseline and ETHZ-CLM scenario was significant.

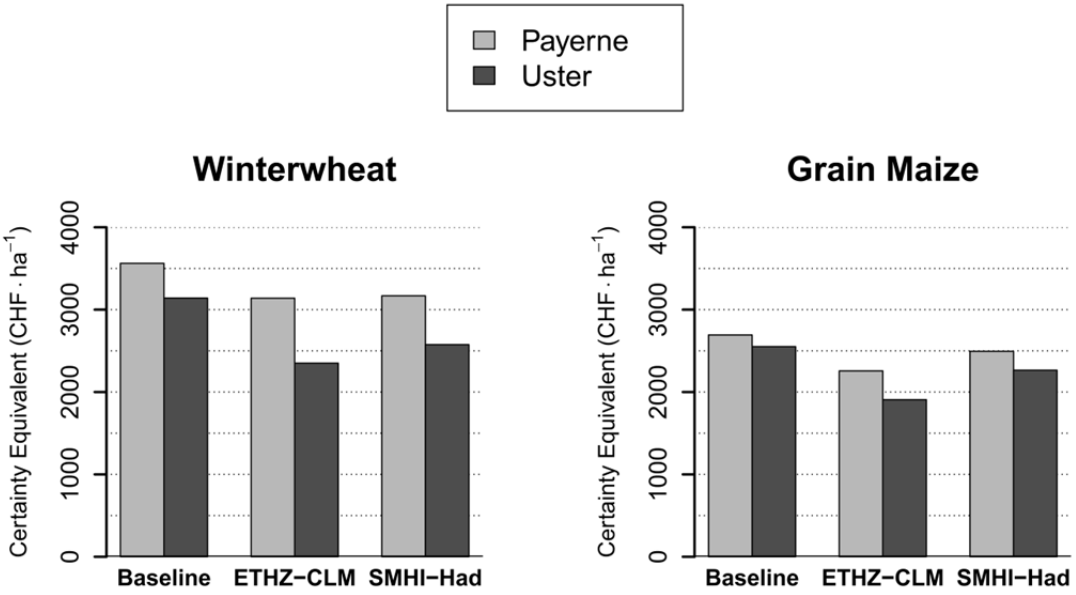

Figure 5.4: Certainty equivalents (CE) in winterwheat and grain maize production in each scenario applying the optimal management schemes (see Table 5.3 and Table 5.4).

5.4 Discussion

The results of our bioeconomic modeling approach indicate that in Switzerland adaptation measures that take economic constraints into account may not be sufficient to counteract the negative impacts of CC on winterwheat and grain maize productivity. Thus, strategies to close the income gap are necessary to support producers under future climatic conditions.

Our analysis clearly showed that impacts and adaptation options depend to large extent on specific site conditions and climate scenarios. For instance, at Payerne reduction in farmers' utility (expressed in CE) in grain maize production amounted only to about 7% under the SMHI-Had scenario as compared to current climatic conditions. In contrast, at Uster a decrease in the CE in winterwheat production of 25% was found under the ETHZ-CLM.

Irrigation was found to be necessary to support maize production in Switzerland. However, for moderate shifts in climate conditions, as suggested in the SMHI-Had scenario, irrigation of grain maize may not be equally profitable in all regions. In fact, at Uster irrigation was identified as optimum strategy only under the ETHZ-CLM scenario.

Flexible irrigation strategies (i.e. with local adjustments of both, the irrigation refill point and maximum allowable depletion) can help to increase the benefits of irrigation under CC. This is because excessive irrigation in sufficiently wet years can be avoided

considerably reducing variable irrigation costs. The increased water demand in maize production under CC indicated by our results, however, may cause additional problems of water allocation between agriculture and other sectors. Thus, water allocation policies should take potential effects of CC on water demand into account.

An increasing importance of irrigation in grain maize production under CC for Northeastern Switzerland was also outlined by Torriani et al. (2007b). Nevertheless, our study showed that for this area, irrigation of grain maize becomes a profitable adaptation measure only under a rather strong CC scenario. This stresses the importance of the consideration of the economic profitability in CC impact assessments.

In contrast to the results for grain maize, irrigation was not found to be necessary for sustaining winterwheat production, regardless of the applied climate scenarios. There are two reasons for this. On the one hand, higher winterwheat yield levels caused by supplemental irrigation cannot completely offset the associated fix costs of sprinkler irrigation systems. On the other hand, the expected decreases of monthly precipitation under CC are highest in summer months, whereas water availability is crucial for wheat growth mainly in spring (Lehmann, 2010). Additionally, winterwheat grown in the Swiss Plateau is more sensitive to high temperatures than to low precipitation levels in summer months (Lehmann, 2010)

For both crops and locations, a decrease in fertilization intensity was proposed by the simulations as adaptation strategy to CC. For winterwheat, the simulation results further suggest consideration of a single application to account for the shorter vegetation period under CC. However, since a single nitrogen application strategy may cause environmental problems compared to split applications (Hyytiainen et al., 2011), the implementation of such a strategy will require changes in the current agri-environmental policies.

5.5 Conclusions

The developed modeling approach consisting of the biophysical crop growth model CropSyst coupled with an economic decision model proved to be suitable for CC impact assessments at the field scale. Due to the application of CropSyst, crop growth and its response to weather and crop management could be simulated under different management and climate regimes for specific locations. Furthermore, the economic evaluation of management strategies led to a more comprehensive analysis of potential adaptation measures in Swiss agriculture. In addition, the application of the GA as optimization technique enabled a direct integration (i.e. a live-linkage) of the simulated

crop yields in the economic decision model and avoided a parametric representation (e.g. production functions) of yield - management relationships.

Nonetheless, the computational load was considerable. As reported in section 2.6, one week was necessary to solve our optimization problem on a PC with Intel Pentium Core™ i5 at 3.33 GHz. Clearly, ways to overcome the computational demands are therefore needed before this approach can be applied in an operational context. Within our GA approach, there are two basic ways to do so. The first is to modify the GA parameter settings specified in Section 5.2.6 in order to accelerate the evolution process. This, however, requires specific investigations that were beyond the scope of this paper. The second, is to reduce the computational time by relaxing the convergence criterion. In the present application, the algorithm stopped when the best fitness value did not change for 1000 generations. However, in all scenarios optimal solution with less than 1% deviation from the global optimum could be obtained already after the first 200 generations. Note also that we repeated each optimization run three times to ensure global convergence. While this is desirable for scientific analyses, in most practical situation a slight loss in accuracy is probably acceptable.

A key element of our modeling system was the crop model CropSyst. Crop models have become indispensable for CC impact studies and will continue to deliver essential information also for years to come. Nevertheless, when used for integrated assessments they present limitations that need to be considered. For instance, a major deficiency of most of the currently available crop growth models is the lack of modules for simulating other biotic components of cropping systems. We think in particular of pests, plant diseases, weeds, beneficial organisms (Bergez et al., 2010). There is little doubt that shifts in the occurrence and distribution of pests, plant diseases and weeds could become one of the major challenges for agriculture during the coming decades (Trnka et al., 2007; Hirschi et al., 2012)

Two other important aspects were also disregarded in our study. On the one hand, we did not consider the CO_2 fertilization effect, because its quantification is still highly uncertain (Körner et al., 2007) and the application of experimental results to crop models opens to debate (see e.g. Tubiello et al., 2007). On the other hand, we neglected the possibility that market constraints and input- and output-prices could change in the future. This could have strong effects on both mean and variability of prices in Switzerland (Finger, 2012b).

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6 Economic and environmental assessment of irrigation water policies: A bioeconomic simulation study[15]

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ABSTRACT

Bioeconomic simulation systems are well suited for the ex-ante exploration of different policy scenarios in agriculture. In this study, we present a bioeconomic modeling approach that links the biophysical crop growth model CropSyst to an economic decision model at field scale. The developed model is used in conjunction with a genetic algorithm to optimize management decisions in potato production. More specifically, agricultural management decisions including nitrogen fertilization and irrigation measures are optimized in the context of different irrigation policy scenarios in the Broye catchment, an agricultural area in the western part of Switzerland. The use of a genetic algorithm for optimization enables the direct integration of the considered decision variables as management input factors in CropSyst without any intermediate steps such as for instance the estimation of production functions. Furthermore, the farmer's certainty equivalent, measured as the expected profit margin minus a risk premium, is employed as objective function. In this way, potential impacts of policy decisions on a farmer's average income in terms of potato production, as well as the income variability, are taken into account.

The study's results show that the region's current water policy, which frequently prevents irrigation during hot and dry periods by banning water withdrawal, not only leads to high income risks, but also to an increased average water demand in potato production. Our simulation results indicate that the introduction of volumetric pricing for irrigation water reduces the irrigation water only if the water price is higher than 2 CHF·m^{-3}. However, at such water prices the farmer's certainty equivalent is reduced by more than 30%. In contrast, the implementation of an appropriate water quota can significantly decrease water consumption in potato production while allowing the farmer's certainty equivalent to remain constant with levels observed under the current irrigation water policy.

KEYWORDS

BIOECONOMIC MODELING; GENETIC ALGORITHM; ENVIRONMENTAL ECONOMICS; IRRIGATION; WATER POLICY

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6.1 Introduction

Although agriculture in Switzerland is mostly rainfed, some regions of the country face climate conditions that require irrigation for crop production (Weber and Schild, 2007). An example region where irrigation is intensively used for cultivation is the Broye catchment, an important potato production region located in western Switzerland (Figure 6.1) (Robra and Mastrullo, 2011). For potatoes, irrigation is of particular importance to avoid yield losses under dry climate conditions in summer months, but also to meet the quality levels demanded by customers and the processing industry (Mühlberger de Preux, 2008). As the region's agricultural water demand for irrigation has increased in recent years due to both changing climate conditions and higher potato quality demands of the processing industry, surface water bodies have repeatedly suffered low water levels during the summer months in the Broye catchment. Such low water levels in the region's rivers caused by water withdrawals for agricultural purposes also resulted in higher water temperatures (Mühlberger de Preux, 2008). The Broye river, for instance, has experienced water temperatures of up to 27°C during summer months in recent years, which is much higher than optimal water temperature required for the river's typical fauna (Mühlberger de Preux, 2008).

Currently, the Swiss law addresses such environmental problems resulting from agricultural water use by imposing water withdrawal bans if a river's flow rate falls below a critical threshold (BAFU, 2000). The occurrence of water withdrawal bans in the canton of Vaud over the period 1998-2011 is presented in Figure 6.2. In seven out of the last nine years, water withdrawal bans, mostly in late summer, have been implemented in the canton of Vaud.

From the potato grower's perspective, withdrawal bans that occur during stages of potato tuber initiation and ripening - when potato yields are most sensitive to water stress (Fabeiro et al., 2001) - are of particular concern, as they can have significant negative consequences for yield levels and quality, and thus profitability. The ability of policy makers to impose water withdrawal bans during dry periods constitutes an institutional risk for farmers, as such legislation leads to uncertainty concerning the profitability of investments in irrigation systems.

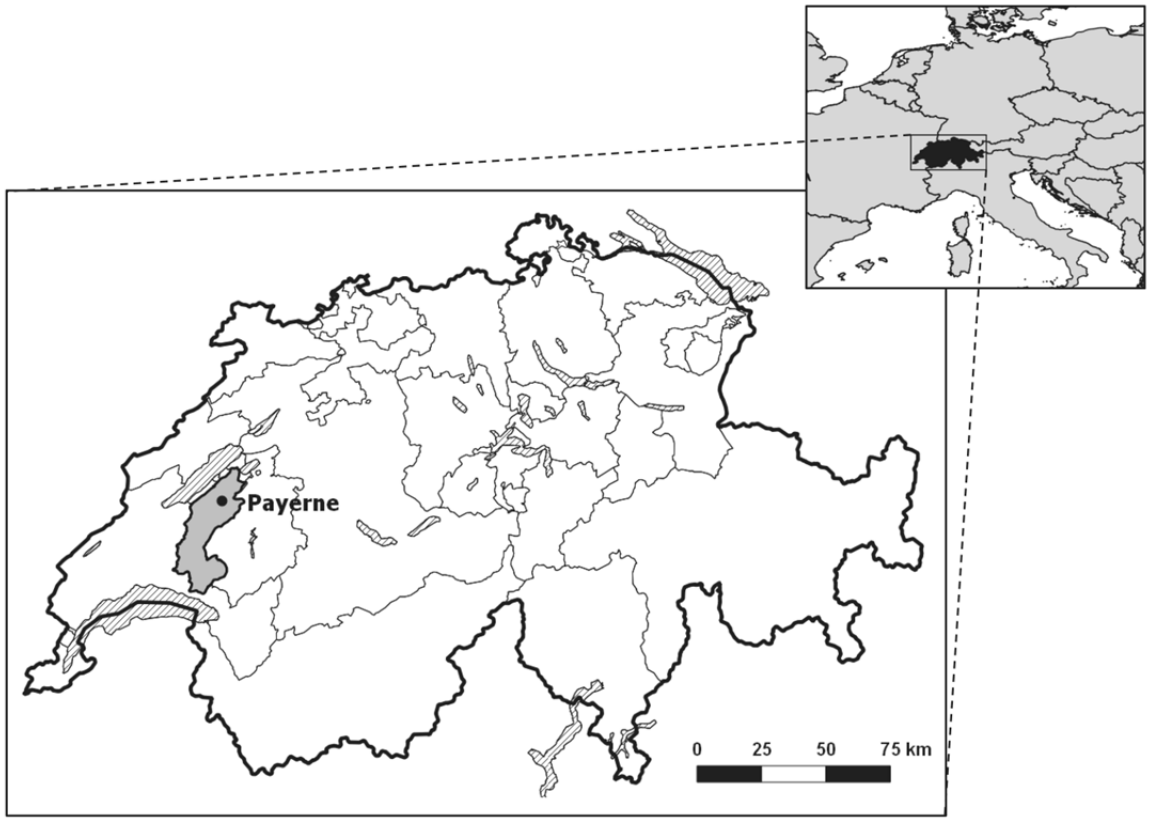

Figure 6.1: The Broye catchment: The lower plot on the left-hand side shows the geographic location of the Broye catchment (gray area). The hatched areas indicate the major lakes in Switzerland. The national boundary and the cantonal boundaries of Switzerland are given by the thick and thin black lines, respectively. The upper plot on the right-hand side shows the geographic situation of Switzerland (black area) in Central Europe.

In the next decades water scarcity is expected to occur even more frequently due to a further expected rise in temperature (OcCC, 2007), which in turn is likely to increase water requirements for irrigation in the Broye catchment (Fuhrer and Jasper, 2009; Lehmann and Finger, 2013). To minimize ecological damages occurring as a result of agricultural water withdrawals in the Broye catchment, alternative water policies are required.

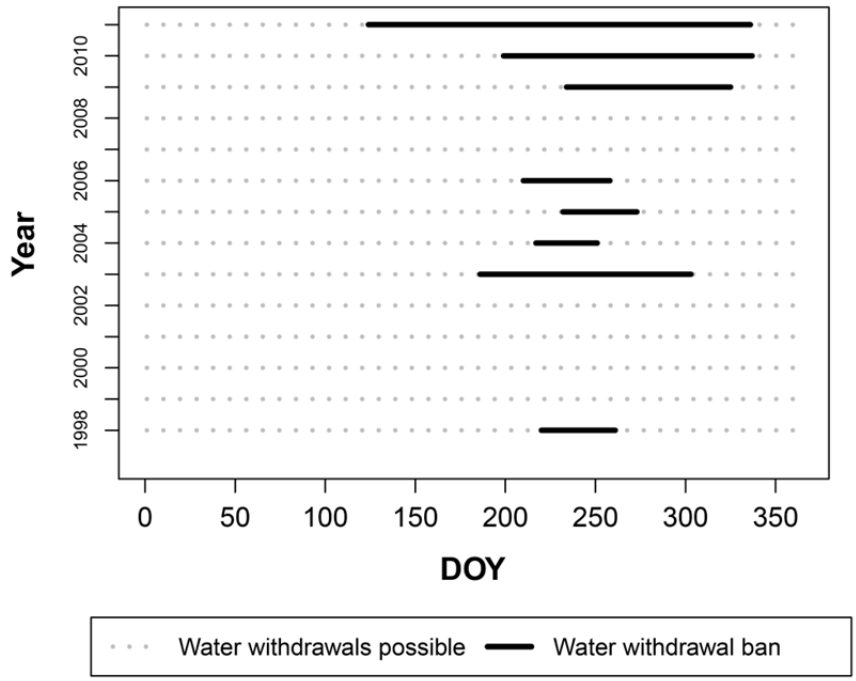

Figure 6.2: Frequency and duration of water withdrawal bans of rivers in the canton of Vaud over the period 1998-2011. Each black line stands for a water withdrawal ban for a specific period (see horizontal axis, DOY = day of the year) in a specific year (see vertical axis). The wider the span of an event indicated, the longer the withdrawal ban.

The effects of crop management decisions such as nitrogen fertilization and irrigation on crop yield levels are typically analyzed using process-based models such as CropSyst (see e.g. Stöckle et al., 2003; Torriani et al., 2007b; Lehmann et al., 2013, for overviews and applications). As these models generally do not consider economic incentives affecting decisions made by the farmer, crop growth models are often combined with economic models. In particular, in situations where complex economic and biophysical processes interact and managers and policy makers are required to ensure long-term sustainability, bioeconomic simulation models can be very helpful decision-making tools (Wise et al., 2007). deVoil et al. (2006) show that models that incorporate biophysical and economic components of agro-ecosystems are appropriate for exploring sustainability issues in cropping systems. By using an evolutionary multi-objective algorithm and the crop growth model APSIM, they maximize the gross margin of a cropping system, while minimizing the risk of erosion and financial income loss. An integrated simulation model, which couples a whole-farm model and a nitrogen discharge function, is also used by Ramilan et al. (2011) in order to predict responses of local producers to alternative nitrogen pollution policies. Semaan et al. (2007) combine the agronomic simulation model EPIC with an economic decision model at farm scale to test the effects of three agricultural policies on a farmer's revenue and nitrate leaching. Furthermore, Finger et al. (2011) link the crop growth model

CropSyst with an economic decision model to evaluate agricultural water consumption and income in grain maize production in different climate and socio-economic scenarios.

Recent developments in bioeconomic modeling approaches have stressed two major points important to our own study. On one hand, several attempts have been made to integrate a farmer's risk preferences in these models, by, for instance, using certainty equivalents instead of profits as objective function (e.g. Ogurtsov et al., 2008; Richards et al., 2008; Finger et al., 2011; Lehmann et al., 2013). On the other, the use of genetic algorithms (GAs) has been introduced as valid alternative for the optimization routine in these models (e.g. Mayer et al., 2001; Ramilan et al., 2011; Lehmann et al., 2013). GAs are a heuristic optimization method which approach the global optimum in an iterative directed search by mimicking natural evolution (Goldberg and Holland, 1988). The main advantage of GAs is their ability to handle any kind of objective functions or constraints defined in the discrete, continuous, or mixed search space (Gen and Cheng, 2000).

6.2 Objectives

The here presented work aims to assess the effects of alternative water policies on water consumption, overall profitability and the financial risks involved in the production of potatoes in the Broye catchment using a bioeconomic modeling approach. We focus on potato production since it is the predominantly irrigated crop in the Broye catchment (Robra and Mastrullo, 2011). The bioeconomic modeling system links the crop growth model CropSyst (Stöckle et al., 2003) to an economic decision model at field scale and optimizes management decisions with regard to irrigation and nitrogen fertilization through the use of a genetic algorithm (GA). CropSyst allows us to compare and contrast potential potato growth under a wide range of management and environmental conditions. At the same time, a simple economic model is developed to evaluate a farmer's certainty equivalent (CE) concerning different irrigation and fertilization management decisions. Finally, a GA is used as an optimization technique, since GAs are superior to deterministic search techniques if the optimization problem is nonlinear, non-convex and includes discrete variables (Panagopoulos et al., 2012), which is the case for the current study.

Our model differs to earlier research approaches in several aspects: (i) the method proposed in this study fully integrates the crop growth model into the optimization engine without any intermediate steps (e.g. estimation of production function); (ii) the modeling approach accounts not only for the overall fertilization and irrigation water, but also for decision variables such as the timing and allocation of fertilization and irrigation; and

finally (iii) using the CE as objective function enables the simultaneous consideration of a farmer's average income as well as income risks as target variables in different scenarios.

6.3 Material and methods

6.3.1 Modelling

For this study, we adapt and extend the bioeconomic modeling approach developed by Lehmann et al. (2013). Figure 6.3 shows a flowchart outlining the optimization procedure. The GA initializes the optimization run by generating a random initial population of individuals. Each individual represents a specific set of decision variables (e.g. nitrogen fertilization amount, irrigation strategy) and thus a candidate solution. These decision variables are used in CropSyst, along with daily weather data and soil information, as input for the simulation of potato crop yields during a simulation period of 25 years. The simulated annual potato yields are subsequently fed into the economic model, which derives the farmer's CE at field scale for the corresponding set of decision variables. Besides CropSyst and the economic decision model, the stochastic weather generator LARSWG (Semenov and Barrow, 1997; Semenov et al., 1998) is used to simulate daily weather data for a simulation period of 25 years. In a next step, the feasibility of each solution is examined. The feasibility of a candidate solution depends on the implemented agronomic restrictions as well as on the considered policy scenario. For instance, the minimal interval of two consecutive fertilizations has to be larger than or equal to ten days (see Table 6.2) or the maximal amount of annually allowed irrigation water cannot exceed a fixed quantity in the *water quota* scenario (see Table 6.3). If a candidate solution violates one of the implemented restrictions, its fitness value is decreased by a linear penalty function. Finally, a new generation of potential solutions is created using the GA operators (selection, mutation, crossover, reproduction). These processes are repeated until the termination criterion of the genetic algorithm is met and the convergence of the GA to a global optimum can be assumed.

The following sections describe the component models employed, the settings of the GA as well as the considered management decision variables and water policy scenarios.

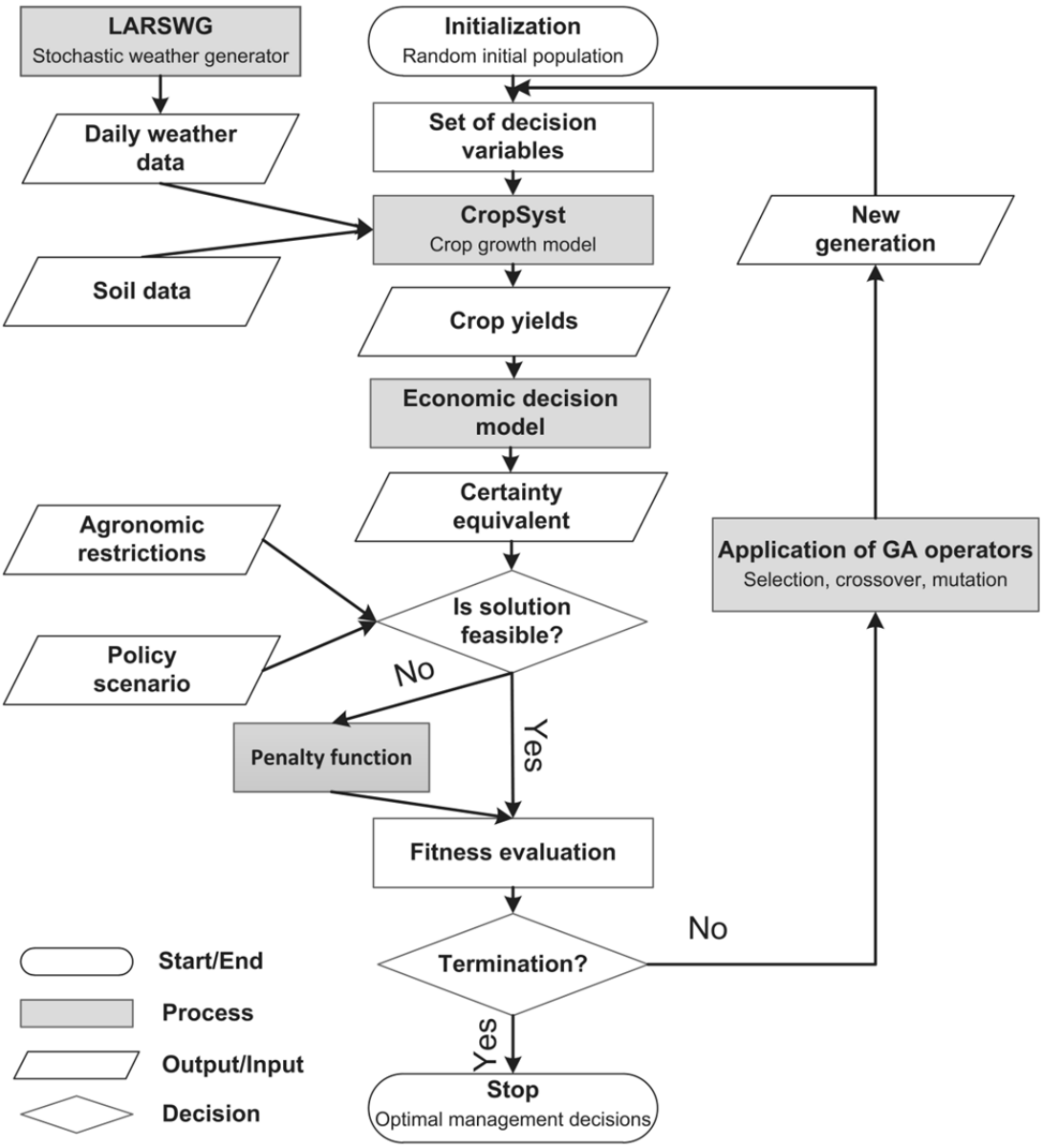

Figure 6.3: Flowchart of the optimization procedure. The genetic algorithms starts with an initial population of candidate solutions (= sets of decision variables). Each candidate solution is used as management input factors in CropSyst to simulate crop yields and to determine the certainty equivalent in the economic decision model. Finally, the genetic algorithm evaluates for each solution its fitness value and generates an offspring population by selecting the fittest candidate solutions and applying the genetic operators mutation and crossover. These processes are repeated until the termination criterion is met and the algorithm converges to a global optimum.

