

THE IMPACT OF CLIMATE CHANGE ON THE PROFITABILITY OF SITE SPECIFIC TECHNOLOGIES

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Abstract

Site Specific Technologies (SST) can reduce environmental pollution caused by common agricultural practice. Using a case study for corn yields, we investigate the impact of climate change (CC) on profitability of SSTs. We find CC to increase spatial variability of soils with respect to optimal input application and yield variability. This leads, *ceteris paribus*, to higher incentives for SST adoption in the future.

Keywords

Climate Change, Site Specific Technologies, Adaptation, Crop Production Function.

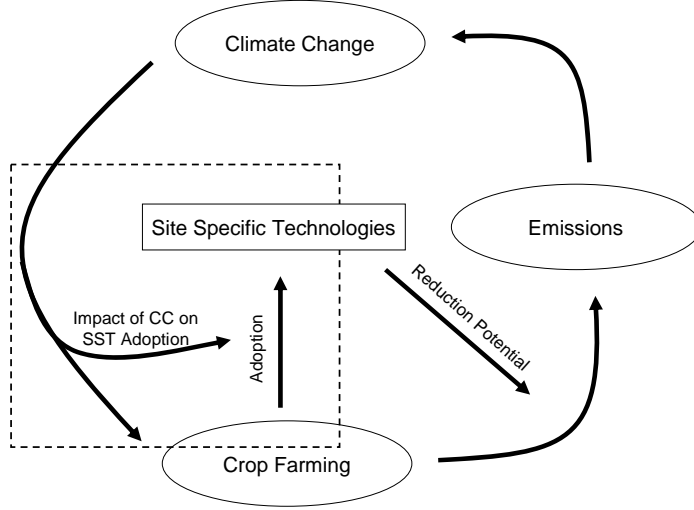
1 Introduction

The relationship between agriculture and the environment is a major issue of agricultural research. It shows that common agricultural practice causes environmental pollution and leads to unsustainable use of resources such as soil and water (OECD, 2001). It is of particular social but also economic interest to foster pollution reduction and sustainable use of resources by agriculture. Site Specific Technologies (SSTs) are potential instruments to reach such goals. In contrast to conventional management practice, where inputs are applied uniformly across the field, management that employs SSTs (i.e. site specific management) is characterized by input application taking spatial variability across the field into account. Various studies show that SSTs lead to lower application rates of harmful inputs, reduce residues of inputs in soil and reduce emissions caused by fertilizer application (ANSELIN ET AL., 2004, ISIK and KHANNA, 2002 and 2003, KHANNA ET AL., 2000, PAMPOLINO ET AL., 2007, ROBLIN and BARROW, 2000). Our analysis is restricted to the crucial agricultural inputs nitrogen fertilizer and irrigation water because application of both can lead to the degradation of environmental systems (IEEP, 2000, and, KHANNA ET AL., 2000). Nitrogen fertilizer is furthermore a major source of climate relevant agricultural emissions (HUNGATE ET AL., 2003).

Projected changes in climatic conditions will cause changes in the productivity of crops and crop yield variability in the next decades. In particular soil characteristics determine the impact of climate change (CC) on crop yields (EITZINGER ET AL., 2003). Therefore, CC is assumed to increase spatial variability of soils with respect to yield potentials, input use and yield variability, respectively. The latter are important for the profitability of SSTs (ISIK and KHANNA, 2003). Thus, CC is assumed to affect adoption of SSTs. Using a case study, this paper focuses on the relationship between CC and the incentive of crop farmers to use SSTs (shown in dashed box of Figure 1).

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Figure 1: The relationship of crop farming, climate change and SSTs.



Source: own illustration

We use simulated corn (*Zea Mays L.*) yields, which are particularly sensitive to field level variations of the soil properties (TITTONELL ET AL., 2006), at the eastern Swiss Plateau considering a base scenario of current climate and a CC scenario for the year 2050.

The remainder of this paper is organized as follows. The economic model that estimates profitability of site specific management is presented in Section 2. Section 3 describes briefly the yield simulation process and the CC scenario. In Section 4, empirical methods and estimation results are presented. Model results and expected differences between conventional and site specific management are shown in Section 5. Finally, the impact of CC on SST adoption is discussed in the concluding section 6.

