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ORIGINAL ARTICLE

Bio-economic analysis of irrigation schedules considering shallow groundwater: lessons from South Africa

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Abstract

Due to the pressure on South Africa's irrigated agriculture to improve efficiency and optimal water use, irrigators must consider alternative water sources, such as root-accessible shallow groundwater tables, to supply the crop evapotranspiration requirement. Devising irrigation scheduling strategies that will optimize conjunctive water use is difficult because the contribution of shallow groundwater tables is not directly observed and is a function of irrigation management decisions; as a result, very few irrigators use these strategies. This paper aims to evaluate the profitability of using shallow groundwater tables as a source of irrigation water to satisfy crop evapotranspiration requirements. A bio-economic simulation model consisting of the soil–water–atmosphere–plant model and an economic accounting module was developed to calculate the profitability of conjunctive irrigation practices under different states of nature. The bio-economic simulation model was linked to a differential evolutionary algorithm to optimize the irrigation scheduling decisions. The results showed that irrigators could substantially increase profitability and water use efficiency if they consider the shallow groundwater table in their irrigation decision. About 51% of crop evapotranspiration could originate from shallow groundwater tables, reducing the irrigation requirements substantially without impacting crop yields. Sequential adaptive irrigation decision-making does not improve the bio-economic indicators much since using the shallow groundwater table mitigates the risk of undersupplying water. Therefore, conjunctive water use strategies using shallow groundwater tables economically benefit irrigators. However, a complex interplay exists between irrigation adjustments, crop yields and economic performance in different states, emphasizing the careful consideration of context-specific factors in irrigation management decisions.

Keywords Irrigated agriculture · Conjunctive water use · Root-accessible shallow groundwater tables · Irrigation decisions · South Africa

Introduction

South Africa's irrigated agriculture is estimated to produce 74% of total field crop and horticultural production, but it uses some 64% of the available surface water in a country where water scarcity is prevalent (de Witt et al. 2021). The water scarcity problem is further magnified by projections that estimate that as soon as 2025 the whole of southern Africa must expect to experience intensified physical and/or economic water scarcity (Mabhaudhi et al. 2018). Additionally, the situation is heightened by concerns around the sector's low water use efficiency. Therefore, the sector is increasingly pressured to release water for redistribution through improved efficiency and optimal water use (Singels et al. 2019; de Witt et al. 2021).

Several water sources may contribute toward satisfying crop water requirements, such as surface water (i.e., rivers, dams and canals), deep groundwater, precipitation and capillary rise from shallow groundwater tables. Conjunctively using all the water sources requires the irrigator to adjust irrigation decisions to maximize the contribution of water sources with the lowest marginal factor cost. Barnard et al. (2021) evaluated the irrigation management practices of farmers in the Vaalharts irrigation scheme in South Africa to determine the extent to which farmers apply best

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management practices related to conjunctive use of surface water, precipitation and capillary rise from shallow groundwater tables. Vaalharts is the largest irrigation scheme in South Africa (±40,000 ha), situated in a semi-arid region with a mean annual rainfall of 487 mm. A canal conveys water from a weir in the Vaalharts river to the Vaalharts irrigation scheme, where water use is regulated using a water quota. The geohydrology of the scheme ensures that the groundwater table is relatively constant at 1.6 m due to lateral groundwater movement from the canal to the Harts River (Verwey and Vermeulen 2011). Results from the irrigation practice evaluations showed that irrigation farmers do not consider either precipitation or the contribution of capillary rise from shallow groundwater tables in their irrigation scheduling decisions. Instead, they apply surface irrigation water to satisfy crop water requirements regardless of current rainfall and the presence of capillary rise.

Not managing irrigation depths and timing of irrigation events to maximize the contribution of capillary rise to satisfying crop evapotranspiration requirements is surprising since research found that shallow groundwater tables could contribute as much as 40% to evapotranspiration requirements (Jovanovic et al. 2004; Liu et al. 2022). Devising irrigation scheduling strategies that will optimize the contribution of different water sources (i.e., surface water, rainfall and shallow groundwater tables) to satisfy crop evapotranspiration requirements is difficult because the contribution of shallow groundwater tables is not directly observed and is a function of irrigation management decisions (Schulthess et al. 2019). Li et al. (2020) pointed out that research only recently started focusing on the contribution of shallow groundwater to satisfying crop evapotranspiration requirements. Consequently, Liu et al. (2022) argued that research is still insufficient to devise adjusted irrigation scheduling strategies considering shallow groundwater table contributions to satisfying crop evapotranspiration requirements. Therefore, a possible explanation for irrigators not considering shallow groundwater tables as a potential water source contributing toward crop evapotranspiration requirements is a lack of information regarding the complex interactions between irrigation scheduling decisions and shallow groundwater table contributions.

Conducting field trials under heterogeneous conditions to develop appropriate irrigation scheduling strategies to optimize groundwater table contributions is laborious and expensive. As an alternative, mechanistic simulation models provide a good compromise between accuracy and simplicity if the simulation models are well-calibrated (Singh 2021; Liu et al. 2022). Simulation models provide a means to evaluate the implications of "what if" scenarios, while linking these models to external search engines provides a powerful method to optimize management decisions through simulation optimization (Lalehzari et al. 2020; Li et al. 2020). The review by Singh (2021) shows that modelers rarely consider the impact of the irrigator's decisions on the modeled system (i.e., feedback loops). Furthermore, certainty is frequently assumed when optimizing irrigation scheduling decisions (Li et al. 2020). The assumption of certainty will result in suboptimal irrigation schedules because the system's future state of nature is known with certainty (e.g., rainfall, etc.) when the irrigation decisions are optimized. Irrigation scheduling strategies that adjust according to unfolding information regarding the state of the soil–plant–atmosphere continuum are typically more helpful than strategies that do not respond to unfolding information (Schulthess et al. 2019). Many exogenous factors, such as irrigation system delivery capacity and efficiency, time-of-use electricity tariff charges and surface water availability, will influence the timing and irrigation application depth. Failure to consider these exogenous factors when devising irrigation strategies to optimize the contribution of shallow groundwater tables will result in unrealistic irrigation schedules (Foster and Brozović 2018).