6.3.2 LARSWG

25 years of daily weather data, representing current climate conditions at Payerne (6°57'E, 46°49'N, 490 m a.s.l., Figure 6.1), are generated by the stochastic weather generator LARSWG (Semenov and Barrow, 1997; Semenov et al., 1998). Stochastic weather generators are able to simulate daily weather data time series as required by crop growth models which are statistically similar to observed weather data (Wilks and Wilby, 1999). Besides the advantage that weather generators can generate arbitrary long time series of daily weather data, they also offer a cost-effective tool to construct site-specific climate scenarios. In this study, the LARSWG weather generator has been calibrated against observed weather from the period 1990-2009 at the climate station Payerne. To determine statistically significant differences between the observed and simulated climate data, the QTest option of LARSWG including t-tests and F-tests has been used (Semenov and Barrow, 2002). These tests have indicated highly similar distributions for the generated and observed weather data.

6.3.3 CropSyst

The generated synthetic weather data are used as input variables in CropSyst to simulate annual potato yields as a function of the season's prevailing weather conditions and the chosen agricultural management decisions (e.g. fertilization amount, irrigation strategy). CropSyst is a process-based, multi-year, multi-crop cropping simulation model, which considers the soil water budget, the soil-plant nitrogen budget, crop canopy and root growth, crop phenology, dry matter production, yield, residue production and decomposition, and erosion (Stöckle et al., 2003). Crop development in CropSyst is based on a thermal time approach, whereas the accumulation of thermal time may be accelerated by water stress (Stöckle et al., 2003). The water budget includes precipitation, irrigation, runoff, interception, water infiltration, water redistribution in the soil profile, deep percolation, crop transpiration and evaporation (Stöckle et al., 2003). The water redistribution in the soil is treated by a simple cascading approach. The reference crop evapotranspiration (ET_o) can either be calculated by the Penman-Monteith (Monteith, 1965) or the Priestley-Taylor model (Priestley and Taylor, 1972). This study has employed the first approach. The mineral nitrogen budget differentiates between separate budgets for nitrate and ammonium and accounts for nitrogen transformations, ammonium sorption, symbiotic nitrogen fixation, crop nitrogen demand and crop nitrogen uptake processes (Stöckle et al., 2003). More information about all processes implemented in CropSyst can be found in Stöckle et al. (2003).

In this study, we use a region-specific calibration version of CropSyst, adapted from Klein et al. (2012). Klein et al. (2012) calibrated crop-specific parameters of CropSyst against local yield records from the Farm Accountancy Data Network (FADN). This calibration approach has the advantage that CropSyst is not calibrated against one specific potato cultivar, but the CropSyst calibration used in this study represents characteristics of typical potato cultivars in the Broye catchment. The soil profile used for the simulations is composed of 60% sand, 11% clay and 29% silt, which is representative for the region under investigation. Further information on the texture, hydraulic and chemical characteristics of the soil profile can be obtained from Table B.1 in the Appendix B. In order to avoid distortions due to dynamic effects, identical initial soil conditions are applied for all simulation years (see Table B.1 in the Appendix B). The resulting yield variability can thus only be explained in terms of varying weather conditions and management options applied. Furthermore, we uniformly apply April 5th as the planting date for potato cultivation[16].

6.3.4 Economic decision model

The simulated potato yields are integrated into the economic decision model to derive a farmer's certainty equivalent (CE) in potato production. The CE refers to a specific amount of money, which has the same utility as the expected outcome of a risky prospect and is defined as shown in Equation 6.1:

$$CE = E(\pi) - RP \tag{6.1}$$

Where CE stands for the certainty equivalent, $E(\pi)$ for the expected profit margin and RP for the risk premium (all of them expressed in CHF·ha^{-1}). The RP is the maximum amount of money the decision maker is willing to pay to eliminate risk exposure (Di Falco et al., 2007). According to Pratt (1964), the RP can be approximated by Equation 6.2:

$$RP \approx 0.5 \cdot {\gamma}/{E(\pi)} \cdot \sigma_{\pi}^{2} \tag{6.2}$$

Where γ is the coefficient of relative risk aversion and σ_{π}^{2} is the variance of the profit margin π (CHF·ha^{-1}). For the current study, γ has been set to 2, which corresponds to a moderate risk-averse decision maker (see Gardebroek, 2006, for an overview) and implies decreasing absolute risk aversion (Di Falco and Chavas, 2006).

[16] Since the thermal time emergence model has been used in the potato calibration file, no information on planting density was required (Stöckle and Nelson, 2000).

The annual profit margin π is defined according to Equation 6.3, wherein ρ is the revenue in potato production (CHF·ha^{-1}) and DP are the governmental direct payments (CHF·ha^{-1}). c_{fix} stands for the fixed costs (CHF·ha^{-1}) (excluding the irrigation system), c_{irrig} for the fixed costs of the irrigation system (CHF·ha^{-1}), and c_{var} for the variable costs (CHF·ha^{-1}).

$$\pi = \rho + DP - c_{fix} - c_{irrig} - c_{\mathrm{var}} \tag{6.3}$$

Note that $c_{irrig} = 0$ if irrigation is not considered as a management option. Table 6.1 shows the used revenue and cost elements required for the computation of the profit margin in more detail.

Table 6.1: Considered revenue and cost items in potato production.

Revenue	*Unit*	
Price table potatoes[a,b]	(CHF·kg^{-1})	0.46
Price feed potatoes[a,b]	(CHF·kg^{-1})	0.10
Direct payment		
Direct payment[a]	(CHF·ha^{-1})	1680
Fixed costs		
Seed[a]	(CHF·ha^{-1})	3578
Plant protection[a]	(CHF·ha^{-1})	620
Desiccant[a]	(CHF·ha^{-1})	180
Contract work and machinery costs[a]	(CHF·ha^{-1})	2591
Fixed irrigation costs		
Sprinkler irrigation system cost[d]	(CHF·ha^{-1})	447.41
Variable costs		
Nitrogen fertilizer[a]	(CHF·kg^{-1}N^{-1})	1.4
Other fertilizer costs[a,c]	(CHF·kg^{-1}N^{-1})	3.49
Hail insurance[a]	(% of crop yield revenue)	2.4
Variable irrigation costs[d]	(CHF·m^{-3})	0.1
Interest rate[a,e]	(%)	3.0

[a] Source: AGRIDEA and FIBL (2010)

[b] According to AGRIDEA and FIBL (2010) we assume that 75% of the total potato harvest can be sold as table potatoes. The remaining 25% of the total potato harvest are non-marketable potatoes which can be used or sold as feedstuff.

[c] Since in CropSyst only nitrogen fertilization is considered, we couple the costs of P_2O_5, K_2O and Mg fertilizer to the applied nitrogen amount.

[d] Source: Spörri (2011)

[e] Interest claims have been calculated on the invested capital (fixed costs, fixed irrigation costs and variable costs) for an average commitment of 6 months..

6.4 Decision variables

Twelve decision variables, specifically regarding nitrogen fertilization and irrigation strategy, are taken into account (Table 6.2). Both, nitrogen fertilization and irrigation, are important yield-determining factors, and make up a large part of the total costs of potato production (see Table 6.1). The combined effects of nitrogen and water supply on potato yields have been stressed by several studies (e.g. Ojala et al., 1990; Bélanger et al., 2000). Therefore, both factors have been considered simultaneously in this study.

Table 6.2: Considered management variables.

Decision Variable	*Management variable*	*Unit*	*Range (min-max)*	*Variable increment*	*Number of alternatives*
1	Total nitrogen amount[a]	kg·ha^{-1}	0-150	10	16
2	Number of N fertilization events	0-4	-	1	5
3	Percentage of 1st N application	%	0-100	10	11
4	Timing of 1st N application[b]	Days after sowing	0-120	10	16
5	Percentage of 2nd N application	%	0-100	10	11
6	Timing of 2nd N application	Days after sowing	0-120	10	16
7	Percentage of 3rd N application	%	0-100	10	11
8	Timing of 3rd N application	Days after sowing	0-120	10	16
9	Percentage of 4th N application	%	0-100	10	11
10	Timing of 4th N application	Days after sowing	0-120	10	16
11	Maximum allowable depletion (MAD)	-	0-1	0.1	11
12	Irrigation refill point	-	0-1	0.1	11

[a] Nitrogen amounts above 150 kg·ha^{-1} are not considered because such high nitrogen fertilization applications are not used in practice due to their negative impacts on potato quality (A. Zimmermann, personal communication).

[b] To consider the fact that frequent fertilization applications increase labor and machinery costs, a minimum interval of 10 days is specified between two consecutive fertilization applications.

To derive optimal nitrogen fertilization strategies, we account for ten different decision variables with regard to a) the total applied amount of nitrogen fertilization b) the number of fertilization events, c) the timing of each fertilization event, and d) the allocation strategy of the total nitrogen amount to the different fertilization events (Table 6.2). Currently, 2-3 fertilizer applications and a total nitrogen fertilization amount of 100-120 kg·ha^{-1} are recommended in rainfed Swiss potato production (Flisch et al., 2009).

Regarding the optimal irrigation strategy, we use the automatic irrigation option available in CropSyst while taking two decision variables into account. Firstly, we consider the

maximum allowable depletion (MAD) as decision variable. The MAD is the lowest soil water content at 1 m soil depth before irrigation is triggered and it is expressed as the percentage of the maximum available soil water where 0% is equal to the field capacity and 100% is equal to the plant wilting point (Stöckle and Nelson, 2000). Besides the MAD, we use the refill point as decision variable for the determination of the optimal irrigation strategy. The refill point defines the soil water content after each irrigation application and is expressed as percentage of the maximum available soil water where a value of 100% is equal to the field capacity and 0% is equal to the plant wilting point (Stöckle and Nelson, 2000). Since the two variables are complementary, the refill point must be specified to exceed (1-MAD). The irrigation amount of each irrigation application depends on the difference between (1-MAD) and the refill point whereas the applied irrigation water is largest if the MAD is equal to 100% (i.e. the soil's water content before irrigation goes to permanent wilting point) and the refill point is equal to 100% (i.e. the soil's water content is refilled to field capacity).

The current study assumes an irrigation efficiency of 77% corresponding to a sprinkler irrigation system (Brouwer et al., 1989), the most common technique used in Switzerland (Weber and Schild, 2007). To account for the hydraulic limitations of a typical sprinkler system, a minimum irrigation quantity of 15 mm per irrigation event is specified. Thus, irrigation is delayed if less than this threshold of 15 mm is required to reach the refill point.

6.5 Optimization engine

In order to optimize the considered management variables with regard to irrigation and nitrogen fertilization and to maximize the farmer's CE, we use a genetic algorithm (GA) as optimization technique. GAs belong to the class of evolutionary algorithms and are inspired by the natural evolution process involving natural selection and population genetics (Savić et al., 2011). They evolve a population of solutions through an iterative application of randomized processes of selection, recombination (also referred to as crossover) and mutation (Goldberg and Holland, 1988). In contrast to conventional optimization techniques, which require rigid assumptions, such as linearity of constraints, and a linear or quadratic objective function, GAs can even be applied when the optimization problem cannot be formally expressed by a set of equations (Krink et al., 2009). This particular advantage of GAs enables in this study the direct integration of simulated potato yields in the economic model without any intermediate steps such as the estimation of production functions.

We use the C++ based GA library package GAlib and apply a steady-state GA (for technical details see Wall, 1996). The steady-state GA uses overlapping populations creating for each generation a temporary population of offspring, which are generated through the application of the genetic operators selection, mutation and crossover and added to the previous population. Then, the worst individuals (i.e. individuals with the lowest fitness score) are removed to bring the population back to its original size (Wall, 1996). The replacement percentage (i.e. how much of the population is replaced in each generation) can be specified by the proportion of replacement value. Compared to single GAs, steady-states GAs are known to drastically reduce simulation time (Srivastava et al., 2002). Furthermore, in accordance to Mayer et al. (2001), we apply the following control parameters to the GA: genome size = 8 bits; population size = 50; proportion of replacement = 0.2; selection routine = roulette wheel; mutation probability = 0.15; crossover probability = 0.5; and a sigma truncation scaling (Wall, 1996) is used as fitness function (Equation4):

$$f_i^{'} = f_i + (\overline{f} - c \cdot \sigma) \tag{6.4}$$

where $f_i^{'}$ is the fitness score, f_i is the objective score of the individual i, $\overline{f}$ is the population's average and σ is the population's standard deviation of the objective score. The multiplier c has been set for this study to a value of 2. This sigma truncation scaling is recommended if the objective score can be negative (Wall, 1996), which is the case in the here presented optimization problem. Moreover, constraints coming from the allowable search space (see Table 6.2) and the water policy scenarios (see Table 6.3) are handled with a simple linear penalty function . Finally, the optimization procedure stops when less than a 1% improvement is achieved for the target variable during the last 500 consecutive generations. Since GAs present a stochastic optimization technique, the obtained optimal solutions can vary between different simulation runs. To control whether the GA converged to a global optimum, the optimization runs for all scenarios have been performed three times using different random initial populations (following Lehmann et al., 2013). This led in all scenarios to nearly the same optimal solutions, which can thus be interpreted as global optima.

6.6 Policy scenarios

Four different policy scenarios are used to compare the effects of different governmental water policies on the water consumption, average income and income risks in potato production, as well as the farmer's CE (see Table 6.3). The scenario *no restriction*s is used as the baseline scenario; in this case no constraints on the application of irrigation are

implemented. The scenario *withdrawal bans* refers to the currently applied water policy in the Broye catchment as described above, considering no general limitation on water withdrawals. However, water withdrawal bans are imposed for a region if the rivers' water flows limits are undercut (for details see BAFU, 2000). Since farmers in the Broye catchment take water for irrigation purposes almost exclusively from rivers (Robra and Mastrullo, 2011), irrigation is impossible during such withdrawal bans. In the first and second scenario, variable irrigation costs of 0.1 CHF·m^{-3} are assumed representing energy costs of pumping water from the river to the field (Table 6.3). No variable water price is currently charged in the Broye region for irrigation. In the third scenario (*water price*), we simulate the effects of implementing a constant volumetric water price of 1 CHF·m^{-3}, which corresponds to the range of currently valid drinking water prices in Switzerland (EDV, 2011). In this scenario, the total variable costs of irrigation thus amount to 1.1 CHF·m^{-3}. Since volumetric water pricing may not necessarily reduce the agricultural water demand (Molle, 2009), we consider a fourth scenario (*water quota*), which limits the annual applicable irrigation water amount to a maximum quantity of 1500 m^3·ha^{-1}.

It is well known from other studies (e.g. Massarutto, 2002; Gomez-Limon and Riesgo, 2004) that the demand for water is almost inelastic up to a certain threshold price. Nevertheless, this threshold price depends on the specific crop considered as well as on local climate, soil and market conditions. To identify the threshold price level for the presented case study, we repeat the optimization run for the water price scenario increasing the volumetric water prices from 0 CHF·m^{-3} to 4 CHF·m^{-3} in 0.5 CHF·m^{-3} steps. A sensitivity analysis is also performed for the water quota scenario whereby the assumed annual applicable water amount is stepwise increased (in 250 m^3 steps) from 0 m^3 to 2000 m^3.

Table 6.3: Water policy scenarios.

Policy	*Variable irrigation costs (CHF·m^{-3})*	*Maximum annual irrigation amount (m^3)*	*Temporal restrictions*
no restrictions	0.1	Unlimited	None
withdrawal bans	0.1	Unlimited	Irrigation is banned for a random period if $\sum_{i=1}^{n} WB_i < -200mm$ [a]
water quota	0.1	1500	None
water price	1.1	Unlimited	None

[a] WB_i is the daily water balance in the month i (i =May, June and July). The random period of the water withdrawal bans and thus the irrigation prohibition is generated by a truncated normal distribution (Robert, 1995) based on historical observed mean and standard deviation values for the starting point and length of water withdrawal bans.

Regarding the *withdrawal bans* scenario, a proxy variable is required to predict the occurrence of water withdrawal bans in the 25 simulation years based on daily weather data. For this purpose, an analysis of observed daily weather data at the climate station Payerne and observed water withdrawal bans in the canton of Vaud during the period 1998-2011 (Figure 6.2) has been performed. This analysis indicates that the sum of the daily water balance[17] in the months of May, June and July serves as a good proxy variable for the occurrence of water withdrawal bans. More specifically, our empirical analysis shows that the implementation of a temporary water withdrawal ban was likely to occur when the sum of daily water balances in these three months was smaller than -200 mm. The validity of this proxy variable is demonstrated in Table 6.4 which compares the observed water withdrawals bans in the canton of Vaud with modeled predictions based on this proxy variable. We were not able to identify any correlations between the exact occurrence dates and the lengths of water withdrawal bans and weather conditions specific to Payerne since the water withdrawal bans are generally imposed for the entire area of a canton. To empirically implement the existing information in our simulations, starting points and durations of water withdrawal bans are randomly generated using a truncated normal distribution (Robert, 1995). This distribution is fitted using data from observed starting points and durations of water withdrawal bans in the canton of Vaud from 1998–2011 (Figure 6.2) whereby the earliest (latest) historically observed day in the year of a water withdrawal ban is implemented as the lower (upper) truncation point. In summary, the occurrence of water withdrawal bans are simulated in the *withdrawal bans* scenario using the water balance in early summer months as proxy variable. The employed starting points and durations of the withdrawal bans are simulated by observed probability distributions.

[17] The daily water balance is defined as the daily precipitation sum minus the daily potential evapotranspiration sum, which is computed following the Penman-Monteith method (e.g. Allen et al., 1998).

Table 6.4: Performance of proxy variable predicting occurrences of water withdrawal bans in the canton Vaud

Year	*Observation water withdrawal ban (0/1)*[a]	*Prediction on water withdrawal ban occurrence based on water balance sum (May-July)*[b]
1998	1	1
1999	0	0
2000	0	0
2001	0	0
2002	0	0
2003	1	1
2004	1	1
2005	1	1
2006	1	1
2007	0	0
2008	0	1
2009	1	1
2010	1	1
2011	1	1

[a] A value of 1 indicates the occurrence of a water withdrawal ban in the respective year; a value of 0 stands for a year without a water withdrawal ban.

[b] The water balance sum is defined as the daily precipitation sum minus the daily potential evapotranspiration sum.

6.7 Results and discussion

6.7.1 Optimal management schemes

Scenario-dependent optimal management schemes with regard to nitrogen fertilization and irrigation are presented in Table 6.5. Even though Bélanger et al. (2000) and Ojala et al. (1990) pointed out the important relationship between nitrogen fertilization and irrigation, we do not find differences in the optimal amount of nitrogen fertilizer as a function of water policy. In all considered water policy scenarios, it is optimal to apply a nitrogen fertilization amount of 150 kg·ha^{-1}. This can be explained by the fact that we limited the maximum nitrogen fertilization amount to 150 kg·ha^{-1}, to account for practical restrictions caused by requirements for potato quality. This restriction has been implemented since CropSyst is not able to directly simulate weather- and input-related effects on the quality of crop yields. However, the quality of crop yields is a very important variable in particular for the production of potatoes, and should be explicitly considered in future research efforts. Regarding the total number and the timing of fertilization events, as well as the specific allocation strategy, small differences in the optimal management schemes are found between the considered policy scenarios. For instance, it is optimal to

apply the total nitrogen amount in four fertilization events in all scenarios except the *no restrictions* scenario. In the latter, the total nitrogen amount should be preferentially split into three fertilization applications.

In contrast to nitrogen fertilization, the different policy scenarios have demonstrable effects on the optimal irrigation strategy. Under both, the *no restrictions* and *water price* scenario, the optimal irrigation strategy triggers irrigation at a MAD value of 0.5 with each irrigation event refilling the soil water content to a value of 0.6. This means that irrigation should be initiated if the soil water content is 50% below the field capacity and each irrigation application refills the soil's water content to 60% of the field capacity. This strategy results in both scenarios in an average of annual applied irrigation water of about 1220 $m^3 \cdot ha^{-1}$. Even though the implementation of a defined water price increases variable irrigation costs by a factor 10 or more, there is still no incentive to reduce irrigation. This shows that the demand for irrigation water is inelastic (i.e. the water price elasticity is close to zero) for a water price between 0 and 1 $CHF \cdot m^{-3}$. As mentioned above, the finding that the water demand is inelastic up to a certain threshold water price range is in line with previous findings in the field (e.g. Massarutto, 2002; Gomez-Limon and Riesgo, 2004).

Table 6.5: Optimal management schemes.

Management variable	*Unit*	*no restrictions*	*withdrawal bans*	*water quota*	*water price*
Total N amount	$kg \cdot ha^{-1}$	150	150	150	150
Number of fertilization events	-	3	4	4	4
Percentage of 1st N application	%	60	30	40	60
Timing of 1st N application	Days after sowing	50	50	50	40
Percentage of 2nd N application	%	20	30	20	20
Timing of 2nd N application	Days after sowing	70	60	60	50
Percentage of 3rd N application	%	20	20	20	10
Timing of 3rd N application	Days after sowing	80	70	70	70
Percentage of 4th N application	%	0	20	20	10
Timing of 4th N application	Days after sowing	-	80	80	80
Mean irrigation amount	$m^3 \cdot ha^{-1}$	1222	1396	1223	581
Years without irrigation	-	0	0	0	11
Maximum allowable depletion (MAD)=	-	0.5	0.2	0.5	0.8
Irrigation refill point	-	0.6	0.9	0.6	0.3

The irrigation strategy in the *withdrawal bans* scenario (MAD = 0.2 and soil refill point = 0.9), which is the policy currently in use, results in the highest average amount of irrigation. Note that the optimal MAD is significantly lower than in the other scenarios in the withdrawal bans scenario (Table 6.5) which suggests irrigation even when the soil's water content is only slightly below field capacity. Even though irrigation is frequently banned in hot and dry years, the irrigation strategy in the withdrawal bans scenario leads to the highest annual average of irrigation water applied (1396 $m^3 \cdot ha^{-1}$). The explanation for this counterintuitive finding lies in the fact that in the *withdrawal bans* scenario it is optimal to irrigate very intensively whenever irrigation is possible. This ensures that the soil's water content is always close to maximal field capacity before any implementation of water withdrawal bans which reduces negative effects of withdrawal bans on potato yield levels.

