Evaluating potentials and corresponding risks of optimal deficit irrigation strategies under climate change and other sources of uncertainty

NIELS SCHÜTZE, JENS GRUNDMANN, SEBASTIAN KLOSS & GERD H. SCHMITZ
Institute of Hydrology and Meteorology, Dresden University of Technology, Dresden, Germany
ns1@rcs.urz.tu-dresden.de

Abstract In this contribution we introduce a stochastic framework for decision support for optimal planning and operation of water supply in irrigation. This consists of: (i) a weather generator for simulating regional impacts of climate change on the basis of IPCC scenarios; (ii) a tailor-made evolutionary optimization algorithm for optimal irrigation scheduling with limited water supply; (iii) a mechanistic model for simulating water transport and crop growth in a sound manner; and (iv) a kernel density estimator for estimating stochastic productivity, profit and demand functions by a nonparametric method. As a result of several simulation/optimization runs within the framework, we present stochastic crop–water production functions (SCWPF) for different crops, which can be used as a basic tool for assessing the impact of climate variability on the risk for the potential yield or, furthermore, for generating maps of uncertainty of yield for specific crops and specific agricultural areas. In addition, micro-economic impacts of climate change and the vulnerability of the agro-ecological systems are discussed. Finally, we show how additional sources of uncertainty (e.g. soil conditions and management) can be included in the new stochastic framework.

Key words deficit irrigation; crop–water production function; optimal scheduling; risk assessment; climate uncertainty; climate change

INTRODUCTION

Arid and semi-arid areas that are intensively used for agriculture, are facing water shortage, which is often intensified by an overexploitation of existing water resources. Accordingly, they show an increased sensitivity to water stress and a high vulnerability that can only be reduced by highly efficient and foresighted water resource management practices. One way to achieve this objective is an improvement of water productivity (WP), which needs a good quantitative understanding of the relationship between irrigation practices and grain yield, i.e. crop–water production function (CWPF). With this knowledge, the value of each unit of water applied to a field can be estimated and compared with alternative uses within and beyond the agricultural sector.

Automated soil- and plant-based sensing scheduling methods are one option for reducing watering volumes for full irrigation systems and, at the same time, increasing WP. However, much greater sophistication is required if the objective is to improve the overall irrigation water productivity by applying a deficit irrigation strategy (DI) (Jones, 2004). For deficit irrigation it is necessary to find an optimal irrigation schedule under which crops can sustain an acceptable degree of water deficit and yield reduction. This optimal irrigation scheduling problem is difficult to solve, since the number of decision variables (i.e. the number of irrigations) is *a priori* unknown. For this reason, recent studies tend to simplify the optimization problem either by fixing the irrigation dates (Shang & Mao, 2006) or the irrigation intervals (Gorantiwar & Smout, 2003). A recently developed evolutionary algorithm by Schütze *et al.* (2011) avoids most of the disadvantages and reduces the computational effort for calculating optimal schedules considerably, but disregards the influence of the stochastic properties of the relevant climate factors (e.g. precipitation and temperature) and of the soil properties, which limits its applicability.

Many recent studies (Brumbelow & Georgakakos, 2007; Semenov, 2007; Soltani & Hoogenboom, 2007 among others) try to analyse possible impacts of climate variability and climate change on agriculture, based on process-based simulation models. Most of the published work deals with rainfed or non-irrigated sites, or assumes a full irrigation management. A few papers (Brumbelow & Georgakakos, 2007; Schütze & Schmitz, 2010) focus on deficit irrigation systems and the impact of climate variability on crop–water production functions (CWPF).

The objective of this study is to demonstrate how to apply an efficient scheduling algorithm for evaluating potential yield and corresponding risks in deficit irrigation strategies, i.e. generating stochastic crop–water production functions (SCWPF) and derivatives such as stochastic productivity functions, profit functions and water demand functions. This is done by a case study of an irrigation site in a Mediterranean region (Montpellier) in France.

STOCHASTIC FRAMEWORK FOR THE GENERATION OF SCWPF AND ITS DERIVATIVES

There is potentially great value in understanding the role of climatic variability on the relationship between yield and the scale of water consumption for irrigation. In the following we briefly present a methodology which allows one to quantify the impact of climatic variability on CWPF by a 2-D probability distribution, which is referred to as stochastic CWPF (SCWPF) (for details see Schütze & Schmitz, 2010).