The main objective of this research is to evaluate the profitability of using shallow groundwater tables as a source of water satisfying crop evapotranspiration requirements, thereby providing some insight into why irrigators in Vaalharts do not use shallow groundwater tables. The first sub-objective of the research was to determine the profitability and water use efficiency of the current irrigation scheduling practice (i.e., baseline) where irrigation is scheduled to satisfy crop water requirements without considering the contribution of shallow groundwater tables. A bio-economic simulation model consisting of the integrated soil–water–atmosphere–plant model, namely, SWAP (Kroes et al. 2017), and an economic accounting module was developed to calculate the profitability of current irrigation practices using the Ruraflex time-of-use electricity tariff under different states of nature. The second sub-objective was to compare the baseline's profitability and water use efficiency with irrigation scheduling decisions that maximize the expected profitability irrespective of which state of nature unfolds. The bio-economic simulation model was linked to a differential evolutionary (DE) algorithm to optimize the irrigation scheduling decisions. Lastly, the bio-economic simulation optimization model was solved recursively over the growing season using a weekly interval to determine the impact of responding to unfolding information regarding the state of nature on profitability and water use efficiency.

Bio-economic optimization model

Overview

The bio-economic optimization model is, in essence, a bio-economic simulation model linked to a DE algorithm to optimize irrigation decisions to maximize the margin above the specified costs of irrigating maize. The bio-economic simulation model uses the SWAP integrated agro-hydrological crop growth simulation model to quantify the impact of alternative irrigation schedules on maize yields and on the state of the agro-hydrological system. The irrigation schedule and crop yield information serve as input into an economic module that determines the profitability of the irrigation schedules.

The complexity of the bio-economic simulation model renders the application of standard linear and nonlinear programming approaches infeasible to optimize irrigation scheduling decisions. According to Bilal et al. (2020), DE has emerged as one of the most frequently applied algorithms for solving complex problems. Recently, Kelly et al. (2023) applied DE to determine the value of adapting irrigation scheduling decisions during the season. DE is a population-based metaheuristic stochastic search algorithm that evolves an initial population of trial solutions through mutation, crossover and selection based on the fitness of the evolved irrigation schedules (Ahmad et al. 2022). Figure 1 shows how the bio-economic simulation model is linked with the DE algorithm to optimize irrigation decisions.

The optimization process starts with the user specifying the DE algorithm initializing algorithm-specific input parameters (population size, crossover probability and differential weight) and the bounds on irrigation depth and the irrigation trigger that determines the timing of irrigation events. The DE algorithm uses the information to randomly generate a trial population of alternative irrigation timing triggers and irrigation depths to represent alternative irrigation schedules. The bio-economic simulation model simulates the maize yield for each irrigation schedule in the trial population with SWAP and determines the margin above the specified costs that indicate the fitness of an irrigation schedule with the economic module. Calculating the margin above the specified costs distinguishes yield and irrigation-dependent costs to reflect irrigation management decisions on profitability better.

During the first iteration of the optimization, the trial population represents the population that needs to iteratively evolve to a better solution through the processes of mutation and crossover if the stopping criterium is not met. In subsequent iterations, the fitness of the newly generated trial population of irrigation schedules is compared with the current population of irrigation schedules to select irrigation schedules from the trial population that will replace schedules in the current population based on a higher fitness. The population of irrigation schedules keeps evolving until the population's fitness converges or the maximum iteration count. The reader is referred to Storn and Price (1996) for the specifics of implementing DE.

Next, the components of the bio-economic simulation model are discussed in more detail.

Integrated agro-hydrological crop growth simulations

SWAP (Kroes et al. 2009; Kroes et al. 2017) is a popular model used to investigate field crop systems under shallow groundwater table conditions (Huo et al. 2012; Xu et al. 2012, 2013, 2015; Wang et al. 2014; Haj-Amor et al. 2017; Kroes et al. 2018). WOFOST (de Wit et al. 2019), a detailed model for the dynamic growth of arable crops, is fully integrated into SWAP. Only the processes and parameters used in simulations for this paper are briefly described below. For some processes, two or more simulation options are available in SWAP.

SWAP uses the Penman–Monteith equation applied to a well-watered reference grass surface (ET_0, Allen et al. 1998) as an index for the evaporating power of the atmosphere. A soil factor (CFBS) is used to convert ET_0 to the potential evaporation rate of a wet, bare soil (Ep_0). Potential soil evaporation (Ep) is simulated using Ep_0, leaf area index (LAI), an extinction coefficient for diffuse (KDIF) and direct visible light (KDIR), and the fraction of the day the crop canopy is wet (Wfrac). Actual soil evaporation rate (Ea) is determined as the minimum value of Ep, Emax or the empirical function of Black (1969), which requires a soil evaporation coefficient (COFRED). The maximum soil evaporation rate that the topsoil can sustain, namely, Emax, is calculated according to Darcy's law, using the average hydraulic conductivity between the soil surface and the first node, the soil water pressure head in equilibrium with the air relative humidity, the soil water pressure head of the first node and the soil depth of the first node. Crop factors (CF) are used to convert ET_0 to potential evapotranspiration of a uniform dry (ETp_0) or wet (ETw_0) crop canopy (these crop factors differ from the well-known FAO56 crop factors). Potential transpiration rate (Tp) is simulated using ETp_0, Ep and Wfrac, potential root water extraction rate at a certain depth (Sp(z)) depends on root length density distribution and Tp. Actual root water extraction at a specific depth (Sa(z)) is determined using Sp(z) and the multiplication of various stress reduction factors (α), i.e., reduction factors for conditions that are too wet, dry, saline and cold.