Finally, the limitation of the annual applicable irrigation amount (*water quota*) leads to the smallest average of irrigation water (581 $m^3 \cdot ha^{-1}$). The optimal irrigation strategy under this scenario implies a MAD and a soil refill point of 0.8 and 0.3, respectively. That is to say that irrigation in this case should only be applied when the plant available soil water capacity is almost fully depleted. Moreover, each irrigation application replenishes the soil's water content to only 30% of field capacity. This extensive irrigation strategy, identified to be optimal in the water quota scenario, abandons irrigation in rather moist years. In contrast to other scenarios where irrigation is applied in all 25 simulation years, potatoes in the *water quota* scenario are cultivated without the application of irrigation in 11 years (Table 6.5).

Besides the average, we are also interested in the specific distribution of the annual amount of irrigation water (Figure 6.4). Note that in dry and hot years the applied irrigation water may exceed the average irrigation water by more than 100% causing water scarcity in the region's rivers. In all scenarios except the *water quota* scenario, annual water amounts of more than 2100 $m^3 \cdot ha^{-1}$ are plausible in very hot and dry years. Neither the implementation of water withdrawal bans in dry seasons nor the volumetric pricing of irrigation water can prevent exceptionally high water withdrawals from surface water bodies and the associated environmental harms. On one hand, constant volumetric pricing of irrigation water cannot reduce the high rates of extraction of surface water bodies, since irrigation water has a higher value of marginal product in dry than in moist years (Bontemps and Couture, 2002). On the other, very intensive irrigation practices in the *withdrawal bans* scenario lead to large amounts of irrigation water even in years with temporal water withdrawal bans. The only effective policy measure to avoid environmental harm due to high water withdrawals during dry periods appears to be the

implementation of a water quota. This policy limits the maximum applicable irrigation water in all years to 1500 $m^3 \cdot ha^{-1}$. Furthermore, in 11 out of the 25 simulation years, irrigation can be abandoned in this particular scenario.

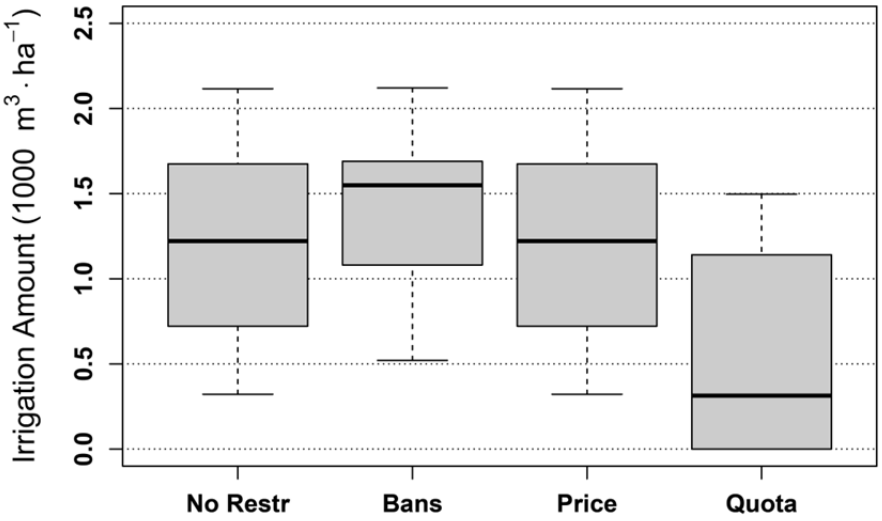

Figure 6.4: Distribution of the annual irrigation amounts in the 25 simulation years. The box contains the middle 50% of the data (=inter–quartile range) while the whiskers extend to the most extreme data points. The median is denoted by the horizontal thick line. Note that the simulated distribution of applied irrigation quantities in the *withdrawal bans* scenario are consistent with the observed irrigation strategies of potato growers in the Broye catchment (Robra and Mastrullo, 2011). No Restr = *no restrictions*; Bans = *withdrawal bans*; Quota = *water quota*; Price = *water price*.

6.7.2 Farm income, income risks and certainty equivalent

So far, we have analyzed the impacts of the different water policy scenarios on the optimal nitrogen fertilization and irrigation strategy. From a potato grower's point of view, the changes in his revenues and crop yield levels may be more important. Figure 6.5 shows the distribution of the annual profit margins, potato yields and the CE resulting from the optimal (i.e. CE maximizing) management schemes that are presented in Table 6.5.

The scenario *no restrictions* not only results in the highest average profit margin and crop yields, but also minimizes the income risks associated with potato production. Consequently, the farmer's CE in potato production, which considers both the average income and income risks, is highest in this scenario. In the *withdrawal bans* scenario, income risks are drastically increased. In this scenario the coefficient of variation (CV) of the profit margins amounts to 30.4% which is clearly higher than the income risks in the *no restrictions* and *water price* scenario. These higher income risks lead to a large reduction of the farmer's CE (-23% compared to the CE in the *no restrictions* scenario) although the

decrease in the farmer's average profit margin still is less than 16%. The negative impacts of the current policy are generally relatively small when only the agricultural income is taken into account. However, the consideration of both, the average income levels and the income risks - as measured by the CE - indicates much higher negative effects. Compared to the baseline scenario (*no restrictions*), the pricing of the irrigation water has almost no impact on the physical yield level distribution, and only slightly increases the variability of the profit margins. Nonetheless, the higher irrigation costs decrease the average profit margin, which lowers the farmer's CE in potato production by about 12% compared to the CE in the *no restrictions* scenario. Finally, the implementation of a water quota reduces the average profit margin when compared to the *no restrictions* scenario by about 18% and increases the farmer's income risks even more than under the *withdrawal bans* scenario (CV=37.6%). Consequently, a significant reduction of the farmer's CE in potato production (-29% compared to the *no restrictions* scenario) can be observed in the *water quota* scenario. This is due to the fact that in presence of water quotas, low yield levels result in years in which the irrigation demand exceeds the applicable irrigation amount, which in turn, contributes to higher income risks. Thus, while the reduced agricultural water consumption in the *water quota* scenario has little impact on the farmer's average profit margin, it leads to a large increase in production and income risks, both of which decrease the farmer's CE.

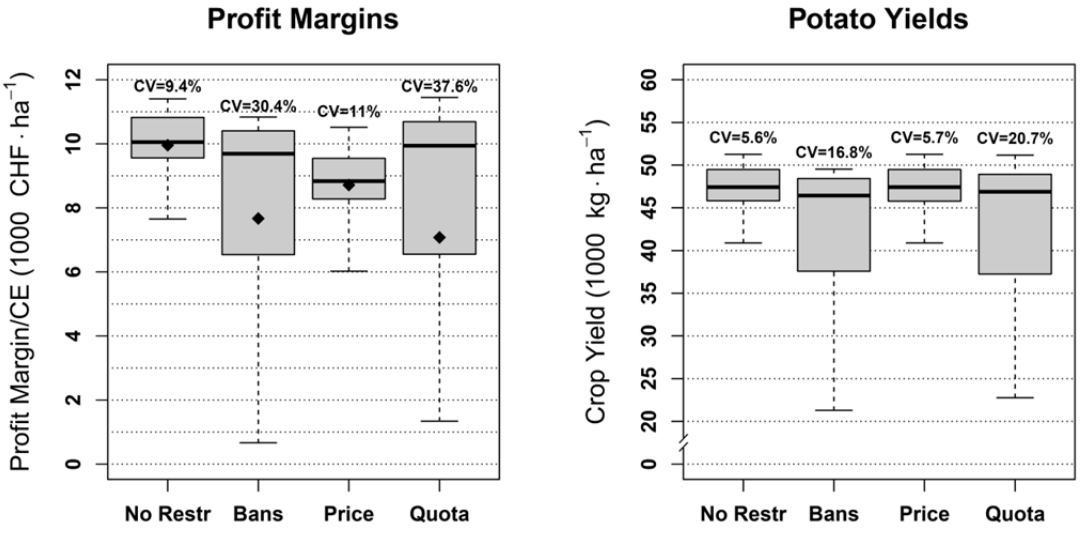

Figure 6.5: Distribution of profit margins (left plot) and potato yields (right plot) in the 25 simulation years. Additionally, the certainty equivalents are shown in the left plot by the black diamonds. The coefficients of variation (CV) are given for both, the annual profit margins and physical potato yields. The box contains the middle 50% of the data (=inter–quartile range) while the whiskers extend to the most extreme data points. The median is denoted by the horizontal thick line. No Restr = *no restrictions*; Bans = *withdrawal bans*; Price = w*ater price;* Quota = *water quota*.

6.8 Sensitivity analysis

The responses of the average water consumption and the farmer's CE to different water price levels and different allowable annual water amounts are given in Figure 6.6. It shows that the implemented volumetric water price has to be above 2 CHF·m^{-3} to significantly decrease the applied average irrigation water (left plot in Figure 6.6). A water price of 2.5 CHF·m^{-3}, for instance, decreases the average irrigation demand by about 15% if compared to the no *restrictions scenario*, while at the same time the farmer's CE is reduced by more than 30%.

Regarding the sensitivity analysis for the *water quota* scenario (right plot in Figure 6.6), we find that the objective of reducing agricultural water is - compared to the *water price* scenario - achieved with much smaller losses in the farmer's CE. A *water quota* in a range of 1500-2000 m^3 can significantly reduce the farmer's water consumption in potato production. For instance, a water quota of 1750 m^3 results in an average irrigation amount and CE of about 790 m^3·ha^{-1} and 8657 CHF·ha^{-1}, respectively. Compared to the *no restrictions* scenario, this equals a reduction of the average irrigation amount of more than 35% while the farmer's CE decreases only by about 13%.

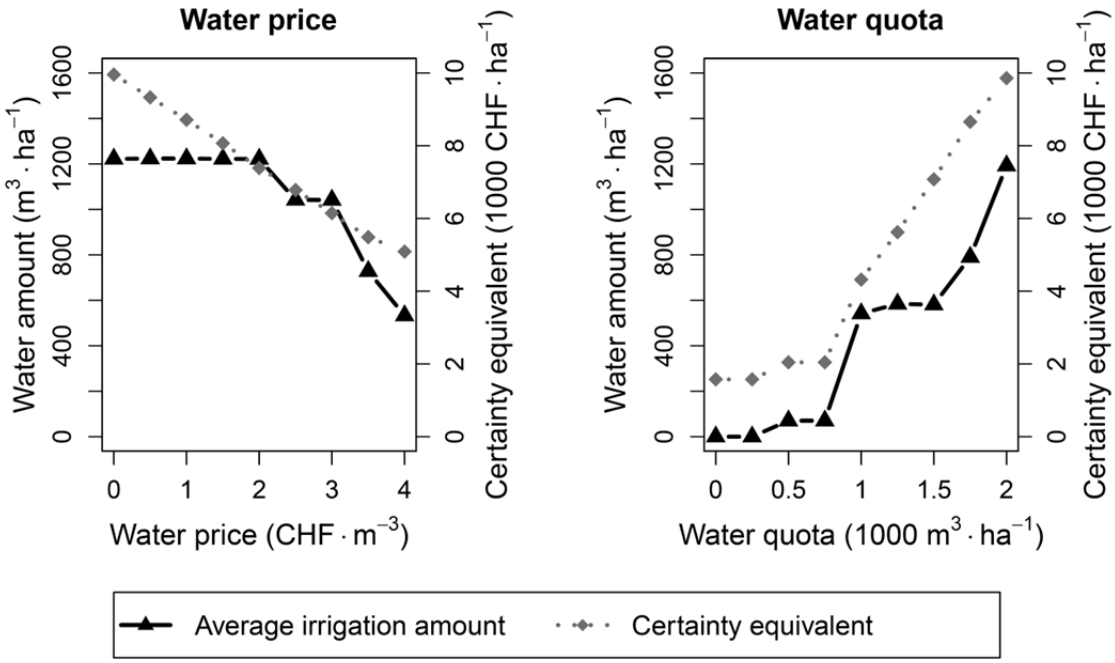

Figure 6.6: Sensitivity analysis with respect of a water price (left plot) and a water quota (right plot). Both plots show the optimal average irrigation water and the maximum certainty equivalent (see vertical axes) for different volumetric water prices and water quotas, respectively (see horizontal axis).

6.9 Conclusions and future research

The bioeconomic optimization model presented in this study is a new approach for simulating economic and environmental impacts of different agricultural policy scenarios on the production of crops. The use of a GA as optimization technique made it possible to directly link the process-based crop growth model CropSyst to the economic decision model avoiding intermediate steps such as the estimation of crop-water production functions (e.g. Finger et al., 2011; García-Vila and Fereres, 2012) which are always subject to a certain loss of accuracy. Besides the direct coupling of the crop growth model with the economic decision model, the GA also enabled the simultaneous consideration of twelve different management decision variables. Note that the exhaustive search over all possible 10^{12} different combinations of decision variables is computationally not feasible, such that a GA is required to determine optimal management schemes for each scenario. Furthermore, maximizing the farmer's CE not only considers impacts of the different water policy scenarios on the farmer's average income but also on the income risks in the model's objective function.

Our modeling study shows that the water policy currently applied in the Broye catchment does not only raise the irrigation demand but also increases income volatility in potato production and thus decreases a farmer's CE. In contrast, our results indicate that the introduction of an appropriate water quota significantly decreases the agricultural water consumption without any negative impact on the farmer's CE compared to the current water policy. Although a policy based on constant volumetric water pricing can achieve similar water savings as a quota base, the losses in the farmer's profit margin and CE are much higher. Nevertheless, it must be kept in mind that the introduction of a higher water price also generates public revenue, which could be redistributed to the farmers in the form of subsidies or used for other public benefits. Further specifications of these effects were, however, beyond the scope of this paper.

Future research efforts will include the optimization of whole-farm systems, which also account for changes in the optimal crop mix, under conditions of different irrigation water policies. As a next step, different irrigation systems should be considered (e.g. sprinklers, drip and furrow irrigation systems) displaying not only different efficiencies but also different associated fixed costs. Finally, since climate change is expected to further intensify water scarcity in the Broye catchment (e.g. Lehmann and Finger, 2013; Lehmann et al., 2013), the bioeconomic modeling approach should also be applied to different climate change scenarios. Note that LARSWG, which is part of the presented modeling approach, provides options to generate site-specific daily weather data not only for current but also for future expected climate conditions.

Acknowledgements

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7 Evaluating water policy options in agriculture: A whole farm study for the Broye River Basin (Switzerland)[18]

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ABSTRACT

In this study, we evaluate the impact of an increased volumetric water price and the implementation of a water quota on management decisions, income, income risk and utility of an arable farmer in the Broye River Basin, western Switzerland. We develop a bio-economic whole-farm model, which couples the process-based crop growth model CropSyst with an economic decision model at farm scale and use a genetic algorithm as optimization technique. This integrated modelling approach is employed to optimize the farmer's management decisions with regard to crop land use as well as crop-specific nitrogen fertilization and irrigation intensities under different climate and water policy scenarios. Our results show that the farm's water demand will increase by almost 100% under climate change. However, both, an increased volumetric water price and a water quota, are under current and future expected climate conditions effective policy measures to reduce the farm's water consumption. At the same time, due to adjustments in the crop mix as well as in crop-specific nitrogen fertilization and irrigation strategies, both policies lead to losses in farm income and in the farmer's utility of only about 10%. Nevertheless, a higher water price as well as a water quota increase under future expected climate conditions the crop farm's downside risk exposure (i.e. probability of low farm incomes).

KEYWORDS

WATER POLICIES; BIO-ECONOMIC MODEL; CROPSYST; LARSWG; GENETIC ALGORITHM

[18] Lehmann, N., Finger, R. (2013). Evaluating water policy options in agriculture: A whole-farm study for the Broye river basin (Switzerland). *Irrigation and Drainage* (In press).

7.1 Introduction

Even though Switzerland is often referred as the 'water tower' of Europe (Mountain Agenda, 1998), water scarcity has become a serious problem in some particular regions. For instance, in the Broye River Basin, which is located in western Switzerland, surface water bodies have in recent years suffered repeatedly low water levels in summer months due to an increasing frequency of exceptionally warm and dry climatic conditions and high water withdrawals for agricultural purposes (Mühlberger de Preux, 2008). Besides decreasing water levels, the combination of dry and hot climatic conditions and high water withdrawals for irrigation led also to an increase of the river water temperatures. In some recent years, the region's rivers faced water temperatures of up to 27 °C in summer months which was far higher than optimal for the aquatic fauna (Mühlberger de Preux, 2008).[19] In the coming years, climate change will further increase water requirements for irrigation in agriculture (Fuhrer and Jasper, 2009) and water shortages in the Broye River Basin can therefore be assumed to become even more frequent.

In order to prevent such low water levels in surface water bodies, governmental institutions impose water withdrawal bans, if a river's flow rate falls below a critical threshold (see BAFU, 2000, for details). Since in the Broye River Basin most water resources for irrigation purposes are taken from rivers (Robra and Mastrullo, 2011), such water withdrawal bans usually prevent the application of irrigation. Furthermore, because withdrawal bans are likely to be imposed under hot and dry weather conditions, when the crops' water requirements are highest, farmers experience losses in crop yields and farm income. Moreover, Lehmann et al. (2012) show that this policy even gives additional incentives to farmers to increase their irrigation intensity whenever irrigation is possible. Thus, the currently used irrigation water policy has significant drawbacks not only for farmers but also for the environment.

Besides climatic and biological factors, economic incentives are also important determinants of agricultural water demand. An increase in volumetric water pricing, for instance, encourages farmers to limit their water use (Easter and Liu, 2006). However, since water services often have the characteristics of a public good (Savenije, 2002), water prices are not determined by the market but have to be set by policy makers. It is therefore important to set up ex-ante evaluations of potential effects of changing water policies on agricultural water use and on agricultural income. One possible tool for such ex-ante

[19] Note that maximum growth rates of brown trout, which is one of the most important fish in Swiss rivers, occur at 13.1–13.9°C (Elliot and Hurley, 2001).

analysis is the application of bio-economic models. These allow us to evaluate the impacts of different policies or more recently the effects of climate change on agricultural production systems (Affholder et al., 2003). Recently, several studies addressed the effects of different water policies on agricultural income and water consumption applying bio-economic modelling approaches (e.g. Garcia-Vila et al., 2009; Finger et al., 2011; Rey et al., 2011; Lehmann et al., 2012). The significance of these studies addressing the relationship between agricultural water use and different water policy scenarios, however, is limited. The main limitation of these studies is their focus on the single crop level which does not allow us to investigate essential parts of farmers' adaptation processes such as changes in land use and diversification of farm activities. Therefore, crop-specific analyses may lead to misleading conclusions because, for instance, they may suggest more intensive irrigation as a response to climate change, while in reality farmers would rather switch to alternative crops (Garcia-Vila et al., 2008). Furthermore, the whole-farm perspective is important to account for restrictions on nutrient balances, farmers' workload and farm-level factor endowments (e.g. machinery).

Based on this background, we aim to model the effects of different water policy scenarios on agricultural management decisions as well as on water consumption and on the income of a whole-farm system located in the Broye River Basin, western Switzerland. In order to account for likely changes in the region's climatic conditions, the impacts of the water policies are assessed not only under current but also under future expected climatic conditions. In doing so, a bio-economic model is developed that links the process-based crop growth model CropSyst with an economic decision model at farm scale. Based on this integrated modelling approach, a farmer's management decisions with regard to crop land allocation as well as crop-specific nitrogen fertilization and irrigation management are optimized by the use of a genetic algorithm (GA). The use of CropSyst allows us to simulate crop yields for different management decisions (e.g. irrigation strategy) and climatic conditions. The economic decision model reflects a risk-averse decision maker and evaluates different management schemes converting related profits and income risks into the farmer's utility. Finally, we use a GA as an optimization technique, since the relations between management decisions and farmer's utility are highly complex and nonlinear.

By the modelling framework used here, we are able to assess the impacts of climate change and different water policy scenarios on the modelled farm's water consumption and the farmer's utility. Additionally, it is investigated how farmers adapt their management decisions to the assumed climate and policy scenarios. Thus, the study's results will provide insights for environmental policy makers in which fields particular attention is needed to maintain sustainable agricultural production in Switzerland.

Furthermore, the outcomes of this study can help farmers and other stakeholders to develop adaptation plans to global warming.

7.2 Methods

The bio-economic whole-farm model used in this study follows the optimization model developed by Lehmann et al. (2013). However, while the model of Lehmann et al. (2013) operates at single crop level, the model presented in this study optimizes management decisions at farm scale with regard to crop land allocation as well as crop-specific nitrogen fertilization and irrigation strategies. The integrated component models are described in detail later in this section. Figure 7.1 illustrates the modelling concept used in this study.

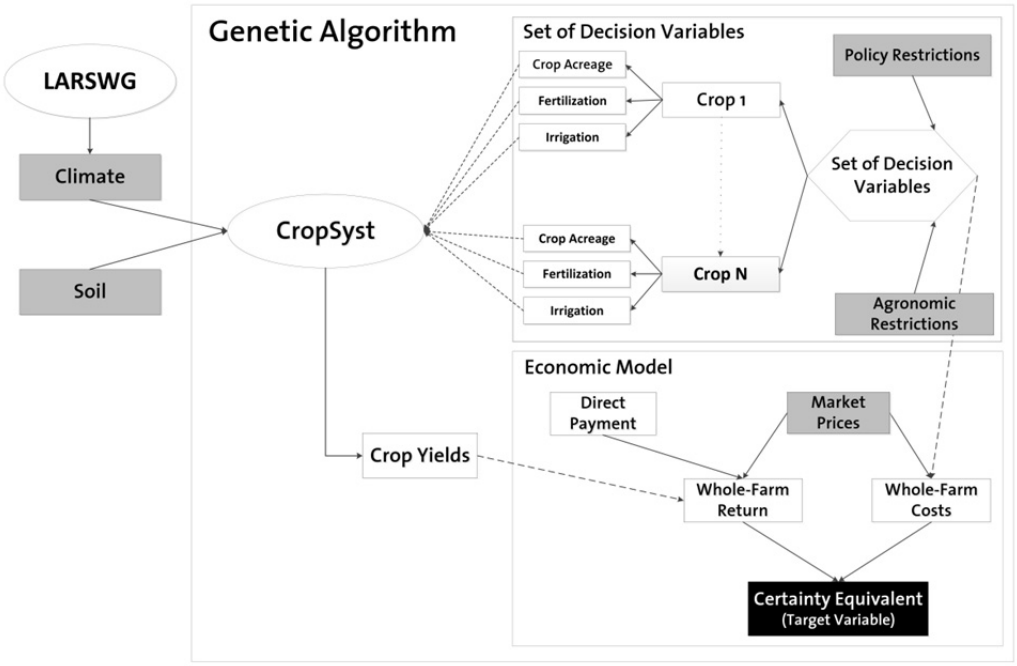

Figure 7.1: Basic modeling concept (modified from Lehmann et al., 2013).

The decision variables generated within the GA (see upper right section in Figure 7.1) are used as management input factors in CropSyst (see centre left section in Figure 7.1), which simulates crop growth and crop yields under a specific climate scenario. The generated crop yields are then fed into the economic decision model (see lower right section in Figure 7.1), where the annual whole-farm returns and costs are computed. Finally, the annual whole-farm returns and costs are used to derive the certainty equivalent (CE), which is the target variable in the optimization problem presented. The CE represents a certain amount of money, which has the same utility as the expected outcome of a risky

prospect. Thus, the objective function used accounts not only for the expected farm income but also for income risks.

In order to represent production risks due to uncertain weather conditions, the crop yields are simulated over 25 years using different weather states generated with the stochastic weather generator LARSWG. Besides variable weather data, variable crop prices are also used for the 25 simulation years.