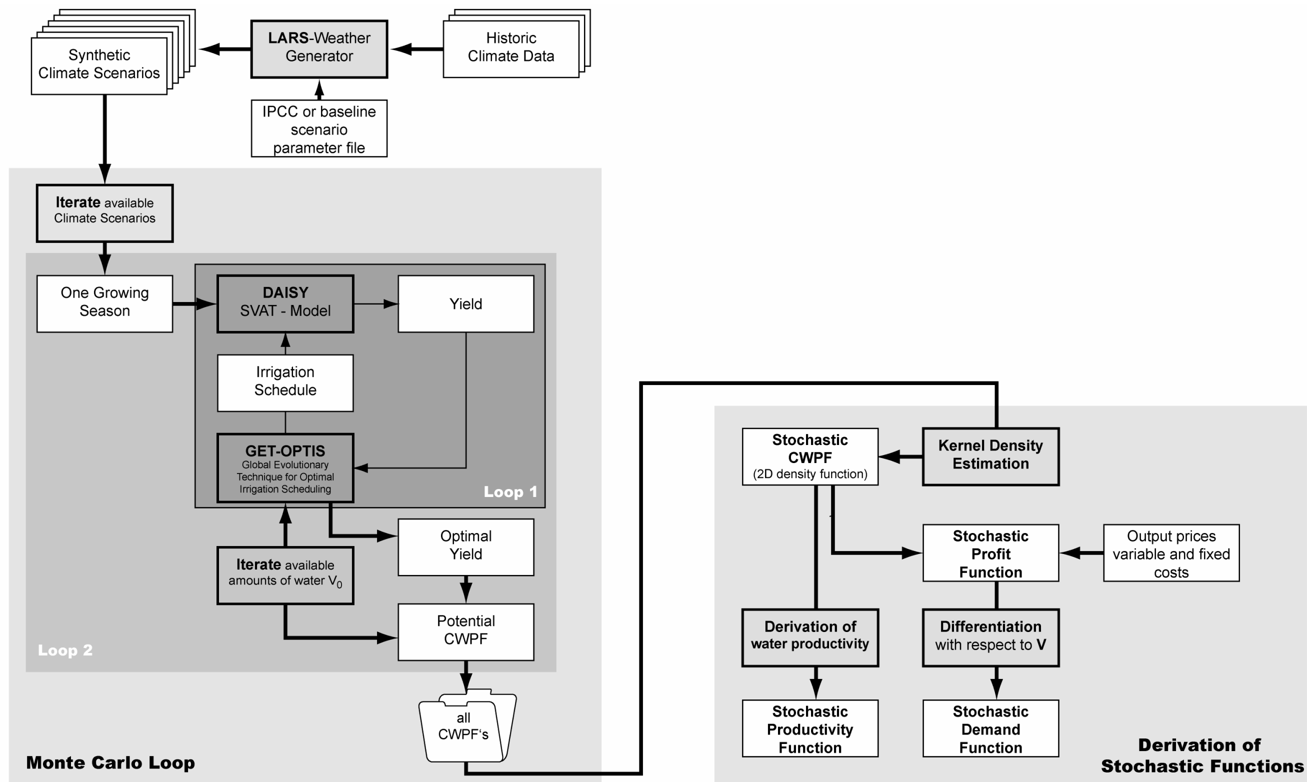

Fig. 1 Layout of the stochastic framework.

The stochastic framework in brief

Generally, two components are necessary to generate reliable simulation-based CWPFs (see Fig. 1, loop 1): an irrigation scheduling optimizer and a simulator of plant growth and water transport. The objective of the most inner iteration loop is to maximize yield for a specific climate scenario and a given amount of water for irrigation during the growing season. With the second loop, which iterates over a range of given water volumes, a complete CWPF can be constructed. The generated CWPF represents the maximum yields that can be achieved with a given amount of water and is referred to as the potential CWPF. The weather generator can be interpreted as a Monte Carlo sampler for providing site-specific weather series with a desired number of scenarios. Thus, in the third loop the necessary amount of CWPFs is generated in order to accurately compute the statistical characteristics of the random sample of CWPFs in a non-parametric way, i.e. the resulting SCWPF is an empirical probability function. To be useful for Monte Carlo simulations, the irrigation scheduling optimizer and the simulation model should be highly efficient and effective in finding the global maximum yield in order to generate a SCWPF within an acceptable computation time. Finally, the generated empirical probability function SCWPF is converted into a continuously differentiable density function for the calculation of derivatives such as productivity, profit and demand function.