2 The Model

Our analysis is based on maximization of expected utility¹, $E(U(\pi, \sigma))$, with $E(U)_{\pi} > 0$ and $E(U)_{\sigma} < 0$. Where E is the expectation operator, π are quasi-rents (revenue minus variable costs) and σ is the standard deviation of quasi-rents. Two management technologies are considered in this model: site specific and conventional management. In a static analysis, the utility maximization problem with respect to management technology choice is defined as follows (ISIK and KHANNA, 2003):

$$(1) \quad \max_I E(U) = \pi^C + I(\pi^S - \pi^C - K), \sigma^C + I(\sigma^S - \sigma^C)$$

Where π^C and π^S are the quasi-rents for conventional and site specific management, respectively. I is an indicator function, i.e. $I = 1$ for SST adoption and $I = 0$ if conventional management is maintained. K denotes the costs of adoption, i.e. variable costs for hiring technology and experts (KHANNA ET AL., 2000). σ^C and σ^S are the standard deviations of quasi-rents for conventional and site specific management, respectively. Therefore, site specific management is adopted if:

$$(2) \quad E(U(\pi^S - K, \sigma^S)) > E(U(\pi^C, \sigma^C)).$$

¹ Subscripts denote derivatives.

Farmers are assumed to adopt site specific management if expected utility exceeds utility of conventional management practice and adoption costs. In our analysis, prices are assumed to be deterministic. Thus, the standard deviation of quasi-rents (i.e. the production risk) simplifies to $\sigma(\pi) = p \sigma^Y(X)$. Yield, with standard deviation $\sigma^Y(X)$, is the only stochastic element of quasi-rents. Hence, the optimization problem with respect to input use is defined as follows:

$$(3) \quad \max_{X,Y} E(U(\pi)) = pE(Y(X)) - ZX - \gamma p \sigma^Y(X) \quad .$$

p and Z are output and input prices, respectively. Moreover, $Y(X)$ denotes the production function, i.e. the input (X) - output (Y) relationship. Expected utility is maximized subject to the production function constraint. The coefficient of risk aversion², γ , indicates risk averse, risk neutral and risk taking behavior if $\gamma > 0$, $\gamma = 0$, and $\gamma < 0$, respectively. $\sigma^Y(X)$, the yield variation, is determined by weather and soil conditions, and input use. Input i is risk decreasing if $\sigma^Y_{x_i} < 0$ and risk increasing if $\sigma^Y_{x_i} > 0$.

The first order conditions of eqn. (3) are:

$$(4) \quad \partial E(U(x^{i*})) / \partial x^i = \partial E(\pi(x^{i*})) / \partial x^i - \partial \gamma p \sigma^Y(x^{i*}) / \partial x^i = 0 \quad \forall i$$

These first order conditions are equivalent to:

$$(5) \quad \partial f(x^{i*}) / \partial x^i - z^i / p - \gamma \cdot \sigma^Y_{x_i} = 0 \quad \forall i.$$

Where, x^{i*} is the optimal factor level and z^i is the price of input i . This tangency condition equals profit maximization if $\gamma = 0$. However, a risk premium, $\gamma \cdot \sigma^Y_{x_i}$, is included if $\gamma \neq 0$.

This is the difference between expected marginal productivity and the ratio of input and output prices at the optimal level of input use. Therefore, the optimal level of input use is smaller for an input that increases yield variation, if a risk averse instead of a risk neutral farmer is considered, and vice versa.

In order to reflect heterogeneous soil conditions, the assumed field with land size M is divided into T sites of equal size³. Soil characteristics are homogeneous within each site but heterogeneous across sites. In our analysis, soil characteristics vary with respect to content of organic matter and soil fertility. Other soil characteristics, such as the soil texture, are assumed to be homogeneous across sites. Details on soil characteristics that are assumed in our analysis are given in the subsequent section 3. In order to model sites at the field, we draw (1000 draws) a site from a binomial distribution of two soils that are abbreviated as $S1$ and $S2$ in the following. In this distribution, probability to draw $S1$ ($p(S1)$) and probability to draw $S2$ ($p(S2)$) is 0.4 and 0.6, respectively.

For every drawn soil composition (i.e. ratio of $S1$ and $S2$), four expected utilities are calculated: for site specific management and for conventional management with three different levels of information. For site specific management the soil type of each site is known and utility is maximized for each site, $j = 1, \dots, T$. Therefore, field level expected utility for site specific management, $E\left(U\left(\pi^S\right)\right)$, is defined as follows:

² The coefficient of risk aversion is defined as $-(\partial U / \partial \sigma^\pi) / (\partial U / \partial \pi)$.