7.2.1 Decision variables

The management decision variables are optimized for an arable farm located at Payerne (6°57' E, 46°49' N, 490 m + MSL (mean sea level)) within the Broye River Basin. The farm's total arable land is set to a for the region representative surface of 30 ha which is used for the cultivation of six arable crops, which are in terms of area, the most important crops in the study region: winter wheat (*Triticum spp. L.*), winter barley (*Hordeum vulgare L.*), winter rapeseed (*Brassica napus L.*), grain maize (*Zea mays L.*), potatoes (*Solanum tuberosum L.*) and sugar beet (*Beta vulgaris L.*). For each crop, the acreage, optimal nitrogen fertilization amount and optimal irrigation strategy are optimized. In order to reduce the computation time of the optimization procedure, all decision variables are integrated as discrete values as shown in Table 7.1. Note that the three decision variables given in Table 7.1 are used for each of the six crops considered, leading to in total 18 decision variables at farm scale.

Table 7.1: Decision variables.

Decision variable	*Unit*	*Increment*	*Range (min-max)*
Land share of crop i	%	1	1-50
Nitrogen fertilization amount of crop i [a]	$kg \cdot ha^{-1}$	10	0-200
Irrigation trigger value of crop i [b]	-	0.1	0-1

[a] The maximum nitrogen fertilization amounts for potato and sugarbeet are restricted due to losses in yield quality associated with higher application levels to 150 $kg \cdot ha^{-1}$ and 130 $kg \cdot ha^{-1}$, respectively (A. Zimmermann, personal communication).

[b] For irrigation, we use the automatic irrigation option in CropSyst, which triggers irrigation as soon as the soil moisture is lower than the user-defined trigger value.

Moreover, following Lehmann and Finger (2012a), restrictions at the crop and farm level that represent real-world constraints due to agricultural policy obligations, resource endowments and crop quality are implemented in the optimization model (see Table 7.2).

Table 7.2: Employed model constraints

Subject	*Constraints imposed in the modeling approach*	*Sources*
Crop acreage	The farmer is obliged to cultivate a minimum of four different crops. Winterwheat is limited to a maximum acreage of 50%. The sum of all cereals (without grain maize) is limited to 66% of the total arable surface. The maximum crop share of grain maize is 40%. The maximum crop share of winter rapeseed, potatoes and sugar beet is 25% of the total surface. The total crop share of winter rapeseed and sugar beet is limited due to rotational restrictions to 40%.	Cross compliance obligations (BLW, 2011). Rotational restrictions (Vullioud, 2005).
Nitrogen use	Maximum yield-depended nitrogen amounts are specified for all crop whereas the nitrogen demand and supply has to be balanced at farm-level. The nitrogen fertilization amount of potatoes and sugarbeets is restricted to a maximum quantity of 150 kg·ha^{-1} and 130 kg·ha^{-1}, respectively.	Cross compliance obligations, following the official Swiss nutrient balance method 'Suisse Bilanz' (AGRIDEA and FIBL, 2010). Higher nitrogen fertilization in potato and sugarbeet production is currently not applied in practice due to quality considerations (A. Zimmermann, personal communication).
Workload	The farmer's maximum available work time per season amounts to 2800 h. We assume a total workload for winter wheat, winter barley of 41 h·ha^{-1}, for winter rapeseed 43 h·ha^{-1}, for grain maize the working time per hectare is assumed to amount to 37 h·ha^{-1} and for potatoes and sugar beet the total workload is set to 258 and 67 h·ha^{-1}, respectively.	Following current practices in Swiss arable farms, derived from AGRIDEA and FIBL (2010).
Field working days	Fieldwork possibilities are restricted to half the days of the vegetation period (due to weather conditions) during 10 h·day^{-1}. Vegetation periods range from 220 (current climate conditions) to 250 days (future expected climate conditions). The required field working time per crop is defined as follows: winter wheat, winter barley: 16 h·ha^{-1}; winter rapeseed: 18 h·ha^{-1}; grain maize: 11 h·ha^{-1}; potatoes: 218 h·ha^{-1} and sugar beet: 27 h·ha^{-1}.	Field working days follow Luder (1996) and Musshoff and Hirschauer (2009). Vegetation period follow Calanca and Holzkämper (2010). Crop-specific field work time follows AGRIDEA and FIBL (2010).

7.2.2 CropSyst

In order to simulate crop yields and yield variability for different agricultural management schemes, the crop growth model CropSyst (see Stöckle et al., 2003, for details) is used. CropSyst is a process-based cropping simulation model, which simulates biological and environmental above- and below-ground processes of a single land block fragment at a daily scale (Stöckle et al., 2003). It is driven by daily weather data and requires information of soil and crop characteristics. For this study, we use for all considered crops a site-specific CropSyst calibration at Payerne generated by Klein et al. (2012). Furthermore, a soil profile

recorded at Payerne with a texture of 62% sand, 12% clay and 26% silt is used as soil input in CropSyst.

7.2.3 LARSWG

The stochastic weather generator LARSWG (see Semenov and Barrow, 1997; Semenov et al., 1998) is used to simulate daily weather data, which is needed as input variables in CropSyst. We apply 25 weather years for a scenario referring to the region's current climate conditions (*Baseline*) and for a climate change scenario referring to the time horizon 2036–2065 (*ETHZ-CLM*). To this end, LARSWG is conditioned for the climate station Payerne located in the Broye River Basin using daily observed weather data from 1981 to 2009. The climate change scenario (*ETHZ-CLM*) is generated using the global change model HadCM3 and the regional climate model CLM (see Lehmann et al., 2013, for further details). The applied changes in climate variables for the *ETHZ-CLM* scenario are summarized in Table 7.3. It shows that monthly average temperatures are expected to increase in all months by between 1.8 and 4.4 °C. Furthermore, the climate change scenario suggests reductions in monthly average precipitation of up to 30% in midsummer months.

Table 7.3: Applied changes in climate variables for the ETHZ-CLM scenario

Month	Δ *Tmin (°C)*	Δ *Tmax (°C)*	Δ *Rad (%)*	Δ *Precip (%)*
Jan	+2.51	+2.51	-3	-4
Feb	+1.82	+2.00	-4	-2
Mar	+1.91	+2.14	-4	-2
Apr	+2.06	+2.15	-2	-3
May	+1.85	+2.07	+2	-6
Jun	+2.18	+3.08	+7	-18
Jul	+2.82	+4.23	+9	-30
Aug	+3.11	+4.39	+8	-28
Sept	+2.78	+3.41	+3	-11
Oct	+2.29	+2.36	+0	-1
Nov	+2.28	+2.23	+0	-4
Dec	+2.69	+2.60	-2	-4

Table 7.3 shows the absolute applied changes in the monthly average minimum temperature (ΔTmin), in the monthly average maximum temperature (ΔTmax), the relative changes in the monthly average radiation (ΔRad) and in the monthly average precipitation sum (ΔPrecip) for the used CC scenario *ETHZ-CLM*.

7.2.4 Economic decision model

The economic decision model at farm scale considers crop revenues, direct payments as well as fixed and variable costs. In a first step, the annual profit margins are computed at farm level for each of the 25 simulation years according to Equation 7.1:

$$\pi = \sum_{i=1}^{N} a_i \cdot \left(\rho_i + DP_i + c_{fix,i} + c_{irrig,i} - c_{\mathrm{var},i} \right) \tag{7.1}$$

where π is the annual profit margin at farm-level, a_i is the cultivated surface of crop i, ρ_i is the revenue of crop i and DP_i are the governmental direct payments for crop i. $c_{fix,i}$ stands for the fixed costs (excluding irrigation systems), $c_{irrig,i}$ for the fixed costs of the irrigation systems and $c_{\mathrm{var},i}$ for the variable costs of crop i. The fixed and variable crop-specific costs as well as average crop prices as currently observed in Switzerland are summarized in Table 7.4.

Besides production risks arising from variable weather states, we also account for crop price volatility. Note that the uncertainty faced by the farmer with respect to output prices is expected to influence farm-management and especially irrigation decisions (Finger, 2012a). Variable crop price data for the 25 simulation years are generated by a multivariate normal distribution (Ripley, 1987) using observed mean, variance and covariance data of Swiss crop prices obtained from the FAOSTAT database in the period 2002–2009 (FAO, 2011). More details on this approach are given in Lehmann and Finger (2012b).

The expected profit margin and its variance are subsequently derived from the 25 annual profit margins, and finally the farmer's CE, which is the target value in the optimization routine, can be computed. The CE is defined as the sure sum of money with the same utility as the expected utility of a risky alternative (Keeney and Raiffa, 1976) and is defined as follows:

$$CE = E(\pi) - \frac{1}{2} \cdot \frac{\gamma}{E(\pi)} \cdot \sigma_\pi^2 \tag{7.2}$$

where $E(\pi)$ is the expected profit margin, σ_π^2 is the variance of the annual profit margins and γ is the coefficient of relative risk aversion. For this study, γ is fixed at a value of 2, which corresponds to a moderate risk-averse decision maker and implies decreasing absolute risk aversion (Di Falco and Chavas, 2006).

Table 7.4: Revenues and costs.

	Winter wheat	*Winter barley*	*Winter rapeseed*	*Grain maize*	*Pota-toes*	*Sugar beets*
Revenue						
Crop price levels (in CHF · t^{-1}). Averages of the period 2002-2010 (*Standard deviation in parentheses*)[a]	514 *(34)*	379 *(36)*	787 *(104)*	379 *(52)*	454 *(30)*	54 *(6)*[b]
Direct payment						
Direct payment (CHF·ha^{-1})[c]	1680	1680	2680	1680	1680	3580
Fixed costs						
Seed (CHF·ha^{-1})[c]	218	143	108	268	3585	407
Plant protection (CHF·ha^{-1})[c]	265	265	250	220	800	525
Plant growth regulant (CHF·ha^{-1})[c]	41	41	0	0	0	0
Contract work and machinery costs (CHF·ha^{-1})[c]	783	783	787	844	2591	1409
Fixed irrigation costs						
Irrigation system costs (CHF·ha^{-1})[d]	447	447	447	447	447	447
Variable costs						
Nitrogen fertilizer (CHF·kg^{-1}·N^{-1})[c]	1.4	1.4	1.4	1.4	1.4	1.4
Other fertilizer costs (CHF·kg^{-1}·N^{-1})[c]	0.72	0.73	0.94	1.54	3.49	1.41
Hail insurance (% of Crop Yield Revenue)[c]	2.4	2.4	5.6	3.6	2.4	2.4
Cleaning, drying costs (CHF·t^{-1})[c]	39.5	32.5	58.5	71.3	1.5	0
Other costs (CHF·t^{-1})[c]	6.7	1.2	16.3	0	0.5	12
Variable irrigation costs (CHF·m^{-3})[d]	0.1	0.1	0.1	0.1	0.1	0.1
Interest rate (%)[c,e]	3.0	3.0	3.0	3.0	3.0	3.0

[a] Source: FAO (2011)

[b] Since in Switzerland in the year 2009 the reference sugar beet price decreased by more than 30%, we used German sugar beet prices. In order to account for higher price levels of agricultural products in Switzerland we multiplied the German prices by a factor of 1.3. This procedure ensures that mean prices and coefficients of variation remain as observed in Switzerland.

[c] Source: AGRIDEA and FIBL (2010).

[d] Source: Spörri (2011).

[e] The interest claim is computed as product of the interest rate and the invested capital (fixed costs, fixed irrigation costs and variable costs) for an average commitment of 6 months.

7.2.5 Optimization routine

Since all decision variables are integrated as discrete variables within a certain range (see Table 7.1), the maximization of the CE can be interpreted as a combinatorial optimization problem, which is characterized by a finite number of feasible solutions. However,

theoretically, more than 10^{23} combinations of different sets of decision variables would be possible and the evaluation of each of these possible combinations would be too time-consuming. Furthermore, the relations between management decisions and the farmer's utility are highly complex and nonlinear which does not allow a proper parametric representation of the optimization problem. For these reasons, we use a genetic algorithm (GA) to solve the optimization problem. GAs belong to the heuristic optimization methods and are based on the biological concept of genetic reproduction (Mayer et al., 1999). A GA starts with a population of random sets of decision variables (= chromosome). This initial population of random solutions (= chromosomes) evolves over time, while in each generation best individuals are selected, which are used to reproduce offspring for the next generation applying recombination, mutation and crossover (Gen and Cheng, 2000). The evolution stops when the algorithm converges to an optimum (Gen and Cheng, 2000).

Since GAs can handle any kind of objective functions and constraints defined in the discrete, continuous or mixed search space, they have been increasingly applied in the agricultural research field, in particular to irrigation optimization problems (e.g Ortega Álvarez et al., 2004; Raju and Kumar, 2004; Karamouz et al., 2010; Lehmann et al., 2012).

For this study, the C++ based GA package Galib (Wall, 1996) has been used, applying a steady-state GA with the following control parameters: genome size = 8 bits; population size = 500; proportion of replacement = 0.2; selection routine = roulette wheel; mutation probability = 0.25; crossover probability = 0.5; and a sigma truncation scaling has been used as fitness function. The algorithm is stopped if an optimal solution has not been changed for a number of 3000 generations. Because GAs do not guarantee that the global optimum solution is reached, each optimization run is repeated three times using different randomly generated initial populations which led in this study in all scenarios to the same optimal solution. Results from the optimization presented in this paper are thus interpreted as global optima.

7.2.6 Water policy scenarios

In order to evaluate the effects of different irrigation water policies, three different policy scenarios with regard to irrigation water were considered (see Table 7.5). In the scenario *No restrictions*, unlimited irrigation at a water price (including costs for pumping) of 0.1 CHF·m^{-3} is possible.[20] This water price refers to variable irrigation costs farmers in the Broye River Basin currently face (Spörri, 2011). In the scenario *Higher water price*, the water price is

[20] Our analysis is based on Swiss francs (CHF), for which the average exchange rate to US dollars (USD) in the year 2012 was 0.938 USD/CHF (source: IMF, 2013).

increased to 1.00 CHF·m^{-3}, which corresponds to the range of observed drinking water prices in Switzerland (EDV, 2011). Since at low water prices farmers are insensitive to price increases (Gomez-Limon and Riesgo, 2004), the water price has been sharply increased for this scenario. Besides economic incentives, agricultural water demand can also be controlled by quantitative restrictions on water consumption (e.g. quotas). Molle (2009) found that quotas are in particular consistently preferred to purely economic regulations when water resources are scarce. Thus, we consider another scenario (*Water quota*) in which the farm's annual total water consumption is restricted for the whole surface of 30 ha to a maximum amount of 3000 m^3 (corresponds to an average irrigation intensity of 30 mm).

Table 7.5: Water policy scenarios

Scenario	*Water price (CHF·m^{-3})*	*Maximum irrigation amount (m^3·year^{-1}) at farm-scale*
No restrictions	0.1	unlimited
Higher water price	1	unlimited
Water quota	0.1	3000

7.3 Results

The impacts of the different climate and policy scenarios on the farm's total water consumption and the farmer's income and utility (expressed as the CE) are shown in Figure 7.2. Note that results shown in Figure 7.2 refer to the scenario-dependent optimal management decisions as shown in Figure 7.3 and Figure 7.4. Under climate change (see the *ETHZ-CLM* scenario in Figure 7.2), the farm's water consumption increases in the unrestricted irrigation scenario on average by almost 100% compared to the *Baseline* scenario. This increase is in particular due to higher applied irrigation intensities in potato and sugar beet production (see Figure 7.4). At the same time, future climate conditions lead to a decrease of the average profit margin at farm level of about 13%.

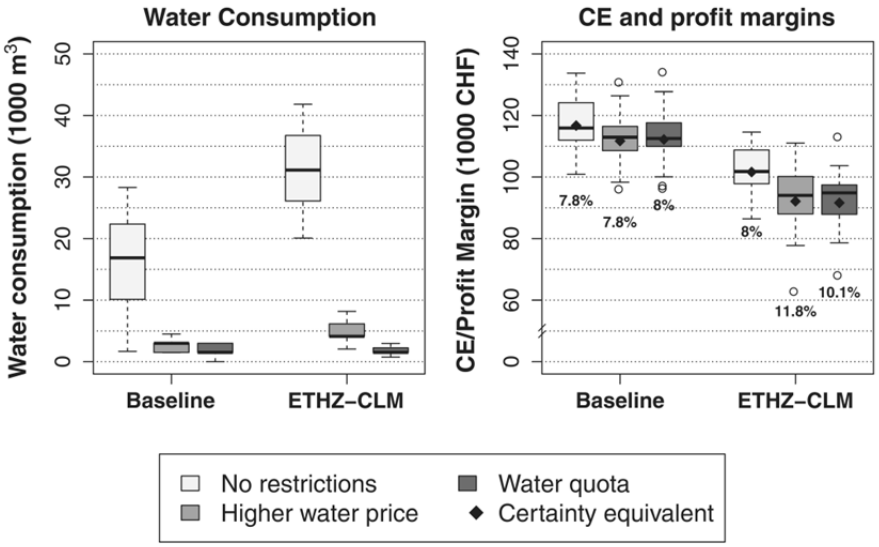

Figure 7.2: Distribution of the annual profit margins and applied irrigation amounts at farm-level. The horizontal line denotes the median. The whiskers extend to a maximum of 1.5 times of the inter-quartile range. The white circles are outliers which are not included in the range of the whiskers. The certainty equivalents are given in the right plot by the black diamonds.

An increase in the water price or the implementation of a water quota reduces the farm's required water amount sharply. For instance, under climate change, the farm's total water consumption decreases under the *Higher water price* scenario from more than 30'900 m^3 (corresponds to an average irrigation intensity of 103 mm) in the *No restrictions* scenario to less than 5'000 m^3 (corresponds to an average irrigation intensity of 17 mm). At the same time, the increased water price decreases the farmer's average profit margin only by about 9%. The implementation of a water quota reduces the farm's water consumption even more, i.e. to 1'800 m^3 (corresponds to an average irrigation intensity of 6 mm), while the loss in the average profit margin amounts to about 10%. Thus, significant decreases in the farm's water consumption can be reached at relatively low costs with both an increased water price and a water quota.

Nevertheless, Figure 7.2 also demonstrates that both water policies lead to higher downside risks of the annual profit margins under climate change. In particular, the income losses farmers suffer in years with unfavourable weather conditions are much higher under the *Higher water price* and the *Water quota* than in the *No restrictions* scenario. These higher downside risks are also reflected in the higher coefficient of variation of the annual profit margins under the *Higher water price* and the *Water quota* scenarios (see percentages shown in the right-hand plot in Figure 7.2).

Under current climatic conditions, the farmer's income risks are only slightly affected by the different water policies. Nonetheless, similar to the climate change scenarios, the farm's total water consumption is reduced by a higher water price and the implementation of a water quota by 83% and 88%, respectively, while both water policies decrease the farmer's average profit margin only by about 4%.

Furthermore, the relative impacts of the different climate and policy scenarios on the farmer's CE (see diamonds in the right-hand plot in Figure 7.2), which was the target variable in the optimization approach, are in the same range as the relative effects of the applied scenarios on the average profit margins.

The reason that the negative impacts of the water policies considered are relatively small even under warmer and drier climate conditions lies in the fact that the model takes a wide range of possible adaptation measures into account. Thus, by adjusting management schemes, farmers can not only minimize utility losses due to climate change (i.e. adaptation), but they can also partially avoid negative effects on their utility due to the implementation of specific water policies. Such adjustments in the farm's crop management scheme are shown in Figure 7.3 and Figure 7.4.

The effects of the different climate and policy scenarios on the optimal crop-specific irrigation and fertilization intensities are shown in Figure 7.3. Due to the warmer and drier climate conditions, the optimal irrigation intensities increase under climate change in the *No restrictions* scenario in potato and sugar beet production whereas no more grain maize is produced (see Figure 7.4). If the farm's total applicable water amount is restricted by a water quota or a higher water price is implemented, irrigation is only applied in potato cultivation, where the additional economic benefit of irrigation is larger than in sugar beet production. Nevertheless, even without irrigation, sugar beet is still cultivated on a surface of at least 20% of the total arable land (see Figure 7.4). Furthermore, in particular under *ETHZ-CLM* climate conditions, potatoes are less intensively irrigated, if a water quota or a higher water price are implemented.

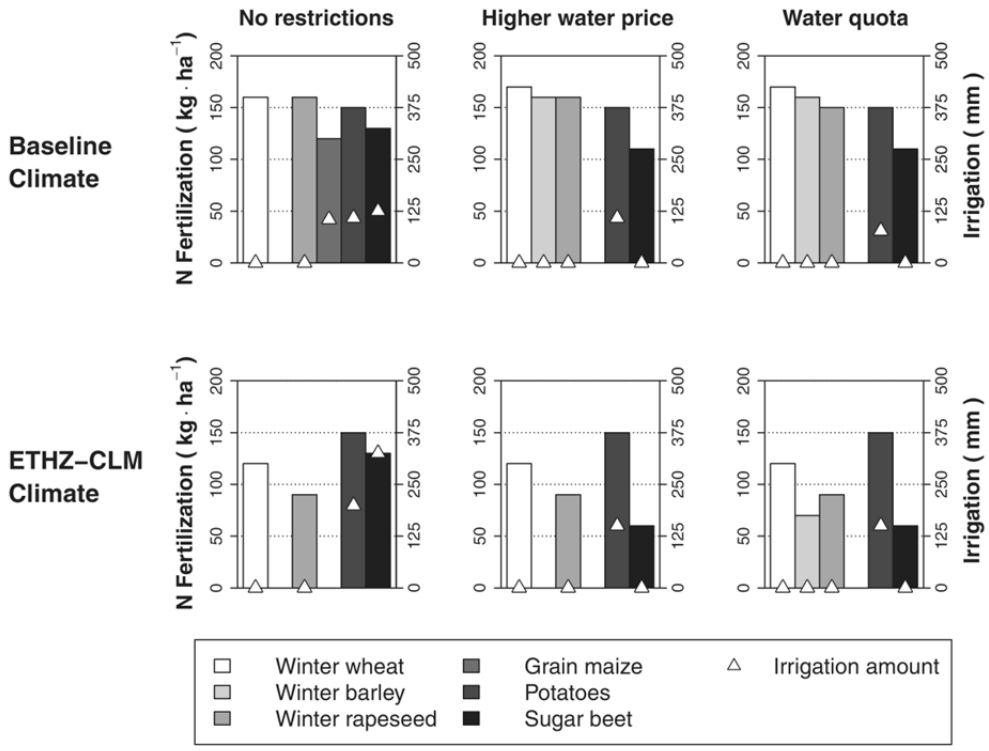

Figure 7.3: Crop-specific optimal nitrogen fertilization and irrigation intensity for each considered climate and water policy scenario.

The different scenarios also influence the optimal crop-specific nitrogen fertilization amounts. Climate change leads to a reduction in the optimal nitrogen intensity of the non-irrigated crops (winter wheat, winter barley and winter rapeseed). The optimal nitrogen amounts of the rainfed crops are only slightly affected by the different water policies. Regarding potato production, it is optimal to apply in all scenarios a nitrogen fertilization amount of 150 kg·ha^{-1} which was set as the maximum fertilization intensity for this crop. For sugar beet, the optimal fertilization intensity is strongly related to the chosen irrigation intensity. Under a higher water price or a water quota, where no irrigation is applied in sugar beet production, a reduction in the optimal nitrogen fertilization intensity can be observed. If sugar beet is irrigated (see *No restrictions* scenarios) a nitrogen fertilization amount of 130 kg·ha^{-1} is found to be most profitable. Thus, switching from irrigated production that implies low production risks to rainfed sugar beet production characterized by high production risks reduces the incentives of risk-averse farmer to apply high levels of inputs.

In addition to crop-specific nitrogen and irrigation intensities, the land allocation to different crops has also been considered as decision variables (see Figure 7.4).

