RESEARCH ARTICLE **(Open Access)**

Evaluating potentials and corresponding risks of optimal irrigation management under weather uncertainty

ADRIANA ZYFI[1], SPIRO GRAZHDANI[1], ALMA AHMETI[1]

[1]Department of Physics and Applied Sciences, Faculty of Forestry Sciences, Agricultural University of Tirana, Albania

*Corresponding author; E-mail: azyfi@ubt.edu.al

Abstract

European Water Framework Directive promotes several measures, e.g., the adoption of adequate water pricing mechanisms or the promotion of water-saving irrigation techniques. Since production conditions such as weather and climate development are uncertain, farmers might be reluctant to invest in a water-saving but capital intensive irrigation system. Climate change will affect agricultural production through changes in water supply, such that optimal irrigation management strategies gain importance. For the Korça region, we firstly apply a stochastic dynamic programming approach to analyze a farmer's optimal investment strategy for either a water–saving drip irrigation system or sprinkler irrigation system under weather uncertainty and assess the probability of adopting either irrigation system until the year 2040. Secondly, we develop optimal irrigation management portfolios for different degrees of risk aversion using climate data from a statistical model and the simulations for specific crops of the biophysical process model EPIC (Environmental Policy Integrated Climate). Investment in drip irrigation systems is not profitable. Sprinkler irrigation has a positive probability of being adopted for the production of sugar beets and carrots and therefore mostly shows a 100% share in the portfolio optimization. This study contributes to the literature in assessing optimal irrigation investment strategies considering weather uncertainty with two different model approaches, the stochastic dynamic programming approach and the portfolio optimization based on CVaR as a risk measure. Future research should be directed towards policy measures, e.g. implementation of water prices or equipment subsidies which can increase the probability of adopting water-saving drip irrigation systems.

Keywords: climate change scenario; EPIC model; irrigation management portfolios; water-saving irrigation techniques; weather uncertainty.