Germination is represented by the start of the simulation. To simulate the length of the growth period and phenological development stage ($1 < DVS < 2$), the temperature sum from emergence to anthesis (TSUMEA), temperature sum from anthesis to maturity (TSUMAM) and effective temperature (DTSM) are required. The latter is a tabular function of average daily temperature (TAV) and needs to be specified. Potential daily biomass production depends on the intercepted amount of irradiation. Hence, the time course of

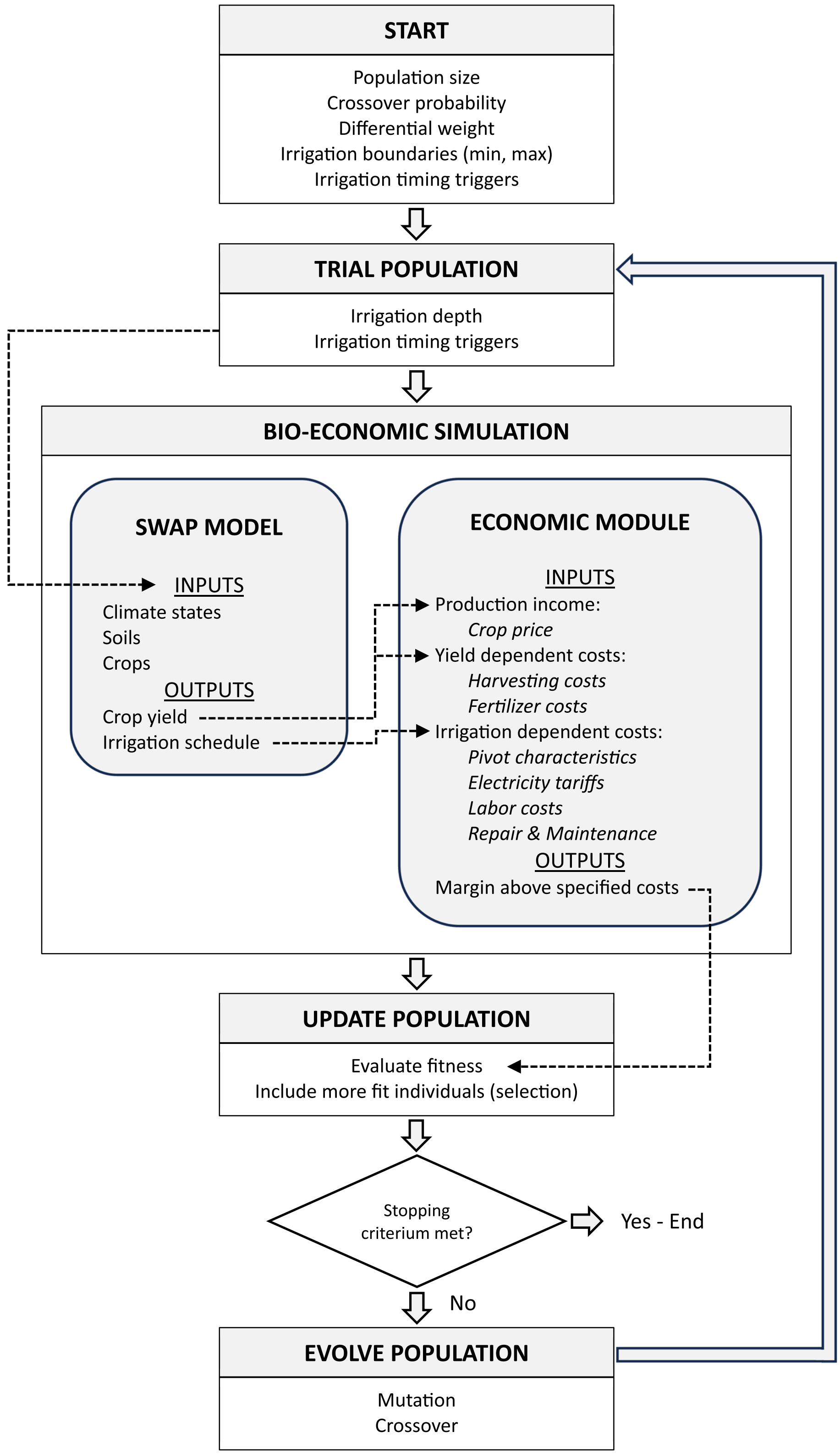

Fig. 1 Bio-economic optimization framework

green leaf mass, the resulting LAI, the fraction of irradiation that is intercepted by the canopy and the time course of total above-ground biomass production are important. Changing the lower specific leaf area parameter (SLATB) can simulate a higher or lower LAI. Biomass production is primarily determined by the daily photosynthesis rate, simulated with a photosynthesis–light response curve. The initial angle (EFF, light use efficiency for real leaf) is generally constant, while the maximum (AMAXTB, maximum CO_2 assimilation rate) is often crop variety specific and can decrease due to nutrient shortage and canopy aging. AMAXTB is specified for a specific development stage (DVS). LAI and light interception at the start and end of the growing season may also be calibrated by the LAI at emergence (LAIEM) and maximum relative increase in LAI (RGRLAI) parameters. Both parameters affect the initial increase in LAI and, therefore, the duration till the linear growth phase starts. During the linear growth phase, a complete light interception occurs. The life span of the leaves (SPAN) influences the simulated time course of LAI during the final growth period. The SPAN value must be increased to simulate a longer period of green leaves and higher LAI and, thus, biomass production near crop maturity. Other parameters that may influence light interception and potential biomass production include initial total crop dry weight (TDWI), lower threshold temperature for the aging of leaves (TBASE), extinction coefficient for diffuse visible light (KDIF), extinction coefficient for direct visible light (KDIR), a reduction factor of AMAX as a function of average daily temperature (TMPF) and a reduction factor of AMAX as a function of minimum day temperature (TMNF). The former first two parameters are specially for simulating green leaf area, while the latter four parameters are associated with assimilation. For the conversion of assimilates into biomass, four parameters that represent the efficiency of conversion into leaves (CVL), storage organs (CVO), roots (CVR) and stems (CVS) are required. The six parameters used in simulating maintenance respiration include the increase in respiration rate with temperature (Q10), the maintenance respiration rate of leaves (RML), storage organs (RMO), roots (RMR) and stems (RMS) and the reduction factor of senescence (RFSETB) as a function of the development stage. Parameters used to allocate the produced assimilates to the different organs are important because they determine leaf mass, light interception and economical products (i.e., the grain). These parameters are the fraction of total dry matter increase partitioned to the roots (FRTB), leaves (FLTB), stems (FSTB) and storage organs (FOTB), which are all a function of the development stage. To simulate root density distribution and growth, the root density (RDCTB) of the specific crop must be entered as a function of relative rooting depth (Rdepth). In addition, the initial rooting depth (RDI), maximum daily increase in rooting depth (RRI) and maximum rooting depth of crop or cultivar (RDC) need to be specified.