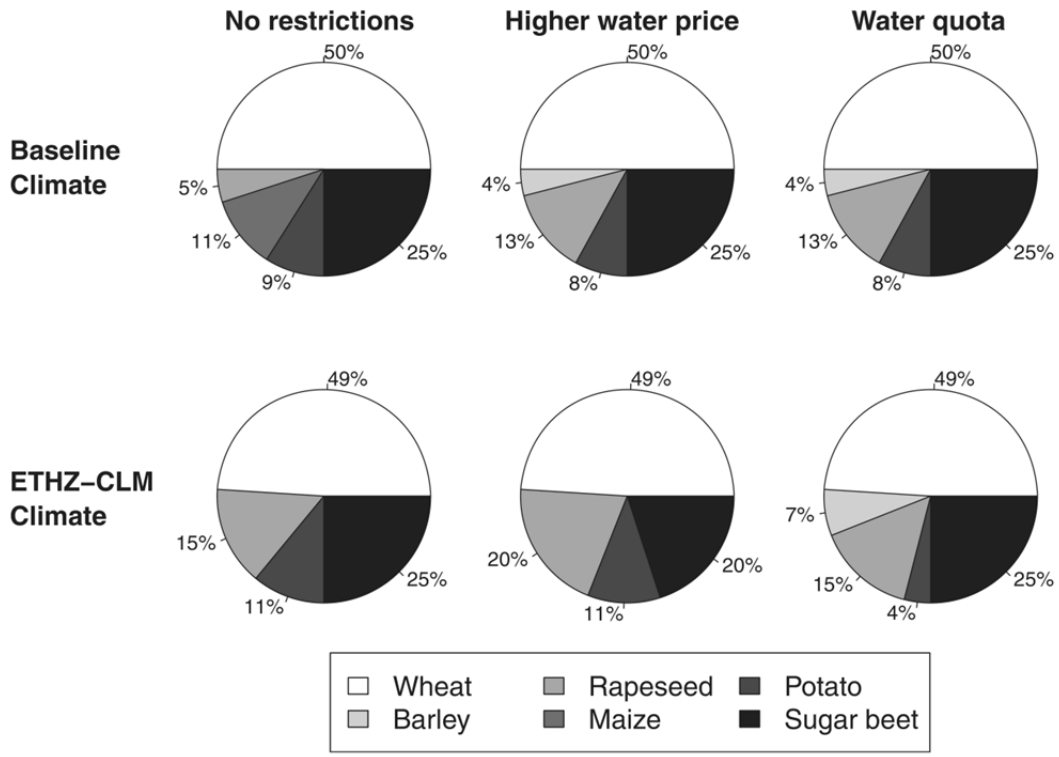

Figure 7.4: Optimal crop land allocation.

We find that climate change generally promotes the cultivation of winter rapeseed. For this crop, climate change has almost no negative impacts on average crop yield levels, and the production of oil crops is highly subsidized in Switzerland (see Table 7.4). Furthermore, under climate change, in none of the scenarios considered is grain maize included in an optimal crop mix. This is mainly due to the relatively low profit margin in grain maize production (compared to the other crops) and the region's dry climate conditions in mid the summer months. Irrigation of maize, however, is not as profitable as for high-value crops such as potatoes and sugar beet (Finger et al., 2011).

The effects on the optimal crop mix of a higher water price or a water quota are particularly obvious under climate change. The implementation of a water quota, for instance, decreases the land used for potato production, which is irrigated in all scenarios, while more land is allocated to rainfed crops (e.g. winter rapeseed and winter barley). Assuming a higher water price, the crop share of sugar beet is reduced by 5% while the proportion of winter rapeseed is increased by the same amount. Note that due to the high direct payments for sugar beet production (see Table 7.4), sugar beet is a profitable crop even without the application of irrigation and thus is maintained at a smaller percentage in an optimal crop mix. Under current climatic conditions, the effects on the optimal crop mix are identical for both water policies considered. More specifically, the cultivation of

grain maize is given up, while instead the crop share of winter rapeseed is increased and the optimal crop mix includes winter barley as an additional crop.

7.4 Discussion and conclusions

Our results show that if current water prices and irrigation policies are maintained, the applied climate change scenario increases the water demand of cropping farms by almost 100%, while implying lower income and utility levels for farmers in the Broye River Basin. Thus, in order to reduce ecological damage such as low stream flows or high water temperatures in the region's rivers caused by water withdrawals for agricultural purposes, changes in the region's water policies are required. We show that both an increase in the volumetric water price and the introduction of a maximum annual applicable irrigation water amount (i.e. water quota) are effective policy measures for decreasing the region's agricultural water consumption. These policy measures reach the goal of reducing the water demand of the modelled arable farm not only under current but also under future expected climatic conditions. The farmer's losses in utility and income due to these water policies are relatively small (less than 10%), because crop- and farm-level adjustments in management schemes can mitigate the negative impacts of such policies to a large extent. Although both policies have similar impacts on whole-farm water consumption and the farmer's utility, they differ under the climate change scenario in respect of the adjustments of the farmer's management decisions. A higher water price, for instance, does not change the optimal crop share of potato production, while the land allocated to potato production is decreased under a water quota policy. Nevertheless, under both stricter water policies, irrigation is only applied in potato production. This shows that the additional profit above the costs of irrigation is highest for this crop. Furthermore, a higher water price reduces under future expected climatic conditions the surface used for sugar beet production which is less profitable without irrigation. However, since the production of sugar is highly subsidized in Switzerland, sugar beet is maintained in an optimal crop mix in all scenarios even without the use of irrigation.

Besides the lower required quantity of water for irrigation, both water policies also reduce the total applied nitrogen fertilization amount at farm scale, which is a harmful input factor for the environment. Note that in recent years, the Broye river has repeatedly experienced nitrate and ammonium concentrations which were above the permissible range. Thus, stricter water use policies also have positive spillover effects on other environmental targets (e.g. nitrogen leaching).

Nevertheless, under future expected climatic conditions both policies increase downside risks in crop farming. Thus, even accounting for adjustments in the farms' management schemes, a higher water price or a water quota will lead to very low agricultural income levels in exceptionally warm and dry years. The introduction of new agricultural insurance products (e.g. farm revenue insurance, index-based insurance) designed to provide revenue protection might be one option to cope with these increased production risks.[21]

In conclusion, this study indicates that the increasing water demand in agriculture due to climate change can be effectively reduced by introducing a water quota or by increasing the volumetric water price for irrigation. Thus, policy makers should consider these options to cope with climate change-induced increases in agricultural water demand in western Switzerland. Considering a whole-farm perspective significantly reduces the financial burden from these policies for farmers if compared to single crop investigations, because farmers can avoid large reductions in their income from these policies by switching to other crops. However, we expect that the technical implementation of both policies could create some problems, since only farmers face the burdens of these policies. Therefore, future studies should also consider other policy options that allow compensation of farmers for the increased ecological benefits. Furthermore, in order to verify the study's results, other climate change scenarios should be applied to the modelling approach and sensitivity analysis with regard to the chosen water prices and water quotas should be carried out.

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[21] Note that up to now, crop insurance in Switzerland usually includes hail and other risks from the elements (e.g. flooding, storm damage). Products that include drought and heavy rainfall are only to a very limited extent available.

8 The impact of climate and price risks on agricultural land use and crop management decisions[22]

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ABSTRACT

This article aims to investigate the impacts of climate change and of lower and more volatile crop price levels as currently observed in the European Union (EU) on optimal management decisions, average income and income risks in crop production in Western Switzerland. To this end, a bioeconomic whole-farm model has been developed that non-parametrically combines the crop growth model CropSyst with an economic decision model using a genetic algorithm. The analysis focuses on the farm level, which enables us to integrate a wide set of potential adaptation responses, comprising changes in agricultural land use as well as crop-specific fertilization and irrigation strategies. Furthermore, the farmer's certainty equivalent is employed as objective function, which enables the consideration of not only impacts on average income but also impacts on income variability.

The study shows that that the effects of EU crop prices on the optimal management decisions as well as on the farmer's certainty equivalent are much stronger than the effects of climate change. Furthermore, our results indicate that the impacts of income risks on the crop farm's optimal management schemes are of rather low importance. This is due to two major reasons: first, direct payments make up a large percentage of the agricultural income in Switzerland which makes Swiss farmers less vulnerable to market and climate volatility. Second, arable crop farms in Switzerland have by law to cultivate at least four different crops. Due to these diverse cropping systems and high government direct payments risk does neither under climate change, market liberalization nor combinations thereof, play a very decisive role in arable farming in Switzerland.

KEYWORDS

AGRICULTURAL LAND USE; CLIMATE CHANGE; PRICE RISKS; WHOLE-FARM MODEL; BIOECONOMIC MODELLING; GENETIC ALGORITHM

[22] Lehmann, N., Briner, S., Finger, R. (2013). The impact of climate and price risks on agricultural land use and crop management decisions. *Land Use Policy* 35, 119-130.

8.1 Introduction

Production and price risks are important aspects in farmers' decision-making (Saunders et al., 1997; Angus et al., 2009). While market or price risk reflects the variations in prices of agricultural outputs and inputs (Harwood et al., 1999), production risks mainly occur because crop growth highly depends on its environment (e.g., weather conditions and pest pressure) that can rapidly change. Both production and market risks, however, affect the income variability in agriculture. To cope with production and market risks, farmers typically have several on-farm, self-insuring options and risk-mitigation measures to protect against income volatility. One of the most important on-farm risk-reducing strategies is to diversify farm activities, for example by expanding the portfolio of different agricultural land uses (Mishra and El-Osta, 2002). Diversification strategies not only mitigate price risks but also fluctuations of overall farm outputs due to production risks (Mishra and El-Osta, 2002). Besides such large-scale strategies, also adjustments of crop-specific management decisions potentially mitigate income variability (Sandmo, 1971). In general, risk-averse decision makers are expected to invest less in inputs if the returns from these investments are more uncertain and thus increase income variability. For instance, higher nitrogen application on grassland tends to increase yield variability (for discussions and examples, see Finger, 2012). In contrast, more intensive use of irrigation decreases the variability of crop yields, thereby reducing production risks (Finger et al., 2011; Lehmann et al., 2013). Responses of farmers to changing market and production conditions are highly relevant for agricultural and environmental policy makers because the induced changes in land use as well as changes in input allocation have direct impacts on food supply, environmental loads from agriculture and the landscape.

Whole-farm models are appropriate tools to assess the impact of price and climate scenarios on farmers' management strategies, average income and income variability (Pannell et al., 2000). This is because the full potential of adjusting crop-specific management schemes for risk management is only tapped if all activities of a farm are considered simultaneously. In contrast, single-crop investigations may over-estimate the role of production and price risks in agricultural decision-making. In addition, the assessment at the farm level is also of great importance since risk management strategies often are dependent on specific constraints with regard to farm resources (e.g., land and working time) and environmental obligations (e.g., nutrient balances). Most available studies, however, focus on single-crop management decisions (Rosegrant and Roumasset, 1985; Rajsic et al., 2009; Finger, 2012b; Lehmann et al., 2013). Other studies use whole-farm models but address only the optimal land allocation among different crops without considering crop-specific management decisions such as nitrogen fertilization or irrigation

intensities (Chavas and Holt, 1990; Sckokai and Moro, 2006; Musshoff and Hirschauer, 2009).

Based on this background, we combine the process-based crop growth model CropSyst with an economic decision model to develop a whole-farm model that accounts not only for land allocation but also for crop-specific management decisions. The developed bioeconomic whole-farm model is used to maximize a farmer's utility while optimizing farm scale management decisions under different climate and price scenarios. Thus, we use a normative approach based on the neoclassical theory, which perceives economic agents as utility optimizers (Buysse et al., 2007). The outcome of the economic decision model is therefore a management scheme that results in the highest utility levels for farmers. To express farmers' utility levels, the certainty equivalent (CE) at the farm level is used. The CE depends not only on the total average farm income but also on income variability that accounts for different sources of risk. In previous research, the combination of process-based crop growth models with economic models has been suggested to investigate the influence of climate change (CC) and production risks in cropping systems

(for discussions, see Challinor et al., 2009; Reidsma et al., 2010; Finger et al., 2011; Olesen et al., 2011). One of the main advantages of process-based crop growth models is their ability to simulate plant growth under scenarios that exceed the current conditions (Finger, 2009). Thus, process-based crop growth models are suitable tools for the simulation of crop yields under CC scenarios. Yet, crop models generally do not consider market- and policy-driven adaptive responses to crop management (Risbey et al., 1999). By linking crop growth models with economic decision models, however, adaptation decisions of farmers to changing market and policy conditions can be taken into account. In this study, the linkage of the crop growth model CropSyst with the economic decision model and the optimization routine is facilitated by a genetic algorithm (GA). To analyze the influence of changes in climate and market prices on farmers' income, income volatility and farm management decisions, different climate and price scenarios are considered.

The developed model is applied to a representative arable crop farm located in the Broye watershed in the Western part of Switzerland. This region already faces high variability of rainfall within the growing season, which leads to a high crop yield variability and triggers the frequent use of irrigation (Robra and Mastrullo, 2011). The frequent use of irrigation causes environmental problems, such as low water levels in the region's surface water bodies (Mühlberger de Preux, 2008). Land use and crop-specific management decisions taken by the region's farmers are thus of particular relevance for policy makers. This policy relevance is furthermore underlined by the fact that significant changes in risk exposure of Swiss farmers are expected. Currently, average crop prices are much higher, and crop price

volatility is much smaller in Switzerland than in other European countries (El Benni et al., 2012; Finger and El Benni, 2012). For instance, the average price of wheat in Switzerland is about three times higher than in Germany or France (Finger and El Benni, 2012). The relative wheat price volatility (expressed as coefficient of variation) in Switzerland, however, is about fifty percent smaller than those observed in France and Germany (Finger and El Benni, 2012). In the future, trade of agricultural products between Switzerland and the European Union might be liberalized, leading to lower and more volatile prices of agricultural goods in Switzerland. Moreover, significant changes in production risks in Swiss crop production are expected due to CC (Torriani et al., 2007b). These changes, however, are expected to be heterogeneous across different crops (Lehmann, 2010).

The objectives of the presented study are threefold: First, we develop a whole-farm model that is used to identify optimal management decisions for a representative arable farm in the Broye watershed and compare our modelling results with observations from the study region. Second, we assess the impacts of CC and crop price scenarios on the optimal management decisions. Finally, we quantify the impact of CC and crop price scenarios on farmers' income and income risks while adjustments in the optimal management decisions are taken into account.

8.2 Methods

In order to optimize agricultural management decisions related to land-use and crop-specific nitrogen fertilization and irrigation intensities, a bio-economic whole-farm model is used. This bio-economic whole-farm model comprises three different sub-models: the generic weather generator LARSWG (Semenov and Barrow, 1997; Semenov et al., 1998), the mechanistic crop growth model CropSyst (Stöckle et al., 2003) and an economic decision model at farm scale. In addition, a genetic algorithm (GA) is used as optimization technique. More details on the component models and the settings of the GA are presented in the following subsections.

The structure of the modelling approach and the linkages between the sub-models are given in Figure 8.1.

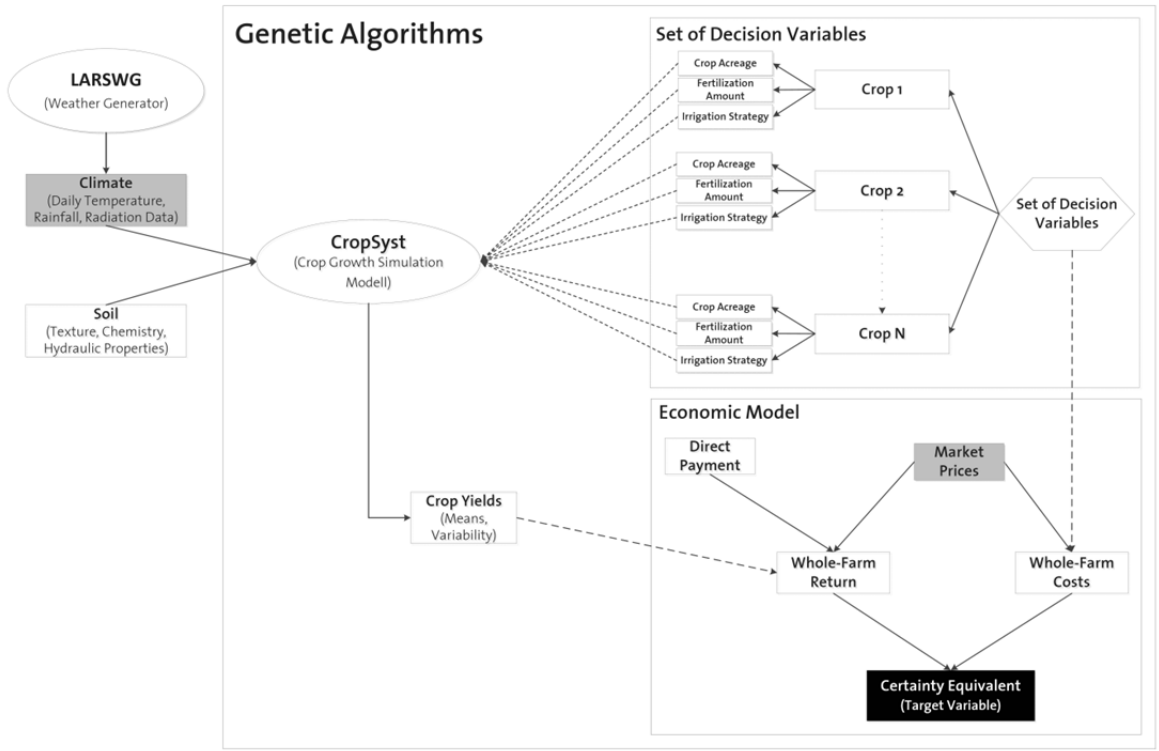

Figure 8.1: Overview of the modeling approach (modified from Lehmann et al., 2013). The scenario-related input factors (i.e. climate variables and market prices) are coloured in grey.

First, a population of candidate solutions is randomly generated by the GA (see upper right part in Figure 8.1). Each candidate solution comprises a specific set of considered decision variables (i.e., nitrogen fertilization amount, irrigation strategy and crop acreage), which are taken as potential solutions for an optimal (i.e., utility maximizing) farm management scheme. These sets of decision variables are passed in a next step to CropSyst (middle panel of Figure 8.1), where they are used as management input variables for crop yield simulations. To represent production risks due to uncertain weather conditions, 25 variable weather years are generated with the stochastic weather generator LARSWG[23]. Thus, crop yields are simulated for each crop and each set of management decisions for a period of 25 weather years. The 25 simulated yields of all crops are then fed into the economic model (bottom-right panel of Figure 8.1) to compute the whole-farm return and the related production costs (e.g., fertilization amount, irrigation and drying costs). Besides production risks, also price risks are taken into account, and a set of stochastic crop prices is generated for the 25 years of simulations (details are presented below). Finally, the whole-farm return

[23] Following Jame and Cuthforth (1996) crop growth simulations should be conducted during at least 25-30 weather years in order to account for the risk associated with unpredictable weather conditions.

and production costs are used to calculate the certainty equivalent (CE) (representing the utility of a risk-averse decision maker) at the farm scale, which is the objective value in the optimization process. Once the objective values (i.e., CE) of all candidate solutions in the initial population are derived, the GA is used to select the most promising candidate solutions (i.e., candidate solutions which lead to the highest CE) and to create applying the genetic operators (i.e., mutation and crossover) a subsequent population of decision variables, which potentially lead to higher objective values. Then again, all sets of decision variables comprised in the new population are used as input variables in CropSyst and the economic decision model in order to evaluate for each solution its objective value and to create a subsequent population. Thus, the processes of the GA described above (i.e., evaluation of the candidate solutions, selection and application of genetic operators) are repeated until the algorithm converges to an optimal solution.

8.2.1 Stochastic weather generator

Daily weather input variables (daily minimum and maximum temperature, rainfall occurrence and amount, and daily total solar radiation) for crop yield simulations with CropSyst are generated for present and future climate conditions using the stochastic weather generator LARSWG (Semenov and Barrow, 1997; Semenov et al., 1998). For the calibration of LARSWG, historical daily weather data of the period 1981–2010 from the climate station Payerne (PAY, 6°57′ E, 46°49′ N, 490 m a.s.l.), which is located within the Broye watershed, is used. After calibration, 25 years of synthetic weather data are generated for a Baseline and two CC scenarios. The *Baseline* scenario, representing current climatic conditions, refers to the period 1981–2010. The CC scenarios (*ETHZ-CLM* and *SMHI-Had*) represent climate conditions for the nominal timeframe between 2036 and 2065, assuming the IPCC SRES emission scenario A1B (Nakicenovic et al., 2000). For both CC scenarios, boundary conditions were obtained from global simulations with the Hadley Centre global climate model HadCM3. Moreover, the *ETHZ-CLM* scenario was conducted with the regional climate model maintained by the Swiss Federal Institute of Technology, while the *SMHI-Had* scenario was completed with the regional climate model of the Swedish Meteorological and Hydrological Institute. Most importantly, both CC scenarios indicate a significant temperature increase throughout the year. Furthermore, the *ETHZ-CLM* scenario is characterized by strong precipitation decreases in summer months, while under the *SMHI-Had* scenario, precipitation increases in winter and decreases in spring and summer months. Further information on the employed climate scenarios and the downscaling approaches is presented in Lehmann et al. (2013) and in Table C.1 in Appendix C.

8.2.2 Crop growth model

We use CropSyst (Version 4.13.09) to simulate climate and management-dependent yields for six crops: winter wheat (*Triticum spp. L.*), winter barley (*Hordeum vulgare L.*), winter rapeseed (*Brassica napus L.*), grain maize (*Zea mays L.*), potatoes (*Solanum tuberosum L.*) and sugar beets (*Beta vulgaris L.*). CropSyst is a process-based crop growth model that simulates biological and environmental aboveground and belowground processes of a single land block fragment using daily weather data and information about soil and crop characteristics as well as a specific management scheme at a daily scale. Stöckle et al. (2003) provide a detailed overview on the model and its components as well as on its applications. CropSyst has already been applied in different studies to estimate the impact of climate change on Swiss crop production (Torriani et al., 2007b; Finger et al., 2011; Lehmann et al., 2013).

For this study, a calibration of CropSyst for the study region by Klein et al. (2012) was used based on yield records from the Swiss Farm Accountancy Data Network (FADN). This approach had the advantage that CropSyst was calibrated against yield records coming from farm observations and not only from field trials, which allowed calibrating CropSyst closer to the real-world situation. Further information on the CropSyst calibration approach used in this study is given in Klein et al. (2012). Furthermore, identical initial soil conditions, with a soil texture of 59.8% sand, 11.3% clay and 28.9% silt, are assumed for each simulation year in this study. The soil's initial content of organic matter is set for the top layer at 2.8% and at 2% for the other layers (Klein et al., 2012). For all soil layers, an initial concentration of 5 kg N ha^{-1} in the form of NO3 and 5 kg N ha^{-1} in the form of NH4 per 0.1 m soil depth is assumed, which is in line with Weisskopf et al. (2001).

8.2.3 Economic decision model

To integrate the previous modelling steps within the economic model, first variable and fixed costs related to a chosen set of management decisions are specified for each of the 25 simulation years. Then, revenues based on the resulting crop yields are calculated for the corresponding years. Combining these figures, the annual gross margin at the farm level is calculated as shown in Equation 8.1.

$$\pi = \sum_{i=1}^{N} a_i \cdot \left(\rho_i + DP_i - c_{fix,i} - c_{irrig,i} - c_{\mathrm{var},i} \right) \tag{8.1}$$

where π is the annual gross margin at farm level (CHF), a_i is the cultivated surface (ha), ρ_i is the revenue (CHF·ha^{-1}) and DP_i are the direct payments depending on the crop i

(CHF·ha^{-1}). $c_{fix,i}$ stands for the fixed costs (excluding irrigation systems), $c_{irrig,i}$ for the fixed costs of the irrigation systems and $c_{\mathrm{var}i}$ for the variable costs of the crop i (all expressed in CHF·ha^{-1}). Note $c_{irrig,i}=0$ if no irrigation is applied. The variable costs $c_{\mathrm{var}i}$ depend on the chosen management decisions (cp. Table 8.4) and the resulting crop yield levels. Fixed costs include costs that depend on the crop but are not subject to management decisions, such as expenditures for seeds, pesticides and agricultural machinery. More details about the assumptions on revenues and costs employed are given in Table 8.1. The expected gross margin $E(\pi)$ and the variance of the gross margin σ_π at farm level are derived from the 25 annual gross margins.