1. Introduction

For Central and Southern Europe, it has been estimated that areas under water stress can increase from 19% in 2007 to 35% in 2070 (IPCC, 2007). Therefore, it is crucial to assess optimal irrigation management strategies. In the Korça region, intensive agriculture has expanded from the 1970s onwards, and has led to a decrease of the annual groundwater level from the 1970s to the 1990s. Even though groundwater levels have recovered, the quality of groundwater is affected negatively by excessive irrigation which can increase nitrate leaching into groundwater. Currently, manly are used surface and sprinkler irrigation systems in Korça. However, drip irrigation systems allow for a precise application of water and have the potential to increase crop yields (Ward and Pulido-Velazquez, 2008). Therefore, it might be viable to adopt drip irrigation systems in the Korça in the future. As drip irrigation is usually capital intensive, a farmer might be reluctant to invest when facing production uncertainty arising from weather uncertainty. We apply a stochastic dynamic programming approach to examine the probability of investing in a water-efficient drip or a less water-efficient sprinkler irrigation system. We assume that farmers are uncertain about which annual precipitation sum will occur in the period 2009-2040. Our investment model contributes insights about the optimal timing to invest in an irrigation system. However, it does not account for how the farmer manages the installed irrigation system, e.g. whether it is employed on all fields in order to diversify production risk under various levels of risk aversion. Therefore, we apply a static portfolio optimization approach using the Conditional Value at Risk as risk metric (Rockfellar and Uryasev, 2000). This approach allows investigating whether irrigation is part of an optimal production portfolio and if so, which share of the production area is irrigated to minimize production losses under various levels of risk aversion. The optimal crop management portfolio suggests for each crop, what percentage of a cultivated hectare land is irrigated by a specific system, or not irrigated in a specified period of time. In our analysis, we use simulation data from the biophysical process model EPIC (Izaurralde et al., 2006) in the region Korça. The climate change scenario is derived from a statistical climate model. The static portfolio optimization approach allows investigating whether irrigation is part of an optimal production portfolio and if so, which share of the production area is irrigated to minimize production losses. Optimal irrigation management portfolios have been developed with respect to different degrees of risk aversion. On the other hand, the stochastic dynamic programming approach examines the probability and the optimal timing of investing in a water-efficient drip or a less water-efficient sprinkler irrigation system until 2040. In the recent scientific literature, climate change impacts on agricultural production in regions all over the world are being thoroughly investigated and widely discussed in the scientific communities and the public (Alexandrow and Hoogenboom, 2000; Lobell et al., 2006; Lobell and Field, 2007; Tebaldi and Lobell, 2008; Balkovič et al., 2011). For the near future until about 2040, the well-known and commonly used climate change scenarios from General Circulation Models (GCMs) and also Regional Climate Models (RCMs) show their weaknesses due to (i) the low climate change signal compared to the model internal variability on decadal time scale, (ii) the random noise, and (iii) the time-lag between changing atmospheric conditions and climatic impacts (Christensen et al., 2007; Randall et al., 2007; Cayan et al., 2008). Moreover, a disadvantage of GCMs and RCMs is that temperatures and solar radiation are often independently bias-corrected, and thus a reasonable correlation with rainfall is not always guaranteed. Also the spatial resolutions are often not high enough to show regional variations at site scale (Tebaldi and Sansó, 2008). For all these reasons, an alternative approach has been developed to produce near future climate changes scenarios', which is based on long-term historical daily weather data and statistical methods such as regression and bootstrapping techniques. These climate change scenarios are more consistent with respect to the physical interdependencies and the spatio-temporal correlations between six weather parameters (i.e. minimum and maximum temperatures, solar radiation, precipitation, relative humidity and wind speed), and also represent well the local inter-annual variability and the small scale climates in the complex topography. The near future climate change scenarios also include deliberate assumptions on changing precipitation patterns, because their future developments remain highly uncertain, such as (i) increases of mean annual precipitation sums, (ii) decreases of mean annual precipitation sums, and (iii) re-allocations in seasonal precipitation (i.e. increases in winter precipitation and decreases in summer precipitation and vice versa). These assumed changes of precipitation sums have been generated according to the suggestions in the literature (IPCC, 2007). Furthermore, several climate change scenarios have been developed, in which the frequency and intensity of future extreme weather events have been manipulated to account for any possible increases of future drought events. In this study, a stochastic dynamic programming approach has been developed to analyze the probability and the optimal timing of investing into either a water-saving drip or a sprinkler irrigation system in the Korça region until 2040. Moreover, an optimal irrigation management portfolio has been developed under consideration of different degrees of risk aversion by using again the CVaR as a risk measure. The latter approach allows investigating whether irrigation is part of an optimal production portfolio and if so, which share of the production area is irrigated to minimize production losses.

2. Material and Methods

2.1. Data collection

The biophysical process model EPIC provides annual outputs on, inter alia, dry matter crop and straw yields, nitrogen emissions, and soil organic carbon contents. The outputs are mainly based on five thematic datasets: land use, topography, soil, cropland management and weather. Cereals are the most important crops in Korça, but also vegetables are commonly cultivated. Therefore, we simulate bio-physical impacts of five crops (winter wheat, sugar beets, potatoes, corn, and carrots) which cover more than 50% of the agricultural land. The statistical climate change model generates weather scenarios via bootstrapping for 2008-2040, based on in-situ weather observations from 1975 to 2007 (provided by the Meteorological Station of Korça). In the period 1975-2007, the average annual maximum/ minimum temperature was 14.8 °C/6.1 °C, which is assumed to increase to 16.7°C/8.0°C in 2040. For 2008-2040, a range of possible precipitation scenarios has been generated. We use one extreme precipitation scenario for the region, which portrays a decrease in annual precipitation sums of -5% until 2016, -10% until 2024, -15% until and 2032, and -20% until 2040. We use simulated annual crop yields, variable production costs, and mean commodity prices from 2005-2009 to calculate annual profits. Capital costs of irrigation systems were surveyed from producers. Notably, the annual capital cost of a drip irrigation system, which are assumed to operate for 15 years, is 400 €/ha/a for carrots and 233 €/ha/a for all other crops, whereas the annual capital cost for sprinkler irrigation is 213 €/ha/a for all crops. Notable differences in labor hour requirements per ha occur to install or run the respective irrigation system (drip irrigation: 30 h/ha/a; sprinkler irrigation: depending on irrigation amounts applied to the fields; variation between on average 1 h/ha/a for winter wheat and 6 h/ha/a for sugar beets). Table 1 provides summary statistics on dry matter crop yields, irrigation water input and respective profits for the period 2009-2040. The crop yields are declining compared to the past (1975-2007). As expected, irrigation in the period 2009-2040, leads to a decrease in crop volatility, except for potatoes.