³ $M = \sum_{j=1}^T M^j$

$$(6) \quad E(U(\pi^S)) = \sum_{j=1}^T M^j \cdot E(U(\pi^j)) = \sum_{j=1}^T M^j \cdot (pE(Y(X^{j*})) - ZX^{j*} - \gamma p \sigma^Y(X^{j*})).$$

In contrast, soil types of sites are not known if conventional management practice is assumed. We assume three different levels of farmers' soil information: a) zero information: every input combination between $X^*(S1)$ and $X^*(S2)$ has the same probability to be applied, i.e. drawn from a uniform distribution. b) ratio of soil components ($S1$ and $S2$) is known, X^C is equal to $0.4 \cdot X^*(S1) + 0.6 \cdot X^*(S2)$. c) rough information of soils, in order simulate an information situation in between the extremes (a, b), input combinations are drawn from a non-uniform discrete distribution⁴. Simulations are conducted with the program @Risk (WINSTON, 1996).

For cases a) to c), farmers maximize, based on their soil information, expected utility $E(U^C(\pi^C(X^C), \sigma^C(X^C)))$. Input application for conventional management, X^C , depends on the soil information scenario (a-c). Field level expected utility for conventional management, $E(U(\pi^C))$, is defined as follows:

$$(7) \quad E(U(\pi^C)) = pE(Y(X^C)) - ZX^C - \gamma p \sigma^Y(X^C).$$

The goal of this paper is to analyze the impact of CC on the profitability of SST adoption. Therefore, the utility maximization problem with respect to technology choice (eqn. 1) is reduced to the expected utility difference between site specific and conventional management (eqn. 8). This expected utility difference is calculated twice, for the base and the CC scenario.

$$(8) \quad \Delta E(U(S, C)) = E(U(\pi^S, \sigma^S)) - E(U(\pi^C, \sigma^C))$$

3 Data

Our analysis is based on corn yield data generated by the deterministic crop yield simulation model CropSyst (STÖCKLE ET AL., 2003). CropSyst parameterization for Swiss corn follows TORRIANI ET AL. (2007). The used yield simulation data sets are provided by the Agroscope Reckenholz-Tänikon Research Station ART in Zurich. Apart from agricultural inputs and CO₂ concentrations, CropSyst is particularly driven by daily values of maximum and minimum temperature, solar radiation, and maximum and minimum relative humidity. Required weather data are provided by the Swiss Federal Office of Meteorology and Climate for six different locations on the eastern Swiss Plateau (see FINGER AND SCHMID, 2007A, for details). We use recordings for the years 1981 to 2003 which represent the base climate scenario. Assumed seasonal changes in temperature and precipitation for the CC scenario (abbreviated in the following as 2050) are presented in Table 1.

Table 1: Seasonal anomalies of temperature [°C] (absolute value) and precipitation [-] (relative value) with respect to the climate of the year 1990.

Climate variable	2050			
	DJF	MAM	JJA	SON
Temperature [°C]	+ 1.8	+ 1.8	+ 2.7	+ 2.1
Precipitation [-]	1.08	0.99	0.83	0.94

DJF: December-February; MAM: March-May; JJA: June-August; SON: September-November.

Source: OcCC (2005)

⁴ Probability (p) to draw $X_i^*(S1)=0.05$, $p(0.8 \cdot X_i^*(S1) + 0.2 \cdot X_i^*(S2))=0.1$, $p(0.6 \cdot X_i^*(S1) + 0.4 \cdot X_i^*(S2))=0.2$, $p(0.4 \cdot X_i^*(S1) + 0.6 \cdot X_i^*(S2))=0.3$, $p(0.2 \cdot X_i^*(S1) + 0.8 \cdot X_i^*(S2))=0.25$, $p(X_i^*(S2))=0.1$

Based on climate anomalies, daily weather data for the 2050 scenario are generated with the stochastic weather generator LARS-WG (SEMENOV ET AL., 1998). Furthermore, CO₂ concentrations are randomly allocated to the observations. These concentrations range from 339ppm to 379ppm for the base and from 495ppm to 561ppm for the 2050 scenario (IPCC, 2000), respectively. The applied soil texture for both soil types (*S1* and *S2*) is characterized by a fraction of 26% sand, 38 % clay and 36% silt. Soil depth amounts to 1.5 m. For soil 1 (*S1*), the soil organic matter content is constant at 2.6%. For soil 2 (*S2*), the latter is 2.6% in the top soil layer (5 cm) and 2.0% in lower soil layers. Due to higher content of organic matter in *S1* than in *S2*, higher amounts of nitrogen are mineralized from organic matter (Table 2). Thus, soil fertility in *S1* is higher than for *S2*.