Both expected gross margin and its variability are used to represent farmers' decision-making. More specifically, they are combined in a certainty equivalent (CE) maximization approach to represent the utility maximization problem of a risk-averse farmer. The CE is defined as the sure sum of money that has the same utility as the expected utility of a risky alternative (Keeney and Raiffa, 1976) and is defined as follows:

$$CE = E(\pi) - RP \tag{8.2}$$

where $E(\pi)$ is the expected gross margin at farm level and RP is the risk premium, both expressed in CHF. The RP is the sure amount of money the decision maker is willing to pay to eliminate risk exposure (Di Falco et al., 2007). According to Pratt (1964), the RP can be approximated by Equation 8.3:

$$RP \approx \frac{1}{2} \cdot \frac{\gamma}{E(\pi)} \cdot \sigma_\pi^2 \tag{8.3}$$

where γ is the coefficient of relative risk aversion and σ_π^2 is the variance of the gross margin at farm level π. For this study, we assume γ to be 2, which corresponds to a moderate risk-averse decision maker and implies decreasing absolute risk aversion (Di Falco and Chavas, 2006). Since there are no estimates of the risk aversion of Swiss farmers available, a sensitivity analysis with regard to the assumed level of risk aversion has been conducted. In doing so, we repeat the optimization procedure for all considered scenarios using risk aversion parameters of $\gamma = 0$ (risk neutral) and $\gamma = 5$ (highly risk averse). This consideration of different levels of risk aversion, including risk-neutral moderate risk-averse and rather strong risk-averse behaviour, further represents the heterogeneity of risk preferences among farmers (Rosenzweig and Binswanger, 1993).

Table 8.1: Revenues and costs.

	Winter wheat	*Winter barley*	*Winter rapeseed*	*Grain maize*	*Pota-toes*	*Sugar beets*
Revenue						
Crop price levels (in CHF·t^{-1}). Averages of the period 2002-2010 (*Standard deviation in parentheses*)[a,b,c]	506 *(41)*	372 *(39)*	788 *(96)*	371 *(53)*	456 *(29)*	66 (8)
Direct payment						
Direct payment (CHF·ha^{-1})[d]	1680	1680	2680	1680	1680	3580
Fixed costs						
Seed (CHF·ha^{-1})[d]	218	143	108	268	3585	407
Plant protection (CHF·ha^{-1})[d]	265	265	250	220	800	525
Plant growth regulant (CHF·ha^{-1})[d]	41	41	0	0	0	0
Contract work and machinery costs (CHF·ha^{-1})[d]	783	783	787	844	2591	1409
Fixed irrigation costs						
Irrigation system costs (CHF·ha^{-1})[e]	447	447	447	447	447	447
Variable costs						
Nitrogen fertilizer (CHF·kg^{-1}·N^{-1})[d]	1.4	1.4	1.4	1.4	1.4	1.4
Other fertilizer costs (CHF·kg^{-1}·N^{-1})[d]	0.72	0.73	0.94	1.54	3.49	1.41
Hail insurance (% of Crop Yield Revenue)[d]	2.4	2.4	5.6	3.6	2.4	2.4
Cleaning, drying costs (CHF·t^{-1})[d]	39.5	32.5	58.5	71.3	1.5	0
Other costs (CHF·t^{-1})[d]	6.7	1.2	16.3	0	0.5	12
Variable irrigation costs (CHF·m^{-3})[e]	0.1	0.1	0.1	0.1	0.1	0.1
Interest rate (%)[d,e]	3.0	3.0	3.0	3.0	3.0	3.0

[a] Source: FAO (2011)

[b] It has been assumed that 75% of the total potato harvest is sold as table potatoes (AGRIDEA and FIBL, 2010) at the average price given in Table 8.1. The remaining 25% of the potato harvest is sold as feed potatoes (AGRIDEA and FIBL, 2010).

[c] Since the sugar market has been liberalized in 2009, which caused a decrease of Swiss reference prices by more than 40%, we used German sugarbeet prices to represent price distributions. In order to account for higher prices levels of agricultural products in Switzerland we multiplied the German prices by a factor of 1.5. This procedure ensures that mean prices and coefficients of variation remain as observed in Switzerland.

[d] Source: AGRIDEA and FIBL (2010).

[e] Source: Spörri (2011).

[f] The interest claim is computed as product of the interest rate and the invested capital (fixed costs, fixed irrigation costs and variable costs) for an average commitment of 6 months.

8.2.4 Price scenarios

Two scenarios with regard to crop price distributions are used: the scenario *CH* considers average price levels and price volatility currently observed in Switzerland. Because crop prices in Switzerland are much higher and price volatilities are much lower than in neighbouring countries (Finger and El Benni, 2012), we employ a second price scenario (*EU*) that assumes the crop price levels and crop price variability that is currently observed in the European Union.

For both scenarios, we use averages, variances and covariance of crop prices in Switzerland (*CH* scenario) and France (*EU* scenario), respectively, in the period 2002–2010 obtained from the FAOSTAT database (FAO, 2011) (see Table 8.2 for the averages and standard deviations and Table C.2 in Appendix C for the correlation structure of the observed crop prices). Thus, we assume that future expected liberalization of agricultural markets in Switzerland will converge average crop prices and increase crop price volatility to the levels currently observed in France. Crop prices in France have been chosen to represent the EU scenario, since France is the most important producer of cereal, oilseed crops and sugar beets in the EU-27 (Eurostat, 2011).

Table 8.2 shows that the average crop price levels in France are between 18% and 60% lower and the crop price volatility is between 50% and 350% higher than in Switzerland. Thus, under the *EU* scenario, crop prices are not only significantly smaller, but the farmer also faces much higher price risks.

Table 8.2: Summary statistics of national crop prices in Switzerland and France in the period 2002-2010.

Crop	*Switzerland*		*France*	
	Average price (CHF·t) [a]	*Coefficient of variation (%)*	*Average price (CHF·t)* [a]	*Coefficient of variation (%)*
Wheat	506	8.2	192	28.7
Barley	372	10.6	177	26.8
Rapeseed	788	12.1	401	22.8
Grain maize	371	14.4	201	26.8
Potatoes	456	6.4	270	21.1
Sugar beets[b]	66	11.9	54	18.4

[a] Source: FAO (2011)

[b] See Table 8.1 for further details.

In order to generate 25 simulation years of volatile crop prices, which represent scenario-specific average crop price levels and crop price variability, we apply a multivariate normal

distribution approach (Ripley, 1987). More specifically, we use the R package MASS 7.3-16 available from CRAN (http://cran.r-project.org) and generate 25 stochastic prices for both scenarios and each crop. This approach ensures not only the mean crop price levels and crop price volatility, but also correlations between prices of the different crops are represented in the decision process.

Besides market prices of agricultural products, government direct payments are also of high importance for Swiss farmers. Currently, government direct payments make up on average almost 30% of total farm revenue in Swiss agriculture (Finger and Lehmann, 2012a). However, since projections of future direct payment levels involve a high degree of uncertainty, we follow Briner et al. (2012) and assume that direct payments are kept constant on today's levels. On the one hand, government support for the agricultural sector has a very long tradition in Switzerland (Haller, 2010). On the other, the liberalization of agricultural markets may not necessarily lead to an adoption of the entire EU agricultural policy framework by the Swiss government.[24]

Table 8.3 presents all possible combinations of the three considered climate and two employed crop price scenarios.

Table 8.3: Overview of the applied scenarios

		Crop price scenario	
		Swiss crop prices	*EU crop prices*
Climate scenario	*Baseline*	Baseline-CH	Baseline-EU
	ETHZ-CLM	ETHZ-CH	ETHZ-EU
	SMHI-Had	SMHI-CH	SMHI-EU

8.2.5 The farm

The proposed modelling approach is applied to a representative arable farm in the Western part of Switzerland, located in the Broye watershed (for details, see Lehmann et al., 2013). In terms of production activities, the model considers the six most important arable crops in Swiss agriculture: winter wheat, winter barley, winter rapeseed, grain maize, potatoes and sugar beets. The developed whole-farm model is used to optimize crop acreage, as well as the crop-specific nitrogen fertilization intensity and irrigation strategy (cp. Table 8.4). To account for restrictions with regard to crop-specific agronomic

[24] For instance, the Swiss cheese market has been liberalized (i.e., there are no trade barriers or distortions with the European Union), but direct payments have not been affected by this liberalization step.

limitations as well as with regard to limitations imposed by the agricultural policy in Switzerland (i.e., cross-compliance requirements), the following constraints are implemented into the model:

- The total farm acreage amounts to 30 ha, representing the average surface of arable farms located in the region of Payerne.[25]
- To ensure an adequate crop rotation, cross-compliance obligations limit the maximum share of several crops: winter wheat is limited to a maximum acreage of 50%; the sum of all cereals (without grain maize) is limited to 66%; the maximum crop share of grain maize is 40%; and the maximum share of winter rapeseed, potatoes and sugar beets is 25% of total arable land (BLW, 2011). Furthermore, we restrict the sum of the winter rapeseed and sugar beet surface due to rotational restrictions to 40% of the total arable land (Vullioud, 2005).
- The farmer is obliged to cultivate a minimum of four different crops to fulfil cross-compliance requirements (BLW, 2011).
- According to the cross-compliance obligations, the farm has to comply with a balanced nitrogen supply and demand at farm level as revealed by the official Swiss nutrient balance method "Suisse Bilanz" (Amaudruz et al., 2011). In this nutrient balance approach, a yield-dependent maximum nitrogen amount is specified for each crop, whereas the nitrogen demand and supply has to be balanced at the farm level.
- The farmer's maximum available working time is assumed to amount to 2800 h per year. Following AGRIDEA and FIBL (2010), the required total amounts of labour (including management and field work) are: 41 h per hectare for winter wheat, winter barley and winter rapeseed; 37 h per hectare for grain maize and 258 and 67 h per hectare for potatoes and sugar beets, respectively.
- In addition, we also account for the fact that field work is limited by weather conditions to half the days of the vegetation period (Luder, 1996) with a maximum daily working time of 10 h (Musshoff and Hirschauer, 2009). For current and future climate conditions, the vegetation period is assumed to last 220 and 250 days, respectively (Calanca and Holzkämper, 2010). The required field working time per crop is defined as follows: winter wheat, winter barley: 16 h per hectare; winter

[25] The average surface of arable farms located within a 15-km radius around Payerne amounts to 33 ha (BLW, 2010).

rapeseed: 18 h per hectare; grain maize: 11 h per hectare; potatoes: 218 h per hectare and sugar beets: 27 h per hectare (all following AGRIDEA and FIBL, 2010).

- Finally, we restrict nitrogen intensity for potatoes and sugar beets to a maximum amount of 150 kg·N·ha^{-1} and 130 kg·N·ha^{-1}, respectively. Higher nitrogen fertilization dosages are not considered in practice because they would have a negative impact on crop quality (A. Zimmermann, personal communication).

Table 8.4: Considered management variables

Decision Variable	*Crop*	*Management variable and unit*	*Range (min-max) considered in the modeling approach*	*Variable increment considered in the modeling approach*	*Number of Alternatives*
1	Winter wheat	Crop acreage in % of total arable surface	0-50	1	51
2	Winter wheat	Nitrogen fertilization amount in kg·ha^{-1}	0-200	10	21
3	Winter wheat	Irrigation strategy (trigger point of irrigation)[a]	0-1	0.1	11
4	Winter barley	Crop acreage in % of total arable surface	0-66	1	67
5	Winter barley	Nitrogen fertilization amount in kg·ha^{-1}	0-200	10	21
6	Winter barley	Irrigation strategy (trigger point of irrigation)[a]	0-1	0.1	11
7	Winter rapeseed	Crop acreage in % of total arable surface	0-25	1	26
8	Winter rapeseed	Nitrogen fertilization amount in kg·ha^{-1}	0-200	10	21
9	Winter rapeseed	Irrigation strategy (trigger point of irrigation)[a]	0-1	0.1	11
10	Grain maize	Crop acreage in % of total arable surface	0-25	1	26
11	Grain maize	Nitrogen fertilization amount in kg·ha^{-1}	0-200	10	21
12	Grain maize	Irrigation strategy (trigger point of irrigation) [a]	0-1	0.1	11
13	Potato	Crop acreage in % of total arable surface	0-25	1	26
14	Potato	Nitrogen fertilization amount in kg·ha^{-1}	0-150	10	16
15	Potato	Irrigation strategy (trigger point of irrigation)[a]	0-1	0.1	11
16	Sugar beet	Crop acreage in % of total arable surface	0-25	1	26
17	Sugar beet	Nitrogen fertilization amount kg·ha^{-1}	0-150	10	16
18	Sugar beet	Irrigation strategy (trigger point of irrigation)[a]	0-1	0.1	11

[a] The trigger point of irrigation represents the level of soil moisture that automatically triggers irrigation, and ranges from 0 (permanent wilting point) to 1 (field capacity).

The choice of management variables shown in Table 8.4 illustrates the wide range of risk mitigation and CC adaptation responses considered in our approach. Farmers can change crop-specific management decisions (i.e., nitrogen fertilization and irrigation intensity), alter the land allocation across crops or may even remove crops entirely from their crop mix.

8.2.6 Optimization routine

Due to the discrete nature of the decision variables (cp. Table 8.4), the maximization of the CE can be interpreted as a combinatorial optimization problem, which is characterized by a finite number of feasible solutions. Nevertheless, more than 10^{23} combinations of different sets of decision variables would be theoretically possible, and the evaluation of each of these possible combinations would be too time consuming. To overcome this problem, we use in this study a GA as optimization technique. GAs are a heuristic optimization technique and mimic the biological concept of genetic reproduction (Mayer et al., 2001), following the concept of "the survival of the fittest" (Aytug et al., 2003). A GA starts with the generation of an initial population of individuals, each representing a possible solution for a given problem (e.g., crop share of winter wheat or the nitrogen fertilization amount for winter wheat). The decision variables in GAs are coded as binary strings of genes on a chromosome (=individual) that represent a potential solution of the optimization problem. The initial population of possible solutions (=chromosomes) evolves over time by selecting the best individuals in each generation and reproducing offspring for the next generation applying recombination, mutation and crossover until the algorithm converges to an optimum (Gen and Cheng, 2000). In this study, this optimum represents the farm level management strategy maximizing the farmer's CE. We use the C++ based GA library package GAlib (Wall, 1996) and apply a steady-state GA. The steady-state GA uses overlapping populations, whereas the user can specify how much of the population should be replaced in each generation (Wall, 1996). The control parameters in the GA are set as follows: genome size = 8 bits; population size = 5000; proportion of replacement = 0.2; selection routine = roulette wheel; mutation probability = 0.25; crossover probability = 0.5; and the GA is terminated when a population's best fitness value does not change for a number of 3000 generations. Since GAs do not guarantee that the global optimum solution will be reached, each optimization run is repeated three times using different randomly generated initial populations. For all scenarios in this study, the repeated runs have led to the same optimal solutions, which are thus presented as global optima.

8.3 Model evaluation

To evaluate the developed whole-farm model, we compare the modelling results obtained under the *Baseline-CH* scenario, which represents current climate conditions and Swiss price levels, with different observed reference data sets. The Swiss agricultural information system (AGIS)[26] has been used to estimate typical crop plans (expressed as land use decisions) of arable farms around Payerne. The yields and the economic viability (expressed as comparable gross margin[27]) of different crops are compared with farm survey data obtained from the farm accountancy data network (FADN) (Mouron and Schmid, 2011). Observed irrigation practices are taken from a survey conducted in the year 2011 in the Broye watershed (Robra and Mastrullo, 2011). Finally, we use recommended yield-dependent nitrogen fertilization amounts in Switzerland (Amaudruz et al., 2011) as references for the obtained nitrogen fertilization intensities.

Table 8.5 provides a comparison between the optimum decision variables obtained from the model applying the *Baseline-CH* scenario and observations made in the Broye watershed. The simulated optimal land shares of all crops except sugar beets lie within the range of what can be observed in reality. On average more than 83% of the arable land is occupied by wheat, barley, rapeseed, grain maize, potatoes and sugar beets, which outlines the high importance of these crops in the study area. Nevertheless, we find the sugar beet area to be overestimated by our model. This can be explained by the fact that sugar beet production in Switzerland is restricted by quotas issued by the manufacturing company. Thus, in reality the free choice for sugar beet cultivation assumed in our model may not be available for all farmers.

Regarding nitrogen fertilization, the modelled optimum fertilization intensities are for all crops close to the yield-dependent nitrogen fertilization recommendations. The higher modelled nitrogen fertilization intensities for grain maize, potatoes and sugar beets can be explained by the fact that these crops are irrigated in our model, which increases the average yield levels and the related nitrogen demand (Di Paolo and Rinaldi, 2008). The recommended fertilization levels reported in Amaudruz et al. (2011), however, are based on rainfed crop production.

[26] The AGIS database is compiled by the Federal Office for Agriculture and records every farm in Switzerland (BLW, 2010).

[27] The comparable gross margin is defined as the sum of the revenues (without direct payments) minus the sum of all variable costs (Mouron and Schmid, 2011).

Table 8.5: Comparison of simulated (*Baseline–CH* scenario) and observed management decisions

Crop	*Modeled optimum crop land share*	*Observed average crop land shares in the year 2009 (± SD)* [a]	*Modeled optimum nitrogen fertilization intensity (kg N·ha^{-1})*	*Recommended nitrogen fertilization intensity (kg N·ha^{-1})* [b]	*Modeled optimum irrigation intensity (mm)*	*Observed range of irrigation intensity in the Broye watershed (min-max) (mm)* [c]
Winter wheat	45%	40% (±8%)	160	160	0	0
Winter barley	0%	4% (±6%)	na[d]	130	na[d]	0
Winter rapeseed	11%	13% (±9%)	160	140	0	0
Maize	10%	7% (±9%)	120	110	105	20-140
Potato	9%	5% (±10%)	150	120	108	5-200
Sugar beet	25%	14% (±10%)	130	110	125	13-120

[a] Sample from the Swiss agricultural information system (AGIS) (BLW, 2010) of the year 2009 considering farms located in municipalities with a geographic centroid within a 15-km radius around the climate station of Payerne. In order to ensure the comparability of the modelling results with the observed data, only farms without any livestock and with a minimum surface of arable land (i.e., grasslands are not considered) of at least 25 ha have been selected. In total, 52 farm records have been used. The crop shares refer to the total arable surface.

[b] Source: AGRIDEA and FIBL (2011)

[c] Source: Robra and Mastrullo (2011)

[d] na: Crop is not included in the optimal crop rotation.

Finally, the model outputs show that irrigation is only profitable under the *Baseline-CH* scenario for grain maize, potatoes and sugar beets. This outcome is in line with the results of the survey conducted by Robra and Mastrullo (2011). Moreover, all modelled irrigation intensities lie within (or close to) the observed range.

Finally, Table 8.6 compares modelled and observed comparable gross margins and crop yields. In order to compare the modelling results with only well managed farms, the upper 75%-percentile of the considered observed farm data has been taken as reference. The modelled average yields tend to be for all crops except winter rapeseed higher than the observations. This difference can be explained by the fact that CropSyst does not account for pests and weeds, which lead to lower crop yield levels in practice. Furthermore, grain maize, potatoes and sugar beets are irrigated in the modelling results, while not all farmers irrigate these crops in reality. Although the simulated crop yields are slightly overestimated, the obtained average comparable gross margins are lower than the FADN observations for all considered crops except grain maize. This is mainly due to the fact that most crops in Switzerland have a quality-related price structure. For instance, the sugar beet price in Switzerland depends on the harvest's sugar content. The FAO prices applied

to the farm model, however, reflect only basic price levels without consideration of quality aspects; that is, they are lower than the prices reported in the FADN records.[28]

Although the presented whole-farm model is based on a normative mathematical programming approach that does not necessarily simulate farmers' actual behaviour, but rather results in normative optimal management schemes (Buysse et al., 2007), the optimization results obtained under the *Baseline-CH* scenario are close to real-world observations. The developed whole-farm model can thus be judged to be appropriate to simulate the management decisions of an arable farm at Payerne.

Table 8.6: Comparison of modeled and observed crop yield levels and comparable gross margins.

Crop	*Modeled average comparable gross margin (CHF·ha^{-1})*	*Observed comparable gross margin (75%-percentile) (CHF·ha^{-1})*[a,b]	*Modeled average crop yield (t·ha^{-1})*	*Observed crop yield (75%-percentile) (t·ha^{-1})*[a]	*Number of farm records*
Winterwheat	2581	2752	8.0	7.4	123
Winterbarley	na[c]	2344	na[c]	8.2	107
Winter rapeseed	1643	1859	3.6	3.6	91
Grain maize	2520	2472	14.0	10.4	33
Potato	9157	10349	44.6	42.5	58
Sugarbeet	3548	5628	87.9	79.9	106

[a] Source: Sample of FADN farms located in municipalities with a geographic centroid within a 15-km radius around the climate station of Payerne. Farm records of the period 2005-2009 have been used as reference.

[b] Since sugarbeet market has been liberalized in 2009 leading to a sharp decrease in sugarbeet prices, FADN data only of the year 2009 (13 farm records) has been used for the derivation of the observed 75%-percentile of the comparable gross margin of sugarbeet.

[c] na: Crop is not included in the optimal crop rotation.

[28] Note that since crop yield quality aspects are not integrated in CropSyst, we focused in this study on crop yield quantity only.

8.4 Results and discussion

8.4.1 Land allocation

It is of particular interest how CC and the applied crop price scenarios affect the management decisions on the modelled arable farm. To this end, we first investigate how the farmer's land use is adjusted under the considered scenarios (Figure 8.2).

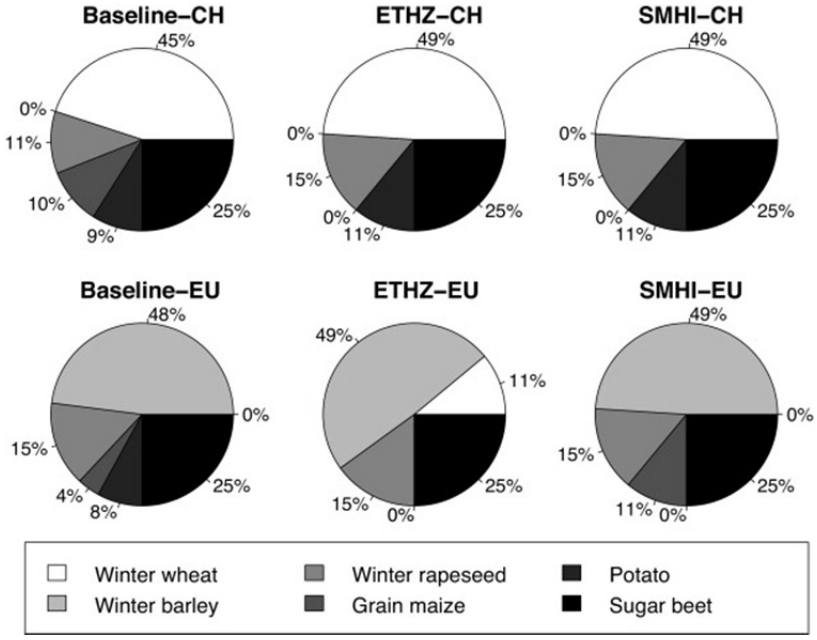

Figure 8.2: Optimal crop land allocation under different climate and crop price scenarios.

Under the *Baseline-CH* scenario, winter wheat and sugar beets are the most dominant crops (Figure 8.2). The remaining surface is allocated to winter rapeseed, potatoes and grain maize. Assuming Swiss prices, CC impacts on the optimal crop plan are rather small. Under both future climate scenarios, grain maize disappears from the optimal crop mix, while the acreages of winter wheat, potato and winter rapeseed are increased. Lehmann et al. (2013) show that the cultivation of grain maize at Payerne is very sensitive to the expected changes in climate conditions. More specifically, their study indicates that even if irrigation is considered as an adaptation strategy, crop yields of grain maize will significantly decrease under future climate scenarios, causing lower profitability. Winter rapeseed gains in importance since direct payment levels for this crop are high (cp. Table 8.2). This guarantees a high and stable economic profitability of winter rapeseed even under scenarios where crop yields decrease. The same is true for sugar beets, which are cultivated at maximum possible crop shares (25%) in all six scenarios. Furthermore, the

share of potatoes is increased since more field work days are possible under CC which promotes the cultivation of this field work-intensive crop.