SWAP deals primarily with hydraulic and hydrodynamic behavior and continuous flow of water in the unsaturated zone above the groundwater table. The model simulates one-dimensional vertical upward and downward soil water flow by numerically solving Richards partial differential equation. Richards equation combines Darcy's and the continuity equations. The former relates the soil water flux density (q) to hydraulic conductivity (K) and soil water potential gradient (ϕ, which include both the matric, ψ, and gravimetric, Z, potentials) over a vertical coordinate. The continuity equation represents the water balance of an infinitely small soil volume. Namely, the change in volumetric soil water content over time is determined by the change in soil water flux density (Darcy equation) over the vertical coordinate and a sink term (S). Highly nonlinear soil hydraulic functions are required for solving Richards equation, i.e., functions that relate volumetric soil water content to soil pressure head (also known as matric potential) and hydraulic conductivity. SWAP uses the Mualem–Van Genuchten functions, which are described by six parameters, namely, saturated hydraulic conductivity (Ks), residual (θr) and saturated volumetric soil water content (θs), and empirical m, n and α shape parameters, where $m = 1 - \frac{1}{n}$. The sink term generally represents the root water extraction rate.

Economic module

The economic model calculates the total gross margin above specified costs (MAS) for a pivot of 30 ha with an application rate of 12 mm day^{-1}, which is the key performance indicator for evaluating the profitability of an irrigation schedule. A distinction is made in the model between costs dependent on irrigation applications and costs dependent on crop yield (i.e., fertilizer and harvesting costs). The electricity cost to pump the water represents most of the irrigation-dependent costs. The electricity cost calculations are based on the Ruraflex time-of-use electricity tariff.

Equation 1 calculates the MAS associated with a specific irrigation schedule:

$$\text{MAS} = p \times Y(i) - \text{ydc} \times Y(i) - \text{IDC}(i) - \text{ADC} \tag{1}$$

where MAS is the margin above specified costs (R ha^{-1}), $Y(i)$ is the simulated crop as a function of the irrigation schedule (ton ha^{-1}), p is the price of maize (R ton^{-1}), ydc is the yield-dependent costs (R ton^{-1}), IDC(i) is the irrigation-dependent cost for a state-specific irrigation schedule (R ha^{-1}) and ADC is the area-dependent cost (R ha^{-1}).

The first term (i.e., $p \times Y(i)$) of the MAS calculates the production income as a function of the irrigation schedule by multiplying the simulated maize yield as a function of the irrigation schedule with the selling price of maize. The second term (i.e., ydc $\times$ $Y(i)$) calculates the costs that depend on the simulated crop yield as a function of the irrigation schedule, which was also taken as the yield expectation. Consequently, ydc includes fertilizer costs and harvesting costs. ADC is the only cost component that does not vary as a function of the irrigation schedule and includes costs such as fuel, microelements, seed, chemical, harvest and mechanization costs. The calculation of irrigation-dependent costs (i.e., IDC(i)) is not straightforward because it depends on the required irrigation hours to apply a given amount of water. Therefore, the calculation of irrigation-dependent costs is discussed in more detail.

Equation 2 shows all the costs associated with applying irrigation water.

$$\mathrm{IDC}(i) = \mathrm{EC} + \mathrm{LC} + \mathrm{RMC} + \mathrm{WC} \tag{2}$$

where EC is the variable electricity costs for crop c (R ha^{-1}), LC is the total labor costs for crop c (R ha^{-1}), RMC is the total repair and maintenance costs for crop c (R ha^{-1}) and WC is the total water costs for crop c (R ha^{-1}) for indirect or direct pricing.