Table 2: Average amount of nitrogen mineralized from organic matter for Soil 1 and Soil 2.

Climate Scenario	Average amount of nitrogen mineralized from organic matter in kg/ha	
	Soil 1 (<i>S1</i>)	Soil 2 (<i>S2</i>)
Base	115.65	88.54
2050	115.22	91.09

Source: CropSyst simulations.

Sowing of corn is placed six days earlier in the 2050 than in the base scenario. Earlier sowing in corn farming is a powerful adaptation option to avoid negative effects due higher temperatures and reduced precipitation in the assumed CC scenario (Torriani et al., 2007). Management scenarios that are applied in the CropSyst simulations include nitrogen fertilizer and irrigation. In order to enhance variability of crop yields with respect to agricultural management, an experimental design is used. To this end, applications of nitrogen fertilizer and irrigation water are varied randomly⁵.

4 Empirical Analysis

Empirical analysis is restricted to two crucial inputs: nitrogen fertilizer (N) and irrigation water (W). The production function ($Y(X)$) is fitted to a square root functional form, which is the best specification of the $Y \sim N, W$ relationship for corn yields on the eastern Swiss Plateau (FINGER and HEDIGER, 2007). CropSyst outputs are used to estimate the production functions. Eqns. (9),(10) and (11),(12) are the production function estimations for soil 1 (*S1*) and soil 2 (*S2*) for the base and the 2050 scenario, respectively.

$$(9) \text{ } S1/\text{Base: } Y = 7872.7 + 158.3 \cdot N^{1/2} + 77.8 \cdot W^{1/2} - 6.7 \cdot N - 2.4 \cdot W + 0.2 \cdot (N \cdot W)^{1/2}$$

$$(10) \text{ } S1/2050: Y = 8368.3 + 180.4 \cdot N^{1/2} + 96.6 \cdot W^{1/2} - 8 \cdot N - 1.2 \cdot W + 2.5 \cdot (N \cdot W)^{1/2}$$

$$(11) \text{ } S2/\text{Base: } Y = 6601.9 + 313.1 \cdot N^{1/2} + 67.1 \cdot W^{1/2} - 10.5 \cdot N - 2.5 \cdot W + 0.4 \cdot (N \cdot W)^{1/2}$$

$$(12) \text{ } S2/2050: Y = 7053.1 + 309.9 \cdot N^{1/2} + 71.6 \cdot W^{1/2} - 9.6 \cdot N - 1 \cdot W + 3.5 \cdot (N \cdot W)^{1/2}$$

Y denotes corn yield (kg ha⁻¹), N nitrogen fertilizer (kg ha⁻¹), and W irrigation water (mm). Comparing the both scenarios, eqns. (9),(10) and (11),(12) show higher model intercepts and higher interaction parameters for $(NW)^{1/2}$ in the 2050 scenario, for both soils. In general, more favorable climatic conditions, the increased CO₂ concentration and earlier sowing lead to higher model intercepts, i.e. to higher corn yield without any input application. The increase of the interaction parameters for $(NW)^{1/2}$ shows that irrigation becomes more important for optimal nitrogen uptake. In the base scenario, nitrogen uptake is sufficiently ensured by

⁵ Further details on data simulation are given in FINGER AND SCHMID (2007A).

precipitation. However, in the 2050 scenario, where summer rainfall is reduced (cf. Table 1), optimal nitrogen uptake is only ensured if irrigation takes place.

Production functions are estimated using the robust regression technique of Reweighted Least Squares (see ROUSSEEUW AND LEROY, 1987, for details). This estimation technique increases the accuracy of estimation. Ordinary least squares estimation becomes inefficient and unreliable for production function estimation if exceptional observations are included in the analysis. Exceptional yield observations are, for instance, caused by climatic extreme events, such as the summer drought of 2003 (FINGER AND HEDIGER, 2007). Furthermore, all estimations are corrected for heteroscedasticity using Feasible Generalized Least Squares regression. The estimation is conducted with the ROBUSTREG and the MODEL procedure of the SAS statistical package (SAS INSTITUTE, 2004), respectively.