The single components of the framework at a glance

The stochastic weather generator produces synthetic daily time series of maximum and minimum temperature, precipitation and solar radiation (Semenov *et al.*, 1998). The weather generator uses observed daily weather data for a given site to determine a set of parameters for probability distributions of weather variables, as well as correlations between them. First, with historical data available for a specific site, the LARS-WG parameters representing the baseline climate will be computed. In a second step, changes in mean and variability of climate variables derived from GCM predictions are taken into account by adjusting the LARS-WG parameter sets for generating daily site-specific weather consistent with the GCM predictions.

DAISY is a 1-D Soil–Vegetation–Atmosphere Transfer (SVAT) model that simulates crop production and crop yield, as well as water and nitrogen dynamics in agricultural soils. For this information on management practices and weather data (daily values) are used: for details see Abrahamsen & Hansen (2000). The agricultural management model of DAISY allows for building of complex management scenarios. The DAISY crop library contains the parameterizations of a number of different crops (maize, wheat, etc.) whose parameters may be calibrated on experimental data sets.

GET-OPTIS (Global Evolutionary Technique for OPTimal Irrigation Scheduling) is a problem-specific implementation of the EA-strategy for optimal irrigation scheduling running with a number of crop growth models. Evolutionary algorithms (EA) represent an alternative to classical optimization methods when dealing with objective functions, which feature many local minima. GET-OPTIS starts with a set of solutions, called population, which is in our case, a random set of schedules. Every member of the set has a fitness value assigned, which is directly related to the objective function – its crop yield. In sequential steps, the population of schedules is modified by applying four steps: selection, cross-over, mutation, and reconstruction. The details of the algorithm are presented in Schütze *et al.* (2011). The tailor-made scheduling EA reduces the computational effort by restricting the individuals, which have to be evaluated by simulation, to feasible solutions. In addition, the overall time necessary for one optimization run can be reduced through extensive parallel processing of evaluation of the objective function for all individuals of one generation at once.

A transformation based on the generated set of CWPFs, i.e. based on the empirical probability function SCWPF, is used to calculate a density function which is continuously differentiable, and thus the calculation of derivatives such as a demand function is feasible. We chose a nonparametric kernel density estimator to estimate the 2-D density function of the SCWPF (Botev *et al.*, 2010). Nonparametric density estimation is an alternative to the parametric approach, in which one specifies a model up to a small number of parameters and then estimates the parameters via the likelihood principle. Since a Gaussian kernel is used, the provided 2-D density function is continuously differentiable as needed.

Irrigation water productivity is defined as the maximum yield received by farmers per unit of irrigation water applied. In this study, we obtained the optimized profit function depending on the water volume V and the optimal schedule as follows:

$$\Pi^*(V) = rY^*(V) - C_f - \sum_{i=1}^{n}(cv_i + C_v) \tag{1}$$

where r is the output price; C_f is the fixed production costs; c is the price for water and pumping; and C_v represents costs due to labour and energy for each irrigation event. The optimal solution for Π^* is strongly related to the optimal solution of $Y^*(V)$ and thus can be provided by the simulation optimization procedure described above. With the profit function Π^* and the assumption that under limited water supply the value of water can be treated as an economic good, we can derive the water demand function as follows (Bontemps & Couture, 2002). Water will be used by farmers as long as the benefits from the use of an additional unit of resource exceed its cost. For a given volume V, the "water value" is defined as the maximum amount of money a farmer would be willing to pay for a m^3 of water. This "opportunity" cost, noted $P(V)$, is defined as the derivative of the optimized profit function: $P(V) = \frac{d\Pi^*(V)}{dV}$ evaluated for the given volume of water. The inverse of $P(V)$ is the "irrigation water demand" function $V(P)$ where P is the irrigation water pricing and V the minimum volume of irrigation water which the farmer decides to use for a certain crop per unit area of land. Since all derivative functions depend on $Y^*(V)$, i.e. on the CWPF, their stochastic counterparts can readily be determined from the continuous SCWPF provided by the nonparametric kernel estimator and the proposed Monte Carlo framework (see Fig. 1). The SCWPF and the other derived stochastic functions, which allow a precise estimation of maximum possible yields, water demands, and corresponding risks under climate variability, are of great value for estimating the maximum possible productivity and minimum vulnerability of a considered agroecological region.