The electricity cost calculation does not include fixed costs since fixed electricity costs must be paid whether the irrigator applies water or not. Variable electricity costs are calculated as follows using the Ruraflex electricity tariff:

$$\mathrm{EC}_c = \sum_{i,t} \left(\mathrm{ta}_{i,t} + \mathrm{rc}_{i,t} + \mathrm{dc}_{i,t}\right)\mathrm{kWPH}_{i,t} + \sum_{i,t} \mathrm{tra}_{i,t}\mathrm{kvar}\,\mathrm{PH}_{i,t} \tag{3}$$

where $\mathrm{ta}_{i,t}$ is the active energy charge on day i in timeslot t (R kWh^{-1}), $\mathrm{rc}_{i,t}$ is the reliable energy charge on day i in timeslot t (R kWh^{-1}), $\mathrm{dc}_{i,t}$ is the demand energy charge on day i in timeslot t (R kWh^{-1}), kW is the kilowatt requirement (kW), $\mathrm{PH}_{c,i,t}$ is the pumping hours to irrigate crop c on day i in timeslot t (hours), $\mathrm{tra}_{i,t}$ is the reactive energy charge on day i in timeslot t (R kVARh^{-1}) and kvar is the kilovar (kVAR).

The active energy, reliable energy and demand energy charge are dependent on the kilowatt required to pump irrigation water, while the reactive energy charge is dependent on the kilovar. However, the reliable energy charge is only applicable during the high-demand season. Both active energy and reactive energy consumption are determined by the required pumping hours, which are calculated as follows (Eq. 4):

$$RPH_i = \frac{\frac{I_i}{\eta_s} PA \times 10}{q} \tag{4}$$

where RPH_i is the required pumping hours on day i (hours), η_s is the irrigation system application efficiency (%), PA is the pivot area (ha) and q is the flow rate (m^3 h^{-1}).

Equation 4 shows that RPH_i is differentiated for each day and is a function of pivot characteristics (i.e., application efficiency, pivot area and flow rate). The Ruraflex electricity tariff charges are differentiated into different time-of-use timeslots (i.e., off-peak, standard and peak) based on the day of the week and time of the day. The irrigator needs to decide during which time-of-use timeslots to irrigate. The assumption is that an irrigator will distribute the required pumping hours over 2 consecutive days to facilitate energy management. The following heuristic (Eqs. 5–7) is used to allocate the required pumping hours to different time-of-use timeslots (Madende, 2017):

$$\mathrm{PH}_{i,\,\}\}\text{off-peak''}} = \min \left| \begin{array}{l} \mathrm{RPH}_i \\ \mathrm{aph}_{i,\,\}\}\text{off-peak''}} \end{array} \right. \tag{5}$$

$$\mathrm{PH}_{i,\,\}\}\text{standard''}} = \min \left| \begin{array}{l} \mathrm{RPH}_i - \mathrm{PH}_{i,\,\}\}\text{off-peak''}} \\ \mathrm{aph}_{i,\,\}\}\text{standard''}} \end{array} \right. \tag{6}$$

$$\mathrm{PH}_{i,\,\}\}\text{peak''}} = \min \left| \begin{array}{l} \mathrm{RPH}_i - \mathrm{PH}_{i,\,\}\}\text{off-peak''}} - \mathrm{PH}_{i,\,\}\}\text{standard}} \\ \mathrm{aph}_{i,\,\}\}\text{peak''}} \end{array} \right. \tag{7}$$

where $\mathrm{aph}_{i,t}$ is the total available pumping hours during time-of-use timeslot t (i.e., off-peak, standard and peak) for allocating required pumping hours on day i (hours), and $\mathrm{PH}_{i,t}$ is day i's required pumping hours allocated to time-of-use timeslot t (i.e., off-peak, standard and peak) when irrigating on day i and the next day (hours).

The irrigation labor and repair and maintenance costs are calculated using the cost estimation procedures developed by Meiring (1989). Irrigation labor costs are calculated with Eq. 8:

$$\mathrm{LC} = \sum_i \frac{\mathrm{RPH}_i}{24} \times \mathrm{lh} \times \mathrm{lw} \tag{8}$$

where lh is the labor hours required per 24 h of irrigation for a certain pivot size (hours) and lw is the labor wage rate (R hour^{-1}), the total repair and maintenance cost is calculated with Eq. 9:

$$\mathrm{RMC}_c = \sum_i \mathrm{RPH}_{i,c}\mathrm{rt} \tag{9}$$

where rt is the repair and maintenance tariff per 1000 h pumped for an irrigation system (R 1000 h^{-1}).

The assumption is that the water tariff is implemented on a volumetric basis. The total water charge payable to the water user association is calculated with Eq. 10:

$$\mathrm{WC}_c = \mathrm{cwr}_c \times \mathrm{wt} \tag{10}$$

where cwr_c is the crop water requirement as given by WUA for crop c (mm) and wt is the water tariff (R mm^{-1}).

Differential evolution optimization

The complexity of the bio-economic simulation model renders the application of standard linear and nonlinear programming approaches infeasible to optimize irrigation scheduling decisions. According to Bilal et al. (2020), DE has emerged as one of the most frequently applied algorithms for solving complex problems. Recently, Kelly et al. (2023) applied DE to determine the value of adapting irrigation scheduling decisions during the season. DE is a population-based metaheuristic stochastic search algorithm that evolves an initial population of candidate solutions through mutation, crossover and selection based on the fitness of the evolved irrigation schedules (Ahmad et al. 2022). In our application, the MAS of an irrigation schedule determines the fitness of the irrigation schedule to optimize irrigation water use.

Model setup and data

Reducing the dimensionality of the optimization problem

The research used a South African weather database that has 50 years of data from across the country in the SAPWAT software (Crosby and Crosby 1999) to define different weather states. Cluster analysis was used to reduce the dimensionality of the weather database to three clusters containing similar weather patterns. Cluster analysis is a technique used to classify cases or groups that are homogeneous within themselves and heterogenous between each other (Yim and Ramdeen 2015).

