Agricultural Water Management 109 (2012) 135–143

Contents lists available at SciVerse ScienceDirect

Agricultural Water Management

journal homepage: www.elsevier.com/locate/agwat

Modeling the sensitivity of agricultural water use to price variability and climate change—An application to Swiss maize production

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ARTICLE INFO

Article history:
Received 22 June 2011
Accepted 9 March 2012
Available online 31 March 2012

Keywords:
Irrigation
Nitrogen
Price risk
Production risk
Switzerland

ABSTRACT

We analyze the sensitivity of crop management under current and future climate scenarios to changes in economic boundary conditions. In particular, we focus on the effects of changing price risks. We combine a bio-economic modeling approach and a crop growth model CropSyst with an economic model that represents the decision making process of a risk-averse farmer. We apply the models to irrigated maize production in Switzerland. To analyze the sensitivity of optimal water and nitrogen use to likely future states of several economic variables, we conduct sensitivity analyses with respect to changes in price variability, the price–yield correlation, water and maize prices as well as farmers' risk preferences. Results show that climate change leads to a strong increase in optimal water use for irrigation, with consequent increases in maize yields. However, our analysis also reveals that the consideration of economic drivers for farmers' irrigation decisions is indispensable. Strong effects on optimal water use are found for changes in crop (positive) and water (negative) prices. We also find strong implications of risk aversion and price variability on irrigation decisions. A doubling of price variability, which would represent a shift from the current Swiss situation to price variability levels in its neighboring countries, could reduce optimal water use by up to 40%. We conclude that investigations of water demand should consider, beyond expectations on output and input price levels, also the variability of prices.

1. Introduction

Increasing competition for water resources is becoming a major challenge for food production, populations, societies and the environment (Pereira et al., 2002; IWMI, 2007; De Fraiture and Wichelns, 2010; Gordon et al., 2010). Climate change is expected to increase the pressure on water resources, either by directly shifting hydrologic cycles and the spatial and temporal availability of water for irrigation due to changes in precipitation patterns, or by increasing agricultural water demand due to temperature increases and higher frequencies of drought events (Bates et al., 2008). The relationship between climate, climate change, and agricultural water use has received particular attention in several empirical studies (e.g. De Silva et al., 2007; De Fraiture and Wichelns, 2010; Guo et al., 2010). Beyond climatic conditions, also economic considerations influence farmers' irrigation decisions and thus agricultural water use. Theoretical and empirical investigations have addressed the relationship between output, inputs, and especially water prices and the adoption of irrigation and the amount of water used (Scheierling et al., 2006; Molle and Berkoff, 2007; Brooks and Harris, 2008; Mullen et al., 2009). Furthermore, the variability of these variables is important for irrigation decisions. Agricultural production is risky; i.e. returns are not certain, but fluctuate over time. These risks, arising from volatile yields and prices, affect farmers' decisions regarding crops and technology, and input use (e.g. Hardaker et al., 1997). Similar to insurance, irrigation is an instrument to cope with production risks because irrigation makes crop production less dependent on natural rainfall patterns and thus reduces yield variability (Lin et al., 2008). Due to this relationship, the effects of production risks, irrigation technology adoption, and water demand have received particular attention in the agricultural water use literature (e.g. Harris and Mapp, 1988; Gómez-Limón and Berbel, 2000; Carey and Zilberman, 2002; Garrido et al., 2006; Gil et al., 2011; Grove and Ossthuizen, 2010; Lavee, 2010). In contrast, the influence of output price variability on agricultural water demand has received inadequate attention. Nevertheless, price variability is highly relevant for optimal water use, as farmers face uncertainty about output prices when the irrigation capacity is determined either before or early in the growing season, and also during the irrigation season (i.e. before the harvest is sold). Thus, water application can be viewed as a short-term investment that is subject to uncertain rates of return.

We present a bio-economic modeling approach that combines a biophysical model (representing the complexity of the relationships between weather, environmental conditions, crop management and plant growth) with an economic model that

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0378-3774/$ – see front matter
doi:10.1016/j.agwat.2012.03.002

represents farmers' decision making with respect to crop management and irrigation. In particular, the economic model aims to look beyond average profits and thus integrates the role of production and price risks. We use the model to investigate management and irrigation decisions in maize production at the Swiss Plateau under current and future climate scenarios. The importance of irrigation is currently highly heterogeneous across European countries, in particular representing a South (high importance) to North (low importance) gradient. In Switzerland, the share of irrigated arable land is currently at about 6% (Berbel et al., 2007). However, the importance of irrigation in crop production is increasing and an intensification of this trend is expected in the next decades due to climate change (Weber and Schild, 2007; Fuhrer and Jasper, 2009). Our goal is to contribute to the quantitative analysis of the drivers of agricultural water demand by providing an analysis of water demand in maize production under current and future climate scenarios. Furthermore, we conduct a large set of sensitivity analyses with respect to price variability, price–yield correlations, water and maize prices, and farmers' risk preferences. In these sensitivity analyses we investigate likely future states of the economic boundary conditions of crop production.