APPLICATION AND EXAMPLE

To illustrate the potential use of the proposed stochastic framework, we analysed the impacts of predicted climate variability on maize grown and irrigated at the experimental field site at the CEMAGREF institute in Montpellier (43°40′N, 3°50′E) in France. To achieve this task we used historical climate data and selected high-emissions global climate change scenarios IPCC-B1 and IPCC-A2 for 2080 published by IPCC (2007). This study is based on field experiments with maize (Pioneer variety) which were carried out with a Mediterranean climate on a loamy soil (18% clay, 47% silt, 35% sand). The maize was grown on a plot of 1.7 ha. Field experiments were conducted here throughout the past 10 years. For a given year, the crop was generally subjected to different irrigation treatments, generally always including at least one full irrigated and one rainfed treatment (for details see Khaledian *et al.*, 2009).

Observed daily weather data recorded over 17 years (1991–2007) of the Lavalette climate station were used to set up the weather generator. The synthetic weather data conformed to the distributions estimated from the observed data. The used climate change scenario 2080HI is based on a climate modelling experiment completed by the Hadley Centre, using HadCM3. The scenario is based on the SRES A2 global emissions scenario for the time period 2080 published by IPCC (2007). The trends for monthly mean variables, such as monthly precipitation, monthly mean minimum and maximum temperature, and monthly mean radiation are taken directly from the LARS-WG scenario database. Data from the regional climate model HadRM3 were used in this study to derive monthly mean values of dry/wet spells. HadRM3 is driven indirectly from the HadCM3 simulations and has been developed to provide spatially-detailed scenarios over Europe. The daily precipitation output series for the grid-cell where Montpellier is located were taken from the PRUDENCE project site and monthly mean variables, such as the relative change in a mean duration of dry and wet spells were calculated. The resulting LARS-WG scenario file is internally used to adjust baseline parameters of LARS-WG for the Montpellier site and the 2080HI climate change scenario. Altogether, 500 realizations of the weather of one year with daily resolution were generated for both the baseline parameters and the adjusted parameters for the 2080HI scenario.

The set-up of the DAISY model is based on soil data taken from the Cemagref experimental site in Montpellier, France. Soil hydraulic characteristics were determined by inverse methods

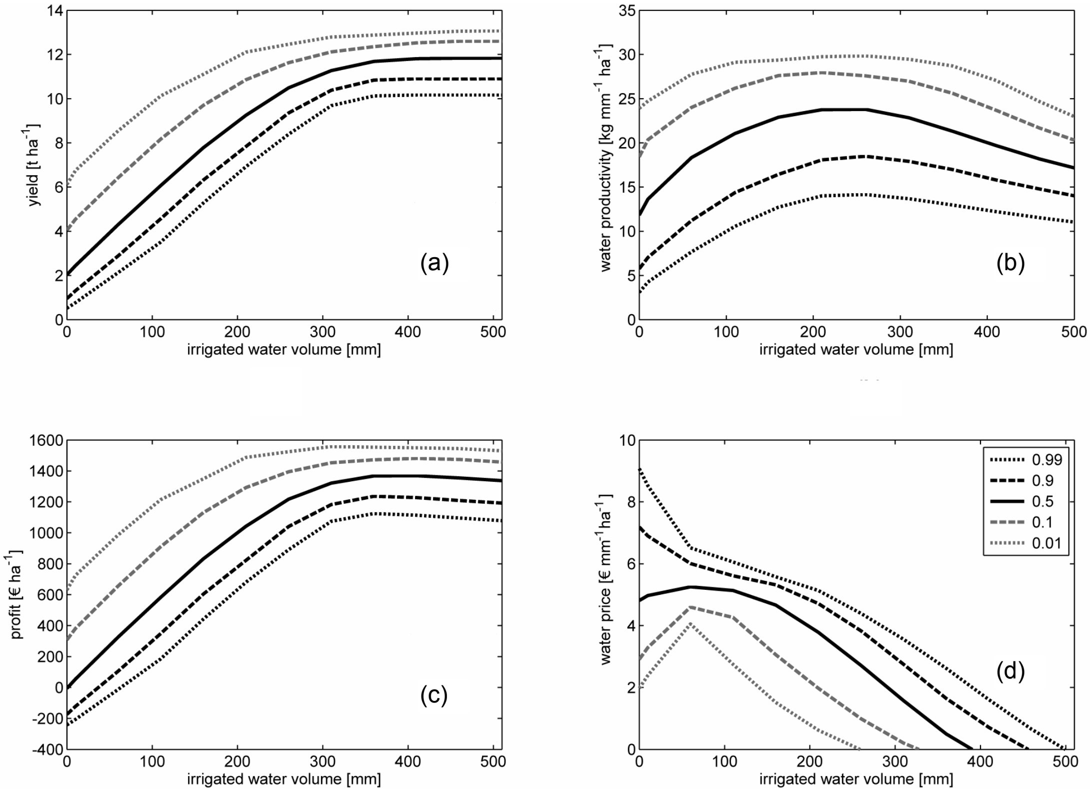

Fig. 2 SCWPF (a), productivity (b), profit (c) and demand (d) functions for maize.