2.2. The stochastic dynamic programming approach

In the dynamic programming model, the farmer decides in each year of the planning period whether to invest into a drip or sprinkler irrigation system and whether to operate the installed system. Investment in irrigation systems is a long-term investment. We assume that a farmer bases his investment decision on his expectation about how annual precipitation will develop over the years 2009-2040.

Table 1. Summary statistics of relevant parameters for the period 2009-2040

	Noirrigation		**Sprinkler**		**Drip**	
	Mean	**Std**	**Mean**	**Std**	**Mean**	**Std**
Dry matter yield t/ha/a						
Corn	6.2	1.2	7.9	0.5	7.9	0.5
Carrots	5.4	0.6	5.5	0.4	5.5	0.4
Potatoes	7.0	0.8	7.1	0.8	7.1	0.8
Sugar beets	7.8	1.1	10.1	0.6	10.3	0.5
Winter Wheat	4.7	0.8	4.8	0.8	4.8	0.8
Irrigation mm/ha/a						
Corn	0.0	0.0	127	51	113	45
Carrots	0.0	0.0	39	36	34	32
Potatoes	0.0	0.0	53	37	47	32
Sug. Beets	0.0	0.0	162	56	143	49
W. Wheat	0.0	0.0	35	35	32	31
Profit €/ha/a						
Corn	130	163	9.4	84.8	-249	70.2
Carrots	8321	1100	8351	843	7909	825
Potatoes	2347	515	2112	512	1815	514
Sug. Beets	48	198	60	104	-167	86
W. Wheat	460	175	204	168	-100	169

We further assume that in each year 300 possible realizations occur with equal probability. Once the system has been installed, the farmer can decide whether to operate the irrigation system or not from the following year onwards depending on his daily information about rainfall. We denote $x_t \in \{0, 1, 2\}$ the state of the system in year t, *0* implying that until period t no irrigation system has been built; *1* that drip has been built; and *2* that sprinkler has been built prior to period t. The investment and operational decisions in year t are denoted as $a_t$and u_t. Both can be chosen from the set {0, 1, 2}, where *0* means that no investment is made/the irrigation system is not switched on; *1* that drip irrigation is adopted/drip is switched on; and *2* that sprinkler irrigation is adopted/sprinkler is switched on. If a system has already been installed, no further investment is possible, $a_t x_t = 0$. The state of the system in the next year is determined by the current state and the investment decision in the current year, $x_{t+1} = x_t + a_t$. It cannot be operated if it has not been installed in a previous year: $u_t \in \{0, x_t\}$. The

precipitation scenarios are given by $P_t \sim (\rho_t^1,\ldots,\rho_t^N)$. In each year, there are w =1,…, N with N = 300 uniformly distributed precipitation values, which affect the farmer's profits.
The inputs are the profits of crop production. The total profit $\pi(u_t, \rho_t^n)$ is derived by operational profits in period *t*, depending on the operational decision and the annual precipitation sums (equation 1), minus the annualized capital cost, $c(x_t+a_t)$, depending on the state in period *t* after the investment decision has been made (equation 2):

$$\pi(u_t, \rho_t^n) = y(u_t, \rho_t^n)p - (c\_Lh_i c + Varc) - q^e(u_t, \rho_t^n)p^e + i\_Lh((u_t, \rho_t^n)c + q_i^n(u_t, \rho_t^n)p^n) \quad (1)$$