Cluster analysis was performed on data covering the growing maize season in the Vaalharts area. Two years were considered outliers and removed from the dataset. After the data were organized to fit the simulation period, daily ET_0 and rainfall amounts were aggregated to weekly averages, and after that, the difference between the two was computed and standardized (Jajuga and Walesiak 2000). The standardized data were used to do a hierarchical cluster analysis using Ward's linkage method using the Statistical Package for the Social Sciences (SPSS) (2017). The 48 years of data were reduced to three clusters of 11, 21 and 16 years in each cluster. Only one of the cluster members was used to represent the weather pattern of a cluster. The representative member was chosen based on the mean absolute deviation (MAD).

MAD is a statistic measuring the accuracy of the predictions within a set of quantitative elements and is useful due to the prediction errors being in the same unit as the observed data (Khair et al. 2017). The MAD was calculated for each member state within a cluster, translating to 11 MAD calculations for cluster 1, 21 MAD calculations for cluster 2 and 16 MAD calculations for cluster 3. The year with the smallest MAD was chosen to represent the weather pattern of the cluster. The probability that each representative weather state could occur was calculated as the number of years in a cluster divided by the 48 years of data used for the cluster analysis. Consequently, the three states had occurrence probabilities of 33%, 44% and 23%. The probabilities were used to calculate the expected performance indicators of the irrigation schedules.

The variation in the identified states is depicted in Fig. 2. The differences arose from the main differences between ET_0 and rainfall, especially toward the end of the period under simulation (week 20), where State 2 has the largest difference between ET_0 and rainfall, meaning that toward the end of the season, the ET_0 was greater than the rainfall present. In State 1, on the other hand, the difference between ET_0 and rainfall in week 4 and week 20 was similar, while State 3 shows a consistent difference from week 4 up until week 16. The identified characteristics of each state of nature, measured by ET_0 and rainfall, set the states apart.

SWAP

Two datasets of Water Research Commission (WRC) funded projects conducted on the same lysimeter facility (i.e., the Department Soil, Crop and Climate Sciences, University of the Free State, Bloemfontein, South Africa) were used for calibration and validation of SWAP in this paper. Trial 1 was conducted by Ehlers et al. (2003) and Trial 2 by Ehlers et al. (2007). The diameter and depth of the static lysimeters are 1.8 m and 2 m, with rims of 0.05 m above the soil surface. In each lysimeter, two neutron access tubes allow soil water measurements (0.3-m intervals up to 1.8 m), while the inner walls and bottom of the lysimeters can be accessed through an underground chamber (1.8 m wide, 2 m deep and 30 m long). A monometer and bucket at the bottom of each lysimeter allow recharging and regulation of shallow groundwater tables (< 1.8 m from surface) and measurement of drainage. Root water uptake from the groundwater was recorded daily and then added through the bottom of the lysimeter to recharge the groundwater table and keep it at a constant depth. Data of maize (PAN 6335) grown on the sandy loam (mean 18% silt-plus-clay) soil (Plinthustalf, according to Survey Staff, 2003) during both trials were used. The planting dates were December 6 and 15, 2000 and 2004, for Trials 1 and 2, respectively, at a density of 50,000 plants ha^{-1}. All the data in the trials, used for calibration and validation, represent optimum conditions for crop growth, allowing for maximum root water uptake and grain yield.

Daily minimum and maximum temperatures, ET_0 and radiation values, measured during the maize growing season of both trials were entered into the model. Rainfall during the growing season of Trial 1 was entered as part of irrigation. During Trial 2, the rain shelter was closed, and hence, no rainfall values were entered.

Vertical discretization of the sandy loam soil profile is shown in Table 1, i.e., six sublayers of 30 cm each, with 30 compartments of 1 cm each in the first layer and six compartments of 5 cm each in the remaining five sublayers. The first