2. Data and methodology

Our bio-economic model links the process-based crop growth model CropSyst with an economic decision-making model that represents a risk-averse farmer. More specifically, CropSyst is used to simulate maize yield responses with respect to nitrogen use and irrigation intensities under different climate regimes. In order to implement information from CropSyst simulations in the economic model, we estimate production and yield variation functions that statistically describe the responses of mean yields and standard deviations to input use. Finally, the economic model that contains information on crop yield relationships, price and cost levels, and on farmers' risk preferences is used to show which levels of input use are optimal (i.e. utility maximizing) for the farmer.

2.1. Economic decision-making model

A farmer's decision making process with regard to water and nitrogen use is represented using a non-linear certainty equivalent (CE) maximization approach. The CE denotes the non-random level of payoff which is rated by the farmer as equivalent in terms of utility to an uncertain (i.e. random) level of payoff. For the risk-averse decision maker, the CE is defined as the difference between the expected profit and the risk premium (RP), which is the amount of money the farmer is willing to pay to eliminate risk exposure:

$$\mathrm{CE} = E(\pi) - \mathrm{RP} \tag{1}$$

The expected (i.e. mean) profit is defined as revenue minus fixed and variable costs. Fixed costs consist of costs for seeds, plant protection, insurance, machinery costs, costs for other inputs than water and nitrogen as well as of fixed costs of the sprinkler irrigation system. Variable costs comprise water and nitrogen costs and the cleaning and drying costs. Thus, the expected profit is defined as:

$$E(\pi) = Y(N, W)p_M - C_F - N_{p_N} - W_{p_W} - Y(N, W)p_D \tag{2}$$

where $E(\pi)$ is the expected profit, $Y(N,W)$ maize yield, p_M the maize price, and C_F the fixed costs. Furthermore, N and W denote the amounts of water and nitrogen used, p_N and p_W are the prices for nitrogen and water, respectively, and p_D are the costs for cleaning and drying. The profit maximization framework is extended by assuming that profits are stochastic, due to the variability of maize yields and due to the variability of crop prices. The calculation of the variability of profits also needs to account for the correlation between crop yield and crop prices. This is motivated by the observation that low crop yields at the farm level often correlate with smaller aggregate supply and thus lead to higher crop prices (e.g. McKinnon, 1967). The resulting negative correlations between yields and prices reduce revenue variability and are thus important for farmers' decisions under yield and price risk. Following Bhornsted and Goldberger (1969), the variance of profit (σ_π^2) is defined as:

$$\sigma_\pi^2 = \sigma_Y^2(p_M - p_D)^2 + \sigma_{p_M}^2 Y^2 + 2Y(p_M - p_D)Cov(Y, p_M) + \sigma_Y^2\sigma_{p_M}^2 + Cov(Y, p_M)^2 \tag{3}$$

The covariance of yield and price is calculated as: $Cov(Y, p_M) = corr(Y, p_M)\sigma_{p_M}\sigma_Y$, where $corr(Y, p_M)$ denotes the correlation between yield and price. σ_{p_M} and σ_Y denote the standard deviation of maize price and maize yield, respectively. The risk premium is now defined as follows:

$$\mathrm{RP} = 0.5\frac{\sigma_\pi^2\gamma}{E(\pi)} \tag{4}$$

γ is the coefficient of relative risk aversion, representing the degree of risk aversion of the farmer. Risk averse behavior implies $\gamma > 0$ and a risk neutral farmer is represented by $\gamma = 0$. The relative risk premium presented in Eq. (4) assumes constant relative risk aversion, which implies decreasing absolute risk aversion (i.e. risk aversion decreases with increasing wealth). To derive optimal water and nitrogen allocation in this model, the certainty equivalent is maximized with respect to nitrogen and water use:

$$\underset{N,W}{Max}\,\mathrm{CE} = E(\pi) - \mathrm{RP} \tag{5}$$

2.2. Production and yield variability functions

2.2.1. Functional forms

To represent the relationship between crop management and yield levels as well as yield variability, we follow Finger et al. (2011) and use non-linear Just and Pope (1978, 1979) production functions that allow inputs to influence both the mean but also the variability of crop yields:

$$\mathrm{Yield} = Y(N, W) + \sigma_Y(N, W)\varepsilon \tag{6}$$

where $Y(N)$ and $\sigma_Y(N)$ denote the production and yield variation function, respectively, and where we further assume that $E(\varepsilon) = 0$ and $\sigma(\varepsilon) = 1$. We estimate the production function in a first step using a square root specification (following Finger and Hediger, 2008):

$$Y(N, W) = \alpha_0 + \alpha_1 N^{0.5} + \alpha_2 N + \alpha_3 W^{0.5} + \alpha_4 W + \alpha_5 (NW)^{0.5} \tag{7}$$

In a second step, the absolute values of the regression residuals associated with the production function estimation, defined as $\hat{w} = Y - \hat{Y}$, are used to estimate the yield variation function using the following specification (Finger and Schmid, 2008):

$$\sigma_Y(N, W) = |\hat{w}| = \beta_0 + \beta_1 N^{0.5} + \beta_2 W^{0.5} \tag{8}$$

To reduce the potential influence of outliers on the regression analyses, the production and the yield variability functions are estimated using the robust regression MM-estimator; see e.g. Finger (2010) for descriptions.

The production and yield variation function are estimated for each climate scenario independently. However, to test if these changes due to climate change are significant, both datasets are merged and dummy variables for the climate change scenario are included in the above described regressions. If the dummy variable is significant for a specific variable, this indicates significant differences of coefficients between current and future climatic conditions.