$$c(x_t + a_t) = a\_Capc(x_t + a_t) + a\_well(x_t + a_t) \quad (2)$$

The components of the operational profit include parameters assumed to be constant overtime: p^c, the constant commodity price for each crop; *c*, the hourly wage; p^e, the cost of electricity per kWh; p^n, the price of fertilizer; and V_{arc}, the variable production costs per crop. The remaining components vary by operational decision and the respective annual precipitation sums, including: $y(u_t, \rho_t^n)$, the crop yields used for the revenue; *c_Lh*, the labor requirement per crop; $q^e(u_t, \rho_t^n)$, the energy cost per irrigation system; $i\_Lh((u_t, \rho_t^n)$, the annual labor requirement for irrigation activity; and $q_i^n(u_t, \rho_t^n)$, the annual amount of nitrogen fertilizer used. The annualized fixed cost of the respective irrigation systems is the sum of the annualized capital cost, $a\_Capc(x_t+a_t)$, and the annualized cost of building a well, $a\_well(x_t+a_t)$.
The problem of the farmer can be formulated as an optimization problem of timing his investment decisions, a_t, and choosing operational action, u_t, so that the expected sum of profits over the planning period is maximized (equation 3). The discount rate is given by *r,* and $e^{-r \cdot t}$ is the discount factor.

$$\begin{aligned} &\mathrm{Max}\left(E\left[\sum_{t=1}^{31} e^{-rt} (\pi(u_t, \rho_t^i) - c(x_t + a_t)) \right] \right) \\ &\text{s.t} \\ &x_{t+1} = x_t + a_t;\ t = ,\ \ldots,\ 31 \\ &x_t a_t = 0,\ t = 1,\ \ldots,\ 31 \\ &u_t \in \{0, x_t\},\ t = 1,\ \ldots,\ 31 \\ &P_t \sim (\rho_t^1, \ldots, \rho_t^{300}) \end{aligned} \quad (3)$$

This is a standard stochastic optimal control problem in discrete time periods on a finite horizon, and can be solved by backward dynamic programming. The annual decisions are obtained recursively by solving the Bellman equation. The result is a matrix of the optimal investment actions for each period, all possible states and weather scenarios. With this information we derive the cumulative probabilities of investment.

2.3. The portfolio optimization model

The Value at Risk (VaR) of a portfolio is the lowest amount *α* such that with probability *β*, the portfolio loss will not exceed *α*. The CVaR is the conditional expectation of losses above that amount *α* for a specified confidence level *β* (Rockafellar and Uryasev, 2000). We suppose that, for *β*=75% a farmer would be relatively indifferent to tail risk (risk neutral), whereas *β*=99% can be interpreted as high loss-aversion (risk averse). For the portfolio optimization model we average the total annual profits, $\pi(u_t, \rho_t^n)$, over the respective years in the three time periods; hence, we have for each period and each of the 300 weather scenarios an average profit, $\overline{\Pi}_{m,w}$ where w=1,…, N, with N = 300 represents the 300 weather scenarios. The optimization is performed for each crop in each period separately. In contrast to the stochastic dynamic programming approach, the decision maker can choose to integrate drip, sprinkler or no irrigation system (index *m*) into his optimal portfolio. The optimization only accounts for scenarios when the irrigation system is actually switched on, $u_t \in \{1,2\}$. The output of our portfolio optimizations are optimal shares of irrigation management for each crop in the three time periods(s_m).