Lower and more volatile crop prices (i.e., *EU* price scenarios) lead to stronger changes in the farm's optimal land allocation than observed for the CC scenarios (see Figure 8.2). Assuming *EU* prices, we find that winter barley replaces winter wheat as most dominant crop in the optimal crop mix. Thus, lower crop prices reduce the self-supply of bread cereals (i.e., winter wheat) in Switzerland. This shift can be explained by the lower relative price decrease (cp. Table 8.2) and the lower production costs of winter barley compared to winter wheat. In addition, the assumption of EU prices leads to a decrease of grain maize production under Baseline climate conditions by 60%. Furthermore, grain maize is not cultivated anymore under the *ETHZ-EU* scenario. Nevertheless, in contrast to the Swiss price scenarios, the optimal crop share of grain maize increases under the *SMHI-EU* scenario. Whereas decreasing yields and higher irrigation costs make grain maize less profitable than winter wheat cultivation under the *ETHZ–EU* scenario, the production of rainfed grain maize is still more profitable than the production of winter wheat under the *SMHI-EU* scenario (Figure 8.2). As in the case of winter barley, the relative price decrease of grain maize under the *EU* price scenarios is smaller than the relative price reductions of winter wheat. Furthermore, assuming *EU* prices, the cultivation of potatoes is profitable only under current climate conditions. Besides the lower crop prices, CC additionally decreases the relative profitability of potato production, causing lower crop yields and increased irrigation requirements. Due to the high levels of crop-specific direct payments, which have not been modified throughout the scenarios, sugar beets and winter rapeseed are cultivated under all *EU* price scenarios at the upper limits set by the cross-compliance regulations and crop rotation restrictions, respectively.

8.4.2 Crop yields and production risks

Irrespective of the market price scenarios, future expected climate conditions have a negative impact on average crop yields (cp. Table 8.7). This decrease is most pronounced for winter wheat and potatoes. For instance, potato yields decrease under the *ETHZ-CH* scenario by 19% compared to the *Baseline-CH* scenario. Nevertheless, CC has only small negative impacts on average yield levels of winter rapeseed and sugar beets. This can be traced back to the fact that sugar beets are expected to benefit from global warming and a longer growing season, provided that sufficient water is available (Olesen and Bindi, 2002). In the case of winter rapeseed, the earlier harvest due to the shorter vegetation period under CC reduces the risk of heat and drought stresses, which may mainly take place in summer months.

Table 8.7: Average crop yields (t·ha^{-1}) and coefficient of variation (in parentheses) for all crops and scenarios

Crop	*Baseline - CH*	*ETHZ-CLM - CH*	*SMHI-Had - CH*	*Baseline - EU*	*ETHZ-CLM - EU*	*SMHI-Had - EU*
Winter wheat	8.0 (9.1%)	6.8 (8.9%)	7.0 (7.4%)	na[a]	6.2 (14.1%)	na[a]
Winter barley	na[a]	na[a]	na[a]	8.0 (9.4%)	5.3 (15.4%)	6.3 (9.9%)
Winter rapeseed	3.6 (7.9%)	3.4 (11.0%)	3.3 (6.7%)	2.9 (10.0%)	2.8 (12.3%)	2.3 (8.9%)
Grain maize	14.0 (3.1%)	na[a]	na[a]	8.9 (18.1%)	na[a]	7.3 (24.3%)
Potato	44.6 (9.3%)	36.4 (9.3%)	39.1 (6.1%)	44.6 (9.3%)	na[a]	na[a]
Sugar beet	84.4 (6.5%)	79.0 (4.4%)	81.7 (3.1%)	84.4 (6.5%)	79.0 (4.4%)	81.7 (3.1%)

[a] na: Crop is not included in the optimal crop rotation.

Furthermore, our results show that CC may not necessarily increase production risks (cp. Table 8.7). Decreasing yield variability is found in this study for winter wheat, sugar beets and potatoes if adjustments in crop-specific management schemes are taken into account. The production of winter-sown crops, such as winter wheat, tends to benefit from more stable yields due to warmer and dryer climatic conditions. In contrast, CC actually increases production risks for spring-sown crops, such as potatoes or sugar beets. However, CC also gives farmers incentives to use irrigation more intensively to mitigate increasing climate risks, finally resulting in decreasing production risks for potatoes and sugar beets.

8.4.3 Nitrogen fertilization and irrigation

Besides the composition of the optimal crop mix, CC and EU prices also affect the optimal crop-specific management schemes, i.e., nitrogen and irrigation strategies (cp. Figure 8.3). Both, *EU* crop price levels and CC, lead to a reduction of nitrogen fertilization levels for all crops except potatoes and sugar beets. Aggregated on the farm level and assuming Swiss prices, the total farm level nitrogen decreases from 4428 kg N in the *Baseline-CH* scenario to 3492 kg N under the *ETHZ-CH* scenario. The implementation of *EU* prices further enhances this effect. More specifically, the total applied nitrogen amount at the farm level amounts to only 1614 kg N under the *ETHZ-EU* scenario.

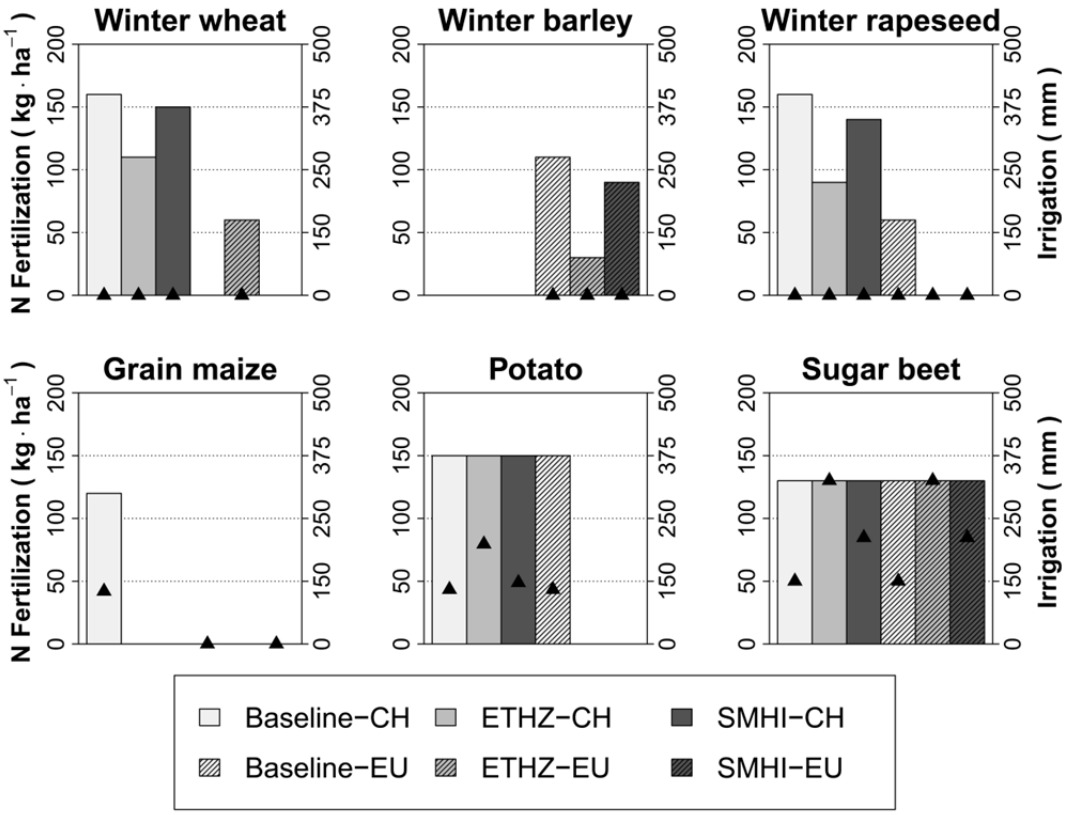

Figure 8.3: Optimal irrigation and nitrogen fertilization intensity. The optimal nitrogen fertilization intensities are represented by bars (left y-axis), the optimal irrigation intensities are depicted by the black triangles (right y-axis). Note that a missing black triangle indicates that a crop is not included in the optimal crop mix.

Due to warmer and dryer climatic conditions in the CC scenarios, the optimal irrigation intensity is increased for all irrigated crops (i.e., grain maize, potatoes and sugar beets). Under the assumption of *EU* prices, however, the optimal irrigation intensity increases only for sugar beets. Potatoes are no longer cultivated under CC, while grain maize is produced without the use of irrigation under the *Baseline-EU* and *SMHI-EU* scenarios and disappears from the optimum crop mix under the *ETHZ–EU* scenario. For winter wheat, winter barley and winter rapeseed, which have their main growing periods in autumn and spring, irrigation is not profitable in any of the scenarios. This is in particular due the fact that CC does not lead to very distinct changes in climate conditions within the growing seasons of these crops. Total farm water consumption increases from 15,458 m^3 under the *Baseline-CH* scenario to 30,965 m^3 and to 19,918 m^3 under the *ETHZ-CH* scenario and the *SMHI-CH* scenario, respectively. Since lower crop prices decrease the economic benefit of irrigation under the *EU* price scenario, the irrigation demand for farms increases only from 11,982 m^3 under the *Baseline-EU* scenario to 24,402 m^3 and to 15,885 m^3 under the assumption of the *ETZH-EU* and the *SMHI-EU* scenario, respectively. Nevertheless, these

results show that irrigation requirements in the Broye watershed will increase under CC independent from the chosen price scenario. Because water already is a scarce resource in the region (Mühlberger de Preux, 2008), CC will further intensify the conflict of water use.

8.4.4 Certainty equivalent, average gross margin and income risks

As shown in Figure 8.4, CC decreases farmers' CE and average gross margin less than changes in the crop prices. Whereas CC decreases the CE under both price scenarios by 8–12%, a change from Swiss to EU prices leads in all climate scenarios to a decrease of the CE of about 50%. Furthermore, CC slightly decreases the farm income variability (i.e., the coefficient of variation, see CV in Figure 8.4) for both price scenarios, whereas under the more volatile EU crop prices, the income risks are increased between 43% (*ETHZ-EU*) and 53% (*Baseline-EU*).

Although farm level income volatility is expected to increase under the *EU* price scenarios, the relative risk premiums (see RP in Figure 8.4) at the farm scale remain at low levels for all considered scenarios. In none of the considered scenarios, the relative risk premiums exceed 2.4% of the expected gross margin, which is far lower than the risk premiums found in other studies. For instance, Kim and Chavas (2003) estimate relative risk premiums for different farm types in Wisconsin to amount between 2% and 20% of the expected profit. Groom et al. (2008) find the relative risk premium of cereal and vegetable farmers in Cyprus to amount to about 20% of the expected profit. Furthermore, using a single-crop approach, Finger (2012b) finds the risk premium to account for more than 16% of the expected gross margin in grain maize production in Switzerland.

There are two main reasons for the rather low relative risk premium found in all scenarios of this study: first, Swiss farmers' income depends to a high degree on direct payments, which are not subject to seasonal weather or price variations (see Finger and Lehmann, 2012). Second, due to cross-compliance requirements in Switzerland, farmers have to cultivate at least four different crops which reduces income risks at the farm level. Thus, the conclusion may change if the model scale moves from the field to the farm scale, i.e., if whole-farm adjustment processes are taken into account. For instance, the coefficient of variation (CV) of the gross margins of grain maize amounts in this study under the *Baseline-EU* scenario to 31%. But still, the CV of the total gross margin at farm level does not exceed 10%. Therefore, the study's results show that the use of diverse cropping systems, as is common practice in Swiss agriculture, provides a valuable risk management instrument. This diversity should be maintained and encouraged by governmental regulations because it will be essential to cope with expected increases in climate and market risks.

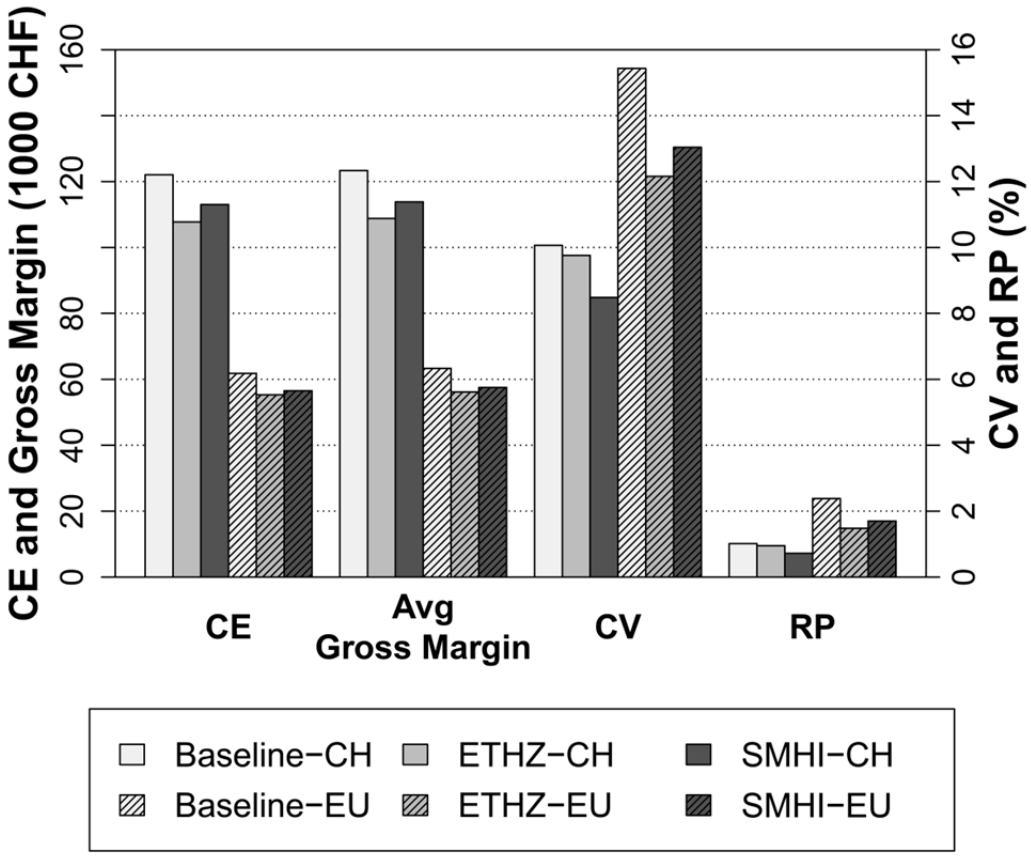

Figure 8.4: Climate change and price risks impacts on the farmer's certainty equivalent (CE), average gross margin, income variability (CV) and risk premium (RP). The CV is defined as the standard deviation divided by the average gross margin. The risk premium (RP) is derived from Equation 8.3.

8.4.5 Sensitivity analysis

In order to analyze the sensitivity of the assumed risk aversion on the modelling results, we also run the optimization model applying a risk aversion of $\gamma = 5$ (i.e., highly risk-averse decision maker) and a risk aversion of $\gamma = 0$ (risk-neutral decision maker). The assumption of a risk-neutral decision maker ($\gamma = 0$) leads exclusively under the *Baseline-CH* and the *Baseline-EU* scenario to small changes in the optimal crop mix. More specifically, under the *Baseline-CH* scenario, the optimal crop share of winter wheat is increased from 45% to 47% at the expense of the grain maize and winter rapeseed acreage, while under the *Baseline-EU* scenario, grain maize (4%) is replaced with winter wheat. If the relative risk aversion is increased to $\gamma = 5$, no changes in the optimal land use patterns are found. The crop-specific management decisions with regard to irrigation are unaffected by the assumed level of risk aversion. Moreover, the assumption $\gamma = 5$ of or $\gamma = 0$ affects the optimal crop-specific nitrogen intensities for all crops only in a range of ±10 kg·ha^{-1}.

The fact that the assumption of the decision maker's risks aversion has almost no impact on the optimal management schemes indicates that risk does, even under future expected climate conditions and more volatile crop prices, not play a very decisive role in Swiss arable farming. On the one hand, it is known that risk aversion is only one of possible reasons for diversification of farm activities (Pannell et al., 2000). Other reasons such as different soil types, resource constraints (i.e., workforce, machinery, land) and benefits of rotation sequences (e.g., disease control, nitrogen fixation by legumes, soil fertility) may have stronger incentives for diversification than the decision maker's risk aversion. On the other, direct payments make up a large proportion of the total agricultural income in Switzerland which generally decreases the importance of production and market risks in Switzerland.

Notwithstanding, it is important to underline that risk has been included in this study in a static framework. This means that the identified optimal management schemes are in all 25 simulation years identical. For farmers, however, it is also important how to respond tactically and dynamically to unfolding threads and opportunities in market and climate conditions (Pannell et al., 2000). This kind of risk management, however, has not been taken into account in this study.

8.5 Conclusions

In this paper, we developed a bioeconomic whole-farm model that combines non-parametrically a crop growth model with an economic decision model using a genetic algorithm (GA). The use of the farmer's certainty equivalent (CE) as objective function enabled accounting not only for changes in average climate and price levels, but also for the climate and price risks. This modelling approach was used to investigate impacts of likely changes in climate and crop prices on an arable farm's responses with respect to land use as well as on crop-specific fertilization and irrigation strategies in Western Switzerland.

The application of the whole-farm model to the six considered scenarios showed that changing crop prices from Swiss to EU average and volatility levels has much stronger impacts on the optimal management decisions than CC. These changes in optimal management patterns are almost exclusively due to decreased average price levels. Because of high levels of direct payments and a diversified crop portfolio, the increased price volatility under the *EU* price scenario has only small impacts on optimal management decisions. Thus, even under more volatile crop prices and under CC, the matter of risk is small in Swiss arable farming. Nevertheless, the assumption of EU crop

prices led to reductions in the farmer's certainty equivalent by up to 51%. However, Tran et al. (2013) show that global warming will increase world crop price levels, which might also raise the crop price levels in the EU. Thus, future research should not only consider crop price levels currently observed in Europe, but also design scenarios of crop price trends. Furthermore, CC is expected to offer the possibility of the emergence of new crops and new varieties in Northern Europe (Olesen and Bindi, 2002; Ewert et al., 2005). Thus, not only crops currently cultivated in the Broye watershed but also the introduction of new crop species should be considered in future studies.

The impacts of CC on farmers' utility and income are much smaller (8–12%). Nevertheless, under both, *CH* prices and *EU* prices, CC increases, the arable farm's irrigation requirements. Since the region already suffers water scarcity in dry and hot summer months (Mühlberger de Preux, 2008), the region's policy makers have to adjust the current irrigation water policy (e.g., implementation of a water price and water quota) in order to reduce the region's agricultural water consumption.

Although the modelling results obtained under current climate and price conditions showed good agreement with real-world observations, future research may also consider non-rational behaviour of decision makers (Mack et al., 2011) and to take into account, that utility optimization is only one of the farmers' goals (Greiner et al., 2009). Another limitation of the presented whole-farm model is that we used a static modelling approach. Static modelling approaches cannot be used to assess how farmers respond tactically and dynamically to unfolding threats and opportunities. In order to integrate tactical adjustments, which are known to increase the importance of risk management in agriculture (Pannell et al., 2000), the presented whole-farm model should be used as basis for a stochastic programming framework with recourse.

Acknowledgements

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9 Synthesis

In this synthesis section the main results are summarized with respect to the thesis' research questions. In a second step, the contribution of the thesis' results to the AGWAM project are discussed and concrete policy recommendations are presented. Furthermore, the most important results of the mixed farm model (not presented in this thesis), which has been developed in the framework of the AWGAM project, are summarized. Then, limitations of the used modeling framework are considered and finally, in the last part of this, an outlook is given, including open questions which could be addressed in future research projects.

9.1 Answers to research questions

9.1.1 How does climate change impact on the profitability and on production risks of cropping systems in the Broye catchment?

Due to lower yield levels for most considered crops, our models predict climate change to decrease the income of whole farm cropping systems located in the Broye catchment by about 8-12% even under consideration of counteracting adjustments in agricultural management. This relative decrease in farm income is robust against varying climate and crop price scenarios.

Nevertheless, regarding climate change impacts at the single crop level, the thesis' results are ambivalent: whilst winter cereals, grain maize and potato production are particularly vulnerable to climate change (i.e., income losses of up to 25%), comparably small effects were found on the average crop yield levels and profitability of winter rapeseed and sugar beet. As explained in Chapter 8, sugar beet most likely benefits from warmer temperatures given there is enough water supply (Olesen and Bindi, 2002). With regard to winter rapeseed cultivation, climate change can be expected to have only minor negative effects, since water and temperature stress are highest in the midsummer months under the applied climate change scenarios and thus after the rapeseed harvest. Furthermore, both winter rapeseed and sugar beets, benefit from high government direct payments, which render the profitability in the production of these crop types less climate-dependent.

As to what concerns production risks, this thesis indicates that the annual income at the whole farm level after adaptation will become slightly less volatile under future expected climate conditions, despite the expected increase of productions risks in winter rapeseed and grain maize cultivation. This decrease in income volatility has been found to be robust against differences in climate and crop price scenarios. Most likely, this is explained by the

fact that on one hand, at the whole farm level, agricultural income risks are per se smaller than for particular crops[29]. On the other, the predicted variability in yield levels of specific crop types (i.e., winter wheat, sugar beets, potatoes) may not necessarily increase under global warming if crop-specific adaptation measures are taken into account.

The findings described above underline the importance of assessing the local impact of climate change at the whole farm level. Crops which suffer from climate change in terms of average yield levels and yield variability can easily be replaced with other crop types, more robust against negative effects induced by climate change. Accounting for such exchanges in crop choice and land allocation, prevents the overestimation of negative climate change effects on cropping systems.

9.1.2 How does climate change influence optimal agricultural management decisions at single crop level as well as for arable whole farm systems?

Chapter 5 presents agronomic adaptation options to climate change in winter wheat and grain maize production for both AGWAM study regions. Climate change reduces the optimal nitrogen fertilization amount for both considered crops in both regions, whereas in the case of winter wheat it is optimal to apply the total nitrogen amount in one single fertilization application. For this crop, irrigation is even under rather strong assumed changes in climate conditions not considered as optimal adaptation option. This in contrast to grain maize cultivation, where irrigation is already under current climate profitable in the Broye catchment. Not surprisingly, the optimal irrigation intensity is further increased for grain maize under climate change scenarios.

Nevertheless, our simulation results at the whole farm level (see Chapter 7 and Chapter 8) indicate that grain maize will disappear from an optimal crop mix of an arable farm in the Broye watershed under climate change. As illustrated in Chapter 8, the profitability of grain maize production is likely to be strongly decreased under the future expected temperature and precipitation conditions, even if higher irrigation intensities are taken into account as adaptation measures. At the same time, winter rapeseed production will probably gain importance in the Broye region, since drier and warmer climate conditions will have an only small negative impact on its yield levels. Furthermore, high government direct payments supporting the cultivation of oil crops guarantee high profitability of winter rapeseed production also under future expected climate conditions. Besides changes in the optimal land allocation, simulations at the whole farm model also predict a

[29] Note that a diversified crop portfolio, which is common practice in Swiss agriculture, reduces not only the farm's production but also its market risk exposure.

decrease in fertilization intensity and a sharp increase in the farm's water demand[30] under future expected climate conditions. Interestingly, this increase in agricultural water consumption is not due to a larger irrigated surface area but solely resulting from higher supplemental water requirements in potato and sugar beet production.

9.1.3 What is the sensitivity of these optimal management decisions to lower agricultural output prices as expected under an ongoing liberalization of agricultural markets in Switzerland?