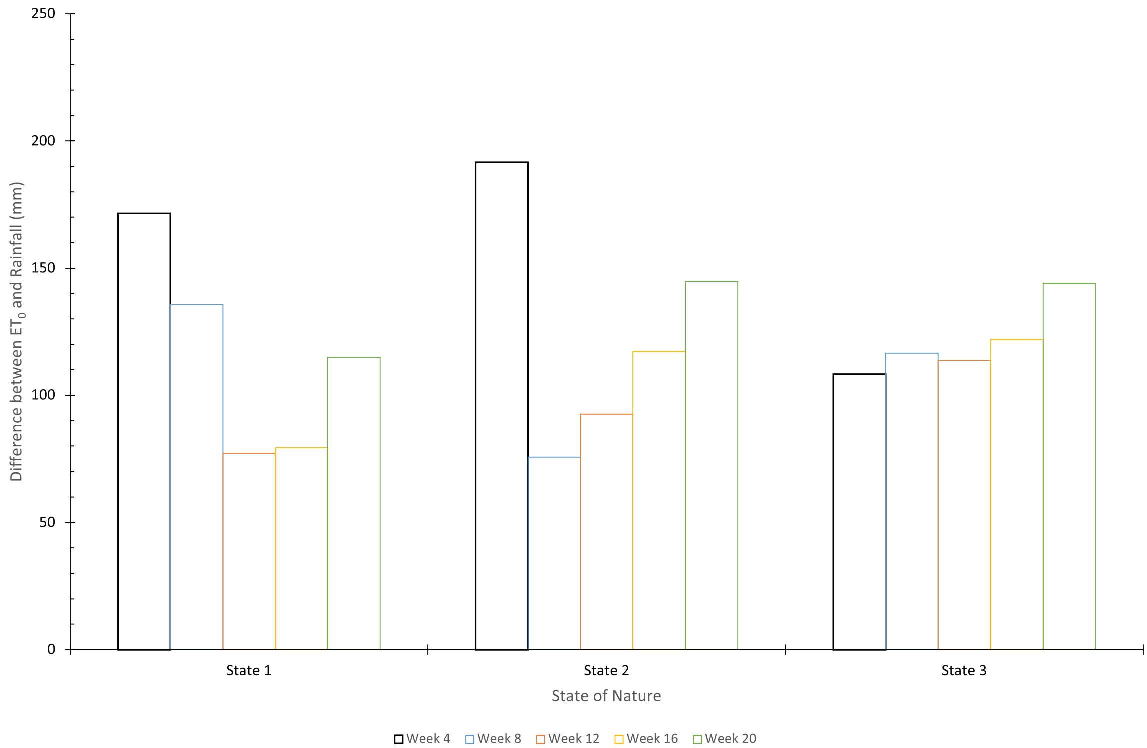

Fig. 2 Variation of the identified states at various weeks

Table 1 Vertical discretization of the soil profile in SWAP

Sublayer	Soil physical layer	Sublayer thickness (cm)	Compartment thickness (cm)	Number of compartments
1	1	30	1	30
2	2	30	5	6
3	2	30	5	6
4	2	30	5	6
5	3	30	5	6
6	3	30	5	6

sublayer represents soil physical layer 1, sublayers 2, 3 and 4 soil physical layer 2 and sublayers 5 and 6 soil physical layer 3. Table 2 lists the Mualem–van Genuchten soil parameters used in SWAP. Three physical soil layers were identified based on the silt-plus-clay measurements, namely, 10%, 18% and 24% as physical soil layers 1, 2 and 3. A locally developed pedotransfer function, RETEN (Streuderst 1985), was used to establish the relationship between volumetric soil water and matric suction (pressure head) for the three physical layers from silt-plus-clay measurements. These values were then entered in the RETC software package (version 6.02, van Genuchten et al. 1991), which estimated the Mualem–van Genuchten parameters, while the saturated hydraulic conductivity was determined with Eq. 11. The measured volumetric soil water at the start of the growing season was entered in SWAP and represents initial conditions.

$$K_s = 2925.8e^{-0.1188(\text{silt-plus-clay})} \quad (11)$$

Table 2 Mualem–van Genuchten parameters of the three identified soil layers in the lysimeters describing the soil hydraulic functions used in SWAP

Soil parameters	Physical soil layer		
	1	2	3
Residual volumetric water content (θ_r, cm^3 cm^{-3})	0.033	0.046	0.061
Saturated volumetric water content (θ_s, cm^3 cm^{-3})	0.336	0.354	0.369
Alfa of main drying curve (α, cm^{-1})	0.0181	0.0196	0.0215
Parameter n	1.447	1.352	1.315
Exponent in hydraulic conductivity function (I)	1.795	−3.501	−6.112
Saturated hydraulic conductivity (K_s, cm d^{-1})	115.57	56.84	34.02

The control treatment for Trial 1, namely, maize grown on a sandy loam soil with no groundwater table was used to calibrate SWAP. The bottom boundary condition was set to the free outflow at the soil–air interface option, which is commonly applied for lysimeters. Table 3 lists the calibrated parameters for SWAP. The normalized root-mean-square error for the simulation of weekly (w) soil water content over a depth of 1.8 m ($WC1.8_{(w)}$) was < 5% and for weekly evapotranspiration ($ET_{(w)}$) < 20%. Seasonal (s) above-ground dry biomass ($BM_{(s)}$) and grain yield were over and under-simulated by 8.9% and 5.9%, respectively.

For validation of SWAP, simulations were repeated in the presence of a constant groundwater table at a depth of 1.5 m (Trial 1) and 1.2 m (Trial 2) using the parameters in Tables 2 and 3. Hence, the bottom boundary condition option 1 in SWAP was selected, namely, a prescribed groundwater table depth. $BM_{(s)}$ was under-simulated by about 20% for the 1.5-m groundwater table depth and over-simulated by about 7% for the 1.2-m groundwater table depth. The difference between measured and simulated grain yield amounted to 15% and −26%, respectively. SWAP was able to simulate the trend in soil water content during the growing season for both groundwater table depths relatively well. In addition, seasonal evapotranspiration and water table uptake (i.e., + bottom flux) were simulated accurately.

Enterprise budgets and differential evolution parameters

The area- and yield-dependent costs for irrigated maize were obtained from the income and cost budgets for the summer crops compiled by BFAP et al. (2021), while the variable electricity charges are based on the Ruraflex structure for 2020/2021 (Eskom 2021). The costs are given in Table 4. The estimated maize price was R2 633 ton^{-1}.

The DE algorithm requires the initial population size, maximum number of iterations, mutation factor, crossover probability, and the lower and upper bounds on irrigation applications. The algorithm generated an initial population of 100 irrigation schedules with irrigation events between 6 and 12 mm. The initial population evolved for 500 iterations while applying a mutation factor of 50% and a crossover rate of 10%.

Bio-economic analyses

Without water table information

The full irrigation strategy represents the baseline whereby the irrigator uses the previous week's observed evapotranspiration and rainfall to calculate the necessary irrigation for the current week. Since the strategy does not consider any soil–water information, it ignores the possible contribution of shallow groundwater tables to satisfy the crop's evapotranspiration requirement for the week.

For each state of nature, the cumulative difference between the previous week's crop evapotranspiration demand and rainfall was taken as the irrigation requirement of the current week. The weekly calculated irrigation requirement was scheduled such that irrigation events start on a Friday and consecutively continue until all the water is applied. The reason for starting on a Friday is that it is cheapest to irrigate over weekends, according to the Ruraflex time-of-use timeslots. The maximum daily application was determined according to the application rate of the pivot. The resulting irrigation schedule was used as input in the bio-economic simulation model to quantify the key economic and biophysical performance indicators.