$$\mathrm{Min}\left(a + \frac{1}{N(1-\beta)} \sum_{m,w} v_{m,w} \right)$$

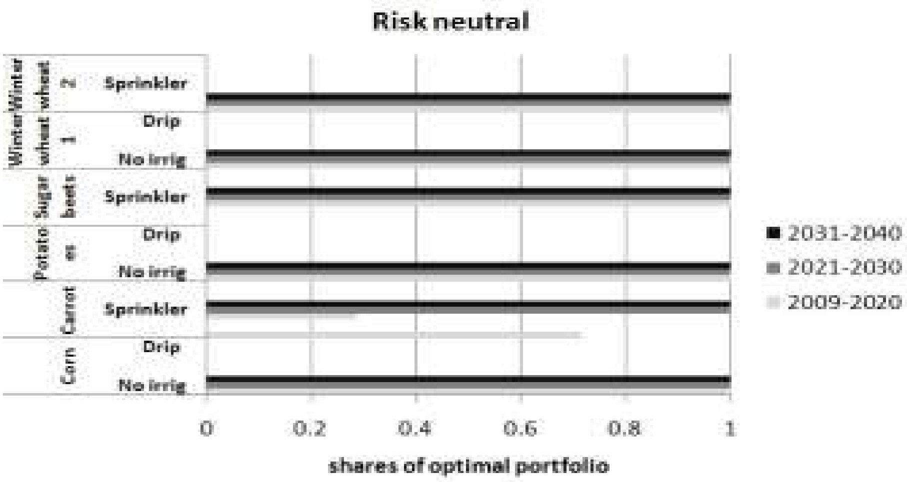
were $v_{m,w} \geq 0$ and $v_{m,w} \geq - \overline{\Pi}_{m,w} s_m - a \;\square w$ (4)

$$\frac{1}{N} \sum_{m,w} \Pi_{m,w} s_m \geq R$$

In the model, $v_{m,w} = [v_1, v_2, ..., v_N]^T \in R$ is an auxiliary variable, α is a threshold, and β is the confidence level. Also, the portfolio shares s_m have to sum up to 1, all s_m and $v_{m,w}$ must be greater than or equal to zero, and a constraint on minimum expected profits, R, has to be fulfilled. In the experiments, we employ values for R such that it is not binding to capture the full effect of risk aversion.

3. Results and Discussion

Results of the analysis with the stochastic dynamic programming approach show that farmers will never invest into a drip irrigation system. The probability that sprinkler irrigation is adopted for production of carrots and sugar beets is 100% in year 2024. Vegetables and sugar beets are the most irrigated crops in the Korça region. According to our climate scenarios, year 2025 marks a decrease in annual precipitation sums by 15% on all randomly drawn precipitation sums. Similarly, drip irrigation never constitutes part of an optimal portfolio for all crops under both risk neutrality and aversion (Figure 1). Under assumption of risk neutrality, the optimal portfolio for sugar beets exclusively includes sprinkler irrigation. For carrots, the optimization shows a 100% share of sprinkler in the periods 2021-2030 and 2031- 2040, but only a lower share of sprinkler irrigation in the first period (~30%) as profits without irrigation are higher (8.645 €/ha compared to 8.571 €/ha with sprinkler system). Thus, the farmer irrigates only 30% of his cultivated land in the period 2009-2020 in order to diversify production risk. By relying on rain-fed production on 70% of his field, he saves the variable cost incurred by employing sprinkler irrigation even though he has previously incurred high capital costs to adopt sprinkler irrigation. For corn, potatoes and winter wheat no irrigation system is part of an optimal portfolio at any time. Assuming risk aversion, the optimal portfolio changes for carrots production. The optimization shows a 100% share of sprinkler irrigation in all periods.



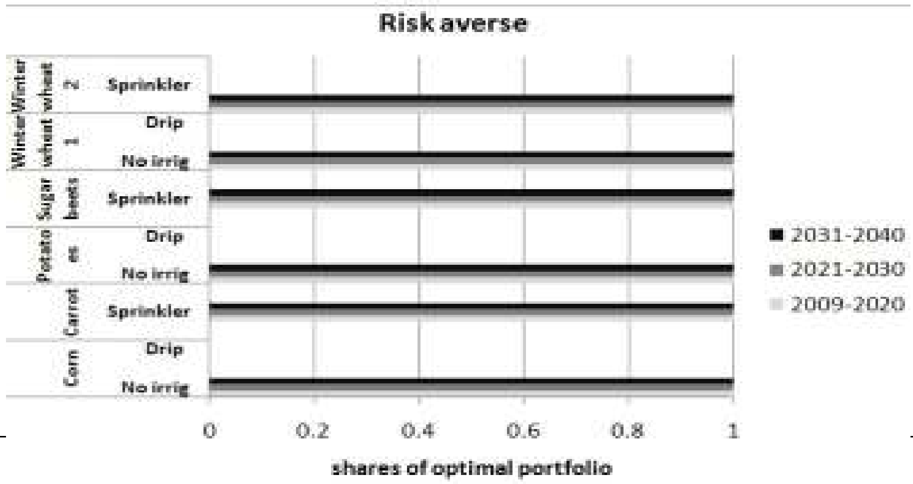


Figure 1. Optimal irrigation portfolios for winter wheat, sugar beets, carrots, potatoes and corn, for risk neutrality and risk aversion in three time periods