The simulation results using the whole farm model presented in Chapter 8 show that lower and more volatile crop prices as currently observed in the European Union (EU) lead to more profound changes in the farmers' management decisions than do changes in climate. Under the assumption of EU crop prices, winter barley instead of winter wheat becomes the dominant crop, because the relative crop price decrease is smaller and production costs are lower for barley compared to wheat. Additionally, potatoes are part of an optimal crop mix only under current climate conditions when assuming lower crop prices. With the predicted climate change, the yield levels of potatoes will further decrease, rendering this crop unprofitable at lower prices in the Broye watershed. Furthermore, EU crop prices will lead to a general decrease in optimal nitrogen fertilization and irrigation intensities for all crop types except sugar beet and potatoes. Thus, in line with other studies (e.g., Flückiger and Rieder, 1997; Finger and Schmid 2008), this thesis highlights the fact that declining crop prices and not climate change will be the predominant driver of changing management schemes in Swiss agriculture.

Nonetheless, some particular climate change effects do not depend on the applied crop price scenarios: First, grain maize is likely not to be cultivated any longer if assuming rather strong climate change effects. Second, the farm's total applied amount of nitrogen fertilization will decrease with altering climate conditions. And lastly, independent of the chosen crop price scenario, climate change sharply increases the farm's demand for irrigation.

In addition, it is important to emphasize the fact that we used a stochastic approach (i.e., multivariate normal distribution) to generate variable crop prices. Thus, the effectively applied crop prices were not in all studies identical, even though assuming the same average crop price scenarios. This is, for instance, the reason why some slight differences

[30] Note that for all simulation studies a sprinkler irrigation system with an irrigation efficiency of 77% has been assumed.

can be found between the farm's optimal management scheme in Chapter 7 and Chapter 8 assuming current climate conditions and Swiss crop prices.

9.1.4 How much does irrigation in the study region gain in importance under warmer and drier climate conditions?

This thesis shows that if all relevant fixed and variable costs associated with irrigation are considered, the latter is not a valuable management measure for winter crops such as winter wheat, winter barley and winter rapeseed even under a rather strong climate change scenario. As mentioned in other studies (e.g., Torriani et al., 2007b), climate change will increase water shortages in the Swiss Plateau mainly in summer and early autumn, hence after the winter crops considered in this work have been harvested. Conversely, our results indicate that for grain maize, potatoes and sugar beets, irrigation may even under current climate conditions be beneficial, which is in line with the currently observed situation in the Broye catchment.

Applying climate scenarios expected for the time horizon around the year 2050 and assuming no further restrictions on irrigation, we found the required water amount at farm scale to increase between 30-100% depending on the specific climate scenario chosen. As mentioned before, this increased water demand at farm scale is only due to more intensive irrigation requirements in potato and sugar beet production, whilst the total irrigated surface is predicted to be even decreased as grain maize, a crop which is already under current climate conditions frequently irrigated in the Broye area, disappears from the optimal crop mix. Furthermore, this relative increase in the farm's total water consumption under climate change is robust against variations in crop price scenarios. Thus, even under the assumption of climate change in combination with EU crop price levels, an increase in the farm's water demand of up to 60% compared to the reference scenario (i.e., current climate conditions and Swiss crop price levels) is found.

Furthermore, Chapter 5 shows that the optimal irrigation intensity is increased by up to 83% in grain maize production under global warming conditions, when the single crop model is applied. However, as mentioned above, results of the whole farm model indicate that grain maize disappears from an optimal crop mix in future climate conditions, which certainly decreases the significance of this finding.

Overall, a more intense use of irrigation will hence be one of the key adaptation measures to climate change for arable cropping systems in the Broye catchment. However, since the region's water availability is already restricted in dry and hot years, this increased agricultural water demand will further intensify water scarcity in the Broye catchment, if no changes in water policies are taken.

9.1.5 Which water policies are suitable to reduce the region's water demand under current and future expected climate conditions?

Currently, no additional costs for water are charged to farmers in the Broye region, but irrigation is nowadays prohibited during hot and dry periods. From Chapter 6, which compares income- and irrigation-related effects of different water policies in potato production, the conclusion can be drawn that the water policy currently in use, does not only encourage farmers to irrigate intensively whenever irrigation is possible, but also increases farmers' income risks in the production of potatoes . On the other hand, a water quota, which limits the annual maximum irrigation amount to an upper threshold, would have the potential to significantly decrease the water consumed for the production of potatoes, while maintaining the farmer's economic utility on actual levels. Due to its inelastic water demand function, volumetric water pricing only reduces the irrigation intensity in potato production at water prices higher than 2 $CHF \cdot m^{-3}$. At such high water prices, however, farmers' utility is reduced by more than 30%.

Based on the study presented in Chapter 6, Chapter 7 further pursues this research field by assessing the consequences of different water policies under current and future climate conditions for the farm's income, income risks and agricultural water consumption at a whole farm's scale. Under future climate conditions, both, the implementation of a volumetric water price and the introduction of a water quota, will significantly reduce the farm's total water consumption. At the same time, the reductions in farm income caused by these policies are relatively small since farmers increase the surface of the most profitable rainfed crops (e.g., winter rapeseed) at the expense of the surface of irrigated crops. Nevertheless, both alternative water policies increase the farm's downside risks of low incomes. Thus, new, innovative agricultural insurance products (e.g., farm revenue insurance, index-based insurance) might be one option to reduce the farm's higher risk exposure low incomes under such water policies.

9.2 Contribution to the NRP61 project AGWAM

Three main objectives have been defined within the AGWAM project (see Chapter 3.1). In the following, the contribution of this thesis to each objective is briefly discussed:

i) What is the water consumption by agriculture in two selected regions (catchments) under present and future conditions (considering climate, economy and agricultural policy), and how large is the risk to agricultural production due to reduced water availability?

This thesis shows that irrigation is already under current climate and crop price conditions a profitable management option for the cultivation of grain maize, potatoes and sugar beets in the northern Broye catchment which is well in line with the observed situation. Assuming expected climate conditions for the year 2050, the agricultural water consumption in arable farming can be expected to further increase by 30-100% at farm level. This increase in agricultural water usage is solely due to increased water requirements for the production of potatoes and sugar beet. For other crops, which are currently rainfed, such as winter cereals and winter rapeseed, irrigation will also under warmer and drier climate conditions not give an advantage from an economic point of view. Furthermore, the cultivation area of grain maize, which is currently frequently irrigated, can according to our results be expected to become smaller under climate change. Thus, our results indicate that the irrigated surface will not necessarily increase in the Broye catchment under warmer and drier climate conditions.

If the water supply is restricted by a water quota (see Chapter 7) agricultural income risks are found to increase under climate change by almost 50%. This can be explained by the fact that crop yields and agricultural revenues are significantly decreased in exceptionally dry and hot years when the crops' irrigation requirements are far beyond the quota. Nevertheless, it is important to mention that even with an increase of 50%, the modeled farm's absolute income risks are still much lower than observed in other countries (see Chapter 8).

ii) How can we optimize strategies for water conservation in agricultural land use (forage, crop and livestock production) at the regional (catchment) scale, and at the scale of individual farms, and what are the environmental impacts of such strategies?

The most important factor determining agricultural water consumption is the crop choice and the crop land allocation. A farm, which uses most of its surface for the cultivation of winter cereals and winter rapeseed, may exhibit a relatively low water consumption. On

the other hand, the cultivation of potatoes, for instance, will be possible under future climate scenarios only with the application of irrigation[31]. Therefore, agricultural policies, which systematically promote the cultivation of typically rainfed crops such as winter cereals or winter rapeseed, might be on option for water conservation in the Broye catchment.

Furthermore, Chapter 7 indicates that both, the introduction of a variable volumetric water price and the implementation of a water quota, are very effective policy measures to reduce an arable farm's water demand. Our simulation results indicate that both policy measures can decrease the farm's water demand by more than 90% whereas the related decrease in the farm's average income is smaller than 10% under a rather strong climate change scenario. Under current climate conditions, the introduction of such water policies decreases the average farm income only by less than 5% while still significantly reducing the farm's water consumption.

Regarding agronomic-related water-conservation strategies, Chapter 6 shows by the example of potato cultivation that it is also possible to save water by adjusting irrigation frequency and intensity. More specifically, the study presented in Chapter 6 shows that the applied irrigation amount can be significantly reduced without any major decreases in yield levels by applying irrigation less frequently and less intensively.

iii) What recommendations for management and policy measures can be made to implement sustainable water use in Swiss agriculture considering a range of possible climate change scenarios?

Given that climate change will sharply increase agricultural water demand in the Broye catchment, the region's water and agricultural policies have to be adjusted. First of all, it is important to keep in mind that cantons and the Confederation currently subsidize about 50% of the total costs of water extraction and the water transportation system. This governmental support facilitates local investments in irrigation systems (Finger and Lehmann, 2012b). Furthermore, since irrigation water is not charged volumetrically[32], farmers have large incentives to make excessive use of irrigation.

A water quota limiting the annual applicable irrigation amount shows not only at the single crop level in potato production, but also at the whole farm scale very promising results. It significantly decreases the agricultural water demand, while its negative

[31] Note that potato is in all scenarios either produced with supplemental irrigation or not included in an optimal crop portfolio.

[32] Note that currently farmers must only bear electricity costs incurred for water pumping.

impacts on the farm income are relatively small. However, a water quota increases the risk for income losses in agriculture, in particular due to potential low crop yields which might occur in years when crop irrigation requirements largely exceed the applicable water amount. Such higher risks may be minimized by promoting new insurance products such as crop yield-based or revenue-based insurances schemes.

Compared to a volumetric water price, which has also been found to be able to drastically reduce the farm's water demand without very large income losses, the water quota might be easier to implement in practice. Farmers can be expected to prefer a water quota, which does not increase production costs, over a volumetric water price, which increases variable production costs for irrigated crops.

Furthermore, our results imply that sugar beet is under all considered climate, crop price and water policy scenarios a highly profitable crop, which is thus always cultivated almost at maximum allowable crop share. This holds true even if sugar beet is produced in the absence of irrigation. The reason for this is to be found in its crop-specific government direct payments of 1'900 CHF per hectare. Since climate change effects are relatively low in sugar beet production compared to other crop type, a partial redistribution of this special direct payments to cereals could help to increase the self-sufficiency of bread cereal in Switzerland also in future climate and crop price scenarios. This in turn would make the cultivation of cereals more profitable compared to irrigated crops and could thus also decrease the region's total irrigated surface.

9.2.1 Livestock model

In addition to the presented bioeconomic modeling approaches, a mixed farm model based on the arable whole farm model has been developed within the framework of the AGWAM research project. Besides different crops, this model also considers different livestock types (i.e., dairy cows, suckling cows, calves fattening and bull fattening) as additional farm activities. This mixed farm model has been used to address similar research questions as presented in Chapter 1.1. The principal results of applications of the mixed farm model (not shown in this thesis) with regard to the Broye catchment can be summarized as follows:

- Under the reference scenario representing current climate conditions and Swiss prices of agricultural outputs, it is optimal for a mixed farm to focus on dairy cow production. In doing so, most of the farm's agricultural surface is used for feed stuff production (i.e., grassland, pastures and silage maize) and for the cultivation of winter wheat. Furthermore, only silage maize is irrigated in an optimal solution in the reference scenario.

- Dairy cow production remains the most beneficial livestock activity for the mixed farm in all considered climate, price and policy scenarios.
- Climate change impacts on the income and optimal production schemes of a mixed farm are much smaller than for arable farms. Nevertheless, climate change in combination with lower agricultural output prices leads to more extensive production schemes (i.e., lower nitrogen fertilization and irrigation intensities), whereby the cultivation of winterwheat is replaced with winter rapeseed production.
- However, as in the case of arable farms, climate change will sharply increase the mixed farm's total water demand if current water policies and Swiss agricultural output prices are assumed. This is particularly due to increased irrigation requirements in grassland and silage maize production. As for arable farms, this higher water consumption can be effectively decreased by the implementation of a volumetric water pricing scheme or a water quota. These water policies reduce a mixed farm's water demand under climate change by more than 70% while the farm income is decreased only by about 2.5%.

Summarizing the above, it can therefore be stated that the identified climate change effects show for both farm types similar general tendencies.

9.3 Limitations of thesis

In this thesis, an integrated bioeconomic modeling approach, consisting of the mechanistic crop growth model CropSyst, an economic decision model at field and at farm scale, respectively, and a stochastic weather generator, has been used to assess climate change impacts on arable cropping systems. Integrated modeling approaches can provide useful support to policy making, since they are able to represent complex interactions taking place in the human-environment system (van Delden et al., 2011). However, it is important to consider two points in particular when using this kind of modeling approaches: First, a chain is only as strong as its weakest link. Thus, a limited validity of one submodel restricts the validity of the overall modeling approach. Second, since all models are per definition abstractions of a complex reality, the degree of uncertainty of an integrated model increases with the number of submodels included.

Furthermore, the integrated bioeconomic modeling approach used in this thesis has some other specific limitations:

- Although the crop growth model CropSyst showed good agreements between simulated and observed crop yield levels (Klein et al., 2012), it cannot account for crop yield quality[33]. However, not only the crop yield quantity but also crop yield quality is an important climate- and management-related factor (Ojala et al., 1990). As a matter of fact, higher prices are paid for better yield quality for most crop types, which thus impacts the farmers' income.
- Besides the neglect of yield quality, CropSyst is not able to account for the effects of pests and plant diseases on crop yield levels and crop yield quality, either. Changing climate conditions, however, will certainly also impact the occurrence and distribution of pests and plant diseases (Fuhrer, 2003; Trnka et al., 2007; Hirschi et al., 2012).
- This thesis did not consider effects of agronomic practices such as soil tillage or residue management on soil moisture and the related irrigate demand. In this context it should be mentioned that the impacts of tillage and residue management practices on soil water are very complex and difficult to simulate by crop growth models (Sommer et al., 2007).
- The stochastic weather generator LARSWG, which has been used throughout this thesis, is very suitable for agricultural applications, since it generates site-specific weather data at daily time scale as required in most crop models. Yet, similar to other weather generators, LARSWG does not explicitly model interannual variability and tends to underestimate in particular temperature interannual variability (Calanca and Semenov, 2012). Thus, the variability of simulated crop yields might be slightly underestimated in this thesis.

9.4 Future research

So far, the models presented in this thesis have been applied to Payerne (single crop models as well as whole farm model) and Uster (single crop model presented in Chapter 5) within the Broye and Greifensee catchment, respectively. In future applications, the model should be expanded to other locations within the two study regions of AGWAM featuring different soil and climate conditions. Besides different locations, also a wider range of climate change scenarios has to be taken into account. Additionally, since the model proved to be very sensitive to different crop price levels, further scenarios on future

[33] In this study, for all crops standard yield quality and corresponding standard crop prices have been assumed.

expected crop prices in Switzerland should be considered. In the course of this, account has also to be taken of the hypothesis that climate change is likely to increase global crop prices (e.g., Tran et al., 2012) which might also influence pathways of future output prices in Swiss agriculture.

The model used in this study has considered income and income risks as main economic decision markers. However, the objective function in this approach did not include other decision influencing processes such as the minimization of workload and thus work effectiveness, personal preferences to the cultivation of particular crops or maximal independence from government direct payments (Greiner et al., 2009). Since all these factors also play a role as economic decision makers, our model would profit from the consideration of such additional parameters in future applications.

Furthermore, we assumed in this thesis that no improvements in crop cultivars occur up to year 2050. Even though the implementation of advanced cultivars is known to occur slowly (Campos et al., 2004; Araus et al., 2008), future studies should consider potential improvements in adaptation to climate change by new crop types. Mechanistic crop growth models offer very valuable tools for this sort of research questions since they allow to test the effects of modified cultivar traits in different climate scenarios (Chenu et al., 2009; Chenu et al., 2011).

Finally, the developed whole farm model provides a good basis for the development of a future agent-based modeling approach. Interactions between different agents are important to better capture management options in agricultural systems, in particular for models of agricultural land use (Schreinemachers and Berger, 2011). Furthermore, agent-based models are able to consider heterogeneity amongst farms and land, and model decision- making using a bottom-up strategy (i.e., taking into account locally interacting farms competing for land) which allows to analyze the properties of a particular system also at a regional level (Brady et al., 2012).

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Appendix A

Table A.1: Tabulated are the absolute changes in monthly mean minimum and maximum temperature (Δ Tmin and Δ Tmax) and relative changes in the monthly mean radiation (Δ Rad) and monthly mean precipitation totals (Δ Precip) as projected for 2050 by simulations with the ETHZ-CLM and SMHI-Had regional climate models.

	ETHZ-CLM								*SMHI-Had*							
Month	*Δ Tmin (°C)*		*Δ Tmax (°C)*		*Δ Rad (%)*		*Δ Precip (%)*		*Δ Tmin (°C)*		*Δ Tmax (°C)*		*Δ Rad (%)*		*Δ Precip (%)*	
	PAY	UST	PAY	UST	PAY	UST	PAY	UST	PAY	UST	PAY	UST	PAY	UST	PAY	UST
Jan	+2.51	+2.58	+2.51	+2.6	-3	-3	-4	-4	+2.33	+2.21	+1.74	+1.67	-6	-5	+14	+8
Feb	+1.82	+1.84	+2.00	+2.07	-4	-5	-2	-2	+1.90	+1.87	+1.34	+1.37	-4	-4	+6	+6
Mar	+1.91	+1.89	+2.14	+2.28	-4	-5	-2	-1	+1.31	+1.31	+1.11	+1.05	-3	-4	+2	+8
Apr	+2.06	+2.12	+2.15	+2.24	-2	-5	-3	+3	+1.03	+1.04	+1.07	+0.90	-2	-2	-2	+8
May	+1.85	+1.92	+2.07	+1.84	+2	-2	-6	+6	+1.48	+1.54	+1.59	+1.43	+0	-2	-7	+1
Jun	+2.18	+2.11	+3.08	+2.64	+7	+5	-18	-7	+2.00	+2.10	+2.13	+2.02	+1	-1	-8	-1
Jul	+2.82	+2.67	+4.23	+3.9	+9	+9	-30	-24	+2.08	+2.21	+2.15	+2.16	+0	-1	-3	+3
Aug	+3.11	+2.96	+4.39	+4.19	+8	+9	-28	-23	+2.00	+2.12	+1.98	+2.04	-2	-2	-1	+6
Sept	+2.78	+2.7	+3.41	+3.29	+3	+5	-11	-5	+1.67	+1.72	+1.61	+1.53	-2	-3	+4	+1
Oct	+2.29	+2.36	+2.36	+2.39	+0	+1	-1	+1	+1.46	+1.43	+1.32	+1.17	-5	-6	+16	+19
Nov	+2.28	+2.44	+2.23	+2.42	+0	+1	-4	-6	+1.86	+1.77	+1.56	+1.45	-8	-8	+24	+22
Dec	+2.69	+2.8	+2.6	+2.81	-2	-1	-4	-6	+2.34	+2.21	+1.92	+1.79	-8	-7	+22	+17

Table A.2: Soil profile and initial soil conditions at Payerne and Uster.

Soil parameters at Payerne					
Depth (m)	0-0.2	0.2-0.3	0.3-0.7	0.7-0.9	0.9-1.2
Sand (%)	56.0	57.0	60.0	57.0	65.0
Clay (%)	14.0	11.0	10.0	10.0	12.0
Silt (%)	30.0	32.0	30.0	33.0	23.0
Organic matter (%)	2.8	2	2	2	2
NO_3 ($kgN \cdot ha^{-1}$)	5	5	5	5	5
NH_4 ($kgN \cdot ha^{-1}$)	5	5	5	5	5
Volumetric permanent wilting point ($m \cdot m_{\cdot}$)	0.105	0.094	0.09	0.09	0.097
Volumetric field capacity ($m^3 \cdot m^{-3}$)	0.221	0.213	0.206	0.212	0.201
pH	7.1	7.3	7.7	8.0	8.2
Soil parameters at Uster					
Depth (m)	0-0.15	0.15-0.35	0.35-0.76	0.76-1.0	1.0-1.2
Sand (%)	52.6	59.2	58.2	74.4	86.0
Clay (%)	17.6	14.4	15.6	8.7	4.0
Silt (%)	29.8	26.4	26.2	16.9	10.0
Organic matter (%)	2.8	2	2	2	2
NO_3 ($kgN \cdot ha^{-1}$)	5	5	5	5	5
NH_4 ($kgN \cdot ha^{-1}$)	5	5	5	5	5
Volumetric permanent wilting point ($m^3 \cdot m^{-3}$)	0.118	0.106	0.111	0.082	0.054 .
Volumetric field capacity ($m^3 \cdot m^{-3}$)	0.236	0..217	0.222	0.176	0.134
pH	6.2	5.9	6.7	7.5	7.5

Appendix B

Table B.1: Texture, hydraulic and chemical characteristics of the soil profile recorded at Payerne.

Soil parameters at Payerne					
Depth (m)	0-0.2	0.2-0.3	0.3-0.7	0.7-0.9	0.9-1.2
Sand (%)	56.0	57.0	60.0	57.0	65.0
Clay (%)	14.0	11.0	10.0	10.0	12.0
Silt (%)	30.0	32.0	30.0	33.0	23.0
Organic matter (%)	2.8	2	2	2	2
NO_3 ($kgN \cdot ha^{-1}$)	5	5	5	5	5
NH_4 ($kgN \cdot ha^{-1}$)	5	5	5	5	5
Volumetric permanent wilting point ($m \cdot m_{\cdot}$)	0.105	0.094	0.09	0.09	0.097
Volumetric field capacity ($m^3 \cdot m^{-3}$)	0.221	0.213	0.206	0.212	0.201
pH	7.1	7.3	7.7	8.0	8.2

Appendix C

Table C.1: Applied changes in climate variables for the ETHZ-CLM and SMHI-Had scenario

	ETHZ-CLM				*SMHI-Had*			
Month	Δ *Tmin (°C)*	Δ *Tmax (°C)*	Δ *Rad (%)*	Δ *Precip (%)*	Δ *Tmin (°C)*	Δ *Tmax (°C)*	Δ *Rad (%)*	Δ *Precip (%)*
Jan	+2.51	+2.51	-3	-4	+2.33	+1.74	-6	+14
Feb	+1.82	+2.00	-4	-2	+1.90	+1.34	-4	+6
Mar	+1.91	+2.14	-4	-2	+1.31	+1.11	-3	+2
Apr	+2.06	+2.15	-2	-3	+1.03	+1.07	-2	-2
May	+1.85	+2.07	+2	-6	+1.48	+1.59	+0	-7
Jun	+2.18	+3.08	+7	-18	+2.00	+2.13	+1	-8
Jul	+2.82	+4.23	+9	-30	+2.08	+2.15	+0	-3
Aug	+3.11	+4.39	+8	-28	+2.00	+1.98	-2	-1
Sept	+2.78	+3.41	+3	-11	+1.67	+1.61	-2	+4
Oct	+2.29	+2.36	+0	-1	+1.46	+1.32	-5	+16
Nov	+2.28	+2.23	+0	-4	+1.86	+1.56	-8	+24
Dec	+2.69	+2.6	-2	-4	+2.34	+1.92	-8	+22

Table C.1 shows the absolute applied changes in the monthly average minimum temperature (Δ Tmin), in the monthly average maximum temperature (Δ Tmax), and the relative changes in the monthly average radiation (Δ Rad) and in the monthly average precipitation sum (Δ Precip) for the applied CC scenarios ETHZ-CLM and SMHI-Had.

Table C.2: Correlation matrix of crop prices

Switzerland						
	Wheat	*Barley*	*Rapeseed*	*Grain maize*	*Potatoes*	*Sugar beets*
Wheat	1	0.84	0.41	0.77	-0.33	0.71
Barley		1	-0.02	0.97	-0.35	0.727
Rapeseed			1	-0.09	0.15	0.29
Grain Maize				1	-0.25	0.67
Potatoes					1	-0.50
Sugar beets						1
France						
	Wheat	*Barley*	*Rapeseed*	*Grain maize*	*Potatoes*	*Sugar beets*
Wheat	1	0.96	0.87	0.92	0.52	-0.51
Barley		1	0.85	0.77	0.40	-0.38
Rapeseed			1	0.77	0.58	-0.73
Grain maize				1	0.65	-0.54
Potatoes					1	-0.57
Sugar beets						1

Table B.2 shows the correlation matrix of crop prices in the period 2002-2010 in Switzerland and France obtained from the FAOSTAT database (FAO, 2011). All values refer to the Pearson correlation coefficient.

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