Yield variation, $\sigma^Y(X)$, is defined as the absolute difference between expected and observed input-output combinations. Thus, absolute regression residuals of the production function estimation, $|e|$, are employed to estimate yield variation:

$$(9) \quad \sigma^Y(X) = |e| = |Y(X) - \hat{Y}(X)|$$

Yield variation is, among other factors such as weather and soil conditions, affected by input use (ISIK AND KHANNA, 2003). The relationship between yield variation and input use, $\sigma^Y(X) \sim N, W$, is modeled using a square root functional form. In this model, the intercept captures effects of soil and weather conditions on yield variation. Eqns. (13),(14) and (15),(16) show yield variation function estimates (for the base and the 2050 scenario) for *S1* and *S2*, respectively.

$$(13) \text{ } S1/\text{Base: } \sigma^Y(N, W) = 613.5 + 25.8 \cdot N^{0.5} - 7.9 \cdot W^{0.5}$$

$$(14) \text{ } S1/2050: \sigma^Y(N, W) = 660.9 + 28.1 \cdot N^{0.5} - 24.7 \cdot W^{0.5}$$

$$(15) \text{ } S2/\text{Base: } \sigma^Y(N, W) = 409 + 39 \cdot N^{0.5} - 8.1 \cdot W^{0.5}$$

$$(16) \text{ } S2/2050: \sigma^Y(N, W) = 468.5 + 39.8 \cdot N^{0.5} - 20.3 \cdot W^{0.5}$$

For both soils, the intercept of the yield variation functions increases from the base to the 2050 scenario. Thus, if neither irrigation nor nitrogen fertilizer application takes place, CC leads to higher yield variation. In general, the application of nitrogen fertilizer increases ($\sigma^Y_N > 0$) and irrigation decreases ($\sigma^Y_W < 0$) yield variability. The propensity of irrigation to reduce yield variation, $|\sigma^Y_W|$, increases from the base to the 2050 scenario for both soils. Due to higher temperatures and lower summer precipitation, irrigation is a more risk decreasing activity in 2050 than it is currently. In contrast, the effect of nitrogen on yield variation, σ^Y_N , is not affected by CC. However, conclusions on the impact of CC on yield levels, yield variation and profitability of SST can be drawn if and only if utility maximization input and output levels are calculated such as in the subsequent section.

5 Results

Maximization of expected utility, as described in section 2, requires assumptions of input and output prices and the coefficient of risk aversion. These assumptions as well as coefficient estimates for production and yield variation functions (section 4) are employed to solve first order conditions (eqn. 5). In order to restrict our analysis to effects induced by CC we apply

similar input and output prices for both analyzed scenarios. We assume prices⁶ of CHF 0.185 kg⁻¹, CHF 0.91 kg⁻¹ and CHF 0.6 mm⁻¹ for corn, nitrogen fertilizer and irrigation respectively (FINGER AND SCHMID, 2007A). Moreover, the analysis is restricted to one numerical example of constant risk aversion, $\gamma = 0.5$. Sensitivity analyses of Swiss corn yields for different scenarios of climate change, prices and risk aversion is given in FINGER AND SCHMID (2007A AND 2007B). Derived optimal levels of input use, expected utility, yield and yield variation for both soils are presented in Table 3.

Table 3: Optimal levels of input use, expected utility, yields and yield variation.

Soil Type - Climate Scenario	Nitrogen (kg/ha)	Irrigation water applied (mm)	Expected Utility per ha	Yield (kg / ha)	Yield variation (kg / ha)
<i>S1</i> -Base	40.07	53.45	1540.11	9055	718.81
<i>S2</i> -Base	91.60	42.30	1486.26	8986	729.27
Absolute Differences between <i>S1</i> and <i>S2</i>	51.53	11.15	53.85	69	10.46
<i>S1</i> - 2050	61.61	210.71	1754.09	10729	522.10
<i>S2</i> - 2050	137.93	208.49	1685.66	10788	643.21
Absolute Differences between <i>S1</i> and <i>S2</i>	76.32	2.22	68.43	59	121.11

Table 3 shows that optimal fertilizer application for both climate scenarios is higher for *S2* than for *S1*. This is because of lower soil fertility of *S2* (Table 2). For both soil types, application of both inputs, irrigation water and nitrogen, is higher in the 2050 than in the base scenario. Yields increase and yield variations decrease from the base to the 2050 scenario. Thus, expected utility is higher in 2050 for both soils. Moreover, Table 3 shows that absolute differences between *S1* and *S2* for expected utility, nitrogen application and yield variations increases from the base to the 2050 scenario. CC causes increasing differences between soils with respect to optimal input use and expected utility.