4. Conclusions

In both models, we observe similar results in optimal irrigation investment and management. The stochastic dynamic programming approach shows a zero probability for drip irrigation investment; the portfolio model shows that drip irrigation is never part in an optimal management portfolio under both risk neutrality and risk aversion. Analyzing the profits (Table 1), we see that average profits of drip irrigation are always lower than of sprinkler irrigation and no irrigation. From a resource point of view, a low utilization of irrigation systems implies that groundwater resources can recover from exploitation. On the other hand, the potential of irrigated agriculture cannot be exploited and less is produced on cropland. Thus, future research should be directed towards policy measures, e.g. implementation of water prices or equipment subsidies which can increase the probability of adopting drip irrigation systems. It must also be kept in mind that the model is run on a site scale, and economics of scale of irrigation investment, have not been taken into account so far. As conclusion, this study demonstrate that the developed climate change scenarios in conjunction with EPIC and economic optimization models are adequate tools to assess the impacts on climate sensitive sectors such as agriculture, which can be used to design effective adaptation strategies.

5. References

1. Alexandrow V, Hoogenboom G.. **Vulnerability and adaptation assessments of agricultural crops under climate change in the Southeastern USA**. Theoretical and Applied Climatology 2000, **67**:45-63.
2. Balkovič J, Schmid E, Skalský R, Nováková M. **Modelling soil organic carbon changes on arable land under climate change - a case study analysis of the Kočín Farm in Slovakia**. Soil and Water Research. 2011. **6**:30-42.
3. Cayan DR, Maurer EP, Dettinger MD, Tyree M, Hayhoe K. Climate change scenarios for the California region. Climatic Change. 2008. **87**(Suppl 1):S21-S42.
4. IPCC (2007): Synthesis Report. **Contribution of Working Groups I, II and II to the 4th Assessment Report of the Intergovernmental Panel on Climate** Change. Geneva.
5. IPCC. 2007. Climate Change 2007 - **The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the IPCC**. ISBN 978 0521 88009-1.
6. Izaurralde, R. C., Williams, J. R, McGill, W. B., Rosenberg, N. J., and Quiroga, M.C. (2006): **Simulating soil C dynamics with EPIC: Model description and testing against long-term data**. Ecological Modelling192, 3-4: 362-384.
7. Lobell DB, Field CB, Cahill KN, Bonfils C. **Impacts of future climate change on California perennial crop yields: model projections with climate and crop uncertainties.** Agricultural and Forest Meteorology. 2006. **141**:208-218.
8. Lobell DB, Field CB. **Global scale climate-crop yield relationships and the impacts of recent warming.** Environmental Research Letters.doi: 2007.10.1088/1748- 9326/2/1/014002.
9. Randall DA, Wood RA, Bony S, Colman R, Fichefet T, Fyfe J, Kattsov V, Pitman A, Shukla J, Srinivasan J, Stouffer RJ, Sumi A, Taylor KE. 2007. **Climate models and their evaluation**. In: Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M, Miller HL (eds) Climate change 2007: **the physical science basis. Contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change.** Cambridge University Press, Cambridge.
10. Rockafellar, R. T. and Uryasev, S. **Optimization of Conditional Value-At- Risk.** The Journal of Risk, 2000. 2, pp. 21-41.

11. Tebaldi C, Lobell DB. **Towards probabilistic projections of climate change impacts on global crop yields.** Geophysical Research Letters. 2008.
12. Tebaldi C, Sansó B. **Joint projections of temperature and precipitation change from multiple climate models: a hierarchical Bayesian approach.** Journal of the Royal Statistical Society A. 2008. **172**(1).
13. Ward, F. A. and Pulido-Velazquez, M. **Water conservation in irrigation can increase water use. Proceedings of the National Academy of Sciences.** 2008. 105. 1815-1822