applied to measurements of capillary tension and moisture content of the soil. For this study, we used maize (variety Pioneer) from the DAISY library of crops which were validated and tested in many environments (Abrahamsen & Hansen, 2000) as an initial parameterization. In addition, we conducted a site-specific calibration of the crop growth parameters based on full and deficit irrigation experiments with Pioneer maize in 2007. The calibration involved an estimation of the model parameters from measured field data (yield, LAI and water balance) using an automatic calibration procedure. The data for our exemplary application involved a sowing on 26 May with a zero initial water deficit which was the case in the field experiments in 1999 (Khaledian *et al.*, 2009). The irrigation schedule was provided by the optimization algorithm GET-OPTIS.

The synthetic weather data in combination with the configured DAISY model and the GET-OPTIS algorithm were used to generate distributions of potential crop yields resulting from climate variability and optimal irrigation scheduling. We analysed the resulting SCWPF with descriptive statistical methods, i.e. we calculated (1, 10, 50, 90, 99)-percentiles, median and statistical moments of a sample of 500 achieved yields. In order to build a continuous density function, i.e. the SCWPF, we randomly chose a sample of a number of 2000 pairs of water amounts and corresponding yields from the set of generated CWPF. For the application of the kernel density estimation, no parameter tuning had been conducted since the bandwidth selection is completely adaptive and data-driven. The economic data used in the study are shown in Table 1.

Figure 2 shows the SCWPF as well as the derived productivity, profit and demand functions for maize. A divergence of the shapes of the water demand (Fig. 2(d)) at different quantiles can be observed. This can mainly be explained by the rainfall, which is included in the calculation and

Table 1 Prices and costs used for deriving the profit function for maize.

r (€/t)	c (€/m^3)	C_v (€/ha)	C_f (€/ha)
156	0.05	25	325

which is beneficial in a few of the weather scenarios, i.e. for a non-exceedence probability of 0.1. In general, Fig. 2(d) shows that prices for water which farmers would be willing to pay for a certain amount of water, are considerable higher than the actual real costs (0.5 €/mm/ha, see Table 1). For the most quantiles water productivity has its maximum at an irrigation amount between 200 and 300 mm. The shape of the profit functions are similar to the shape of the SCWPF. However, it is important to note that the results represent the best yield potential under high management practice for all considered cases and assume a rational behaviour of the farmers.

DISCUSSION AND CONCLUSIONS

The generation of a SCWPF requires considerable computational effort. However, the proposed strategy for an application in water resources planning is to perform by far the majority of the computational effort during a first preparatory phase. During this phase a comprehensive database is established which contains the full range of SCWPFs – representing all the relevant combinations of crops, soils and climate scenarios (growing seasons and/or climate change scenarios) for a considered region or basin. On this basis it becomes possible to quickly access to potential yield or water demand data – including the corresponding probabilities – and to combine it with spatial information in a GIS. Thus, an appropriate database of SCWPFs can help to evaluate and assess management, mitigation and adaption measures for ensuring food security through an analysis of multiple irrigation sites in a considered basin. Another potential application of SCWPF as a building block for estimating water demand is with the process of the design and operation of large multi-quality irrigation water supply systems. In arid countries, for example, these often have to consider interrelations between irrigation water salinity, leaching requirements and yield levels (Sinai *et al.*, 2009). As the used crop model includes water and matter transport, a second type of SCWPF building block can simultaneously be used to estimate e.g. the contamination risk (nutrients and salt) of surface and subsurface water reservoirs in the vicinity of specific irrigation sites. The latter building block is a kind of stochastic damage function, and it is suitable for multi-criteria decision-making for long-term, sustainable water resources management on a larger scale. At present, interfaces to APSIM, DSSAT and DAISY crop growth models, as well as the FAO-33 yield response model, are implemented.

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