In order to analyze the impact of CC on the profitability of SST adoption, we simulate utility differences of site specific and conventional management as described in Section 2. Input application for conventional management follows the three scenarios on soil information levels (a-c) that are described in section 2. For site specific management, optimal inputs such as presented in Table 3 are applied for each site (eqn. 6). Average differences in expected utility between site specific and conventional management (eqn. 8) are shown in Table 4.

⁶ Due to market liberalization, both Swiss input and output prices are assumed to decline in future. Thus, lower than current Swiss prices are assumed in this analysis.

Table 4: Expected utility differences between site specific and conventional management for the base and the 2050 scenario.

Climate Scenario	Expected utility differences between site specific and conventional management		
	Zero Information (a)	Rough Information (c)	Ratio of S1/S2 known (b)
$\Delta E(U(S, C))$ - Base	10.49	8.33	6.22
$\Delta E(U(S, C))$ - 2050	13.71	11.36	9.17

Note: (a), (b) and (c) denote different levels on soil information. All expected utility differences, and differences between the base and the 2050 scenario, are significant at a 0.05 level (using the one sample Wilcoxon and the signed rank test, respectively).

A higher level of information about soil composition leads to smaller differences in expected utilities between site specific and conventional management (Table 4). This is due to smaller differences in input application between site specific and conventional management for higher levels of soil information. Thus, the incentive to adopt site specific management decreases for higher knowledge of soil composition.

Moreover, Table 4 shows increasing differences in expected utilities between site specific and conventional management from the base to the 2050 scenario. The relative increase in this difference is between thirty and fifty percent. Further calculations (not shown) with different states of soil information and different composition of soils indicate relative increases in the same range. However, relative to the levels of expected utility given in Table 3, the expected utility increase caused by adoption of site specific management is small for both climate scenarios (smaller than one percent). The calculations of utility differences between site specific and conventional farming presented in Table 4 do not include adoption costs. These costs and expected effects on SST adoption are discussed in the subsequent section.

6 Discussion and Conclusions

Our case study shows increasing differences in expected utilities between site specific and conventional management from the base to the 2050 scenario. Thus, the incentive to adopt site specific management, *ceteris paribus*, increases. This is in particular due to increasing differences between soils with respect to optimal nitrogen application and corn yield variation (Table 3). Moreover, corn yield variation (i.e. production risk) for both soils is smaller in the 2050 than in the base scenario. Lower production risk leads, in general, to higher rates of SST adoption (ISIK AND KHANNA, 2002). In order to validate our results for Swiss agriculture at large, further soil types, crops and CC scenarios should be considered.

Adoption costs are omitted in the analysis of SST profitability presented in this study. This is due to the fact that site specific management is inexistent in Switzerland yet. There is no information on costs available. For Illinois, KHANNA ET AL. (2000) report costs of about CHF 10 per hectare and year⁷ for hiring service that applies inputs at a varying rate in the field. Due to the lack of experience and the lack of service suppliers we expect, however, higher prices for this service in Switzerland. Taking expected utility differences between site specific and conventional management into account (Table 4), SST adoption is expected to remain small in current climatic conditions. However, these costs for hiring service are assumed to decline in the following years because of technical progress (KHANNA ET AL., 2000, AUERNHAMMER, 2002) and improvements of landscape and plant related indicators (ANSELIN ET AL., 2004,

⁷ KHANNA ET AL. (2000): 5.157 \$/acre (assumed exchange rate: USD/CHF = 1.2)

PAMPOLINO ET AL., 2007). Both higher differences in expected utility between site specific and conventional management and lower prices for SST adoption lead to higher incentives for SST adoption in future.

CC will affect the incentive of SST adoption because effects of CC on crop production particularly depend on soil characteristics (EITZINGER ET AL., 2003). Therefore, we expect increasing spatial variability of soils with respect to input use and yield variation which is supported by this case study. This leads, *ceteris paribus*, consequentially to higher shares of site specific management in crop production under CC. Even though, this case study does not directly address environmental impacts of site specific management practice, it is indicated by other studies that the feedback loop between CC and crop production can lead to a reduction of emissions and pollution caused by agriculture and result in a more sustainable use of natural resources. Only if further research takes into account a broad range of farmers' adaptation options, such as the here presented adoption of site specific management, the impacts of CC on agriculture can be sufficiently assessed.

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