With water table information

Linking the bio-economic simulation model with the DE algorithm allows for the optimization of irrigation decisions while representing the state of the soil–crop–atmosphere continuum probabilistically. Deriving optimal irrigation schedules with the bio-economic optimization model considers the possible contribution of shallow groundwater tables to satisfying crop evapotranspiration requirements because using the shallow groundwater table as a potential water source does not come at a cost when the profitability of alternative irrigation schedules is evaluated. The decision-making framework of Madende and Grové (2020) presented in Fig. 3 is used to guide the optimization of irrigation decisions to maximize the expected margin above specified costs irrespective of the state of nature and to maximize the MAS in the presence of state-specific unfolding soil–crop–atmosphere information. Next, the application of the decision-making framework for the two objectives is discussed in more detail.

Expected outcome maximization

The first decision tree depicted in Fig. 3 shows that irrigation decisions are made to maximize the expected outcome (i.e., MAS) irrespective of the state of nature occurring for a given irrigation area. Thus, irrigation decisions are made once and for all time periods without considering unfolding information on the state of the soil–crop atmosphere continuum. The same irrigation decisions apply to all states, and the DE algorithm evolves the irrigation decisions while considering shallow groundwater table contributions through separate SWAP simulations for each state. Consequently, the optimized irrigation decisions represent the best irrigation water management, regardless of which state of nature unfolds.

Table 3 Parameters used in SWAP for simulating Trials 1 and 2

Parameters	Units	Values
TBASEM	°C	6
TSUMEMEOPT	°C	94
TEFFMX	°C	30.0
TSUMEA	–	994
TSUMAM	–	798
TAV vs DTSM	°C	8 (0); 32 (24); 45 (24)
DLO	hours	1.0
DLC	hours	0.0
SLATB vs DVS	ha kg^{-1}	0.0024 (0.0); 0.00220 (0.78); 0.00150 (2.00)
EFF	kg CO_2 J^{-1} adsorbed	0.49
AMAXTB vs DVS	kg ha $hour^{-1}$	80 (0.0); 80 (1.25); 78 (1.50); 78 (1.75); 56 (2.00)
LAIEM	m^2 m^{-2}	0.04836
RGRLAI	m^2 m^{-2} day^{-1}	0.03530
SPAN	day	38
TDWI	kg ha^{-1}	50.00
TBASE	°C	10.00
KDIF	–	0.60
KDIR	–	0.75
TMNFTB vs Min T	°C	0.00 (5.00); 1.00 (8.00)
TMPFTB vs Ave T	°C	0.10 (0); 0.8 (16); 1.00 (20); 0.95 (36); 0.56 (42)
SPA	ha kg^{-1}	0.0
SSA	ha kg^{-1}	0.0
CVL	kg ha^{-1}	0.6800
CVO	kg ha^{-1}	0.6710
CVR	kg ha^{-1}	0.6900
CVS	kg ha^{-1}	0.6580
Q10	/10 °C	2.00
RML	kg CH_2O kg^{-1} day^{-1}	0.03
RMO	kg CH_2O kg^{-1} day^{-1}	0.01
RMR	kg CH_2O kg^{-1} day^{-1}	0.015
RMS	kg CH_2O kg^{-1} day^{-1}	0.015
RFSETB vs DVS	–	1.00 (0); 1.00 (1.50); 0.75 (1.75); 0.25 (2.00)
FRTB vs DVS	kg kg^{-1}	0.40 (0); 0.34 (0.20); 0.23 (0.50); 0.10 (0.8); 0 (1); 0 (2)
FLTB vs DVS	kg kg^{-1}	0.62 (0); 0.62 (0.33); 0.15 (0.88); 0.10 (1.10); 0 (1.2); 0 (2)
FSTB vs DVS	kg kg^{-1}	0.38 (0); 0.38 (0.33); 0.85 (0.88); 0.40 (1.10); 0 (1.2); 0 (2)
FOTB vs DVS	kg kg^{-1}	0.00 (0.95); 0.50 (1.10); 1.0 (1.2); 1.0 (2)
RDCTB vs Rdepth	cm^3 cm^{-3}	1 (0); 0.74 (0.2); 0.30 (0.4); 0.17 (0.6); 0.9 (0.8); 0.05 (1)
RDI	cm	5.00
RRI	cm day^{-1}	2.20
RDC	cm	75
CFBS	–	1.25
KDIF	–	0.60
KDIR	–	0.75
COFRED	–	0.60
CF vs DVS	–	0.21 (0.30); 0.95 (0.50); 1.34 (0.7); 1.38 (1.00); 1.21 (1.40); 0.93 (2)

Table 4 Irrigated maize production cost estimates (2021)

Dependent costs	Yield	Contracting (R ha^{-1})	1 470
		Crop insurance (R ha^{-1})	308
		Fertilizer (R ha^{-1})	8 564
		Transport (R ha^{-1})	285
	Area	Fuel (R ha^{-1})	926
		Seed (R ha^{-1})	4 975
		Weed control (R ha^{-1})	663
		Pest control (R ha^{-1})	2 397
Variable electricity charges	Active energy	Off-peak (R kWh^{-1})	0.72
		Standard (R kWh^{-1})	1.13
		Peak (R kWh^{-1})	1.64
	Ancillary	Off-peak (R kWh^{-1})	0.63
		Standard (R kWh^{-1})	0.63
		Peak (R kWh^{-1})	0.63
	Demand	Off-peak (R kWh^{-1})	0.41
		Standard (R kWh^{-1})	0.41
		Peak (R kWh^{-1})	0.41
	Other costs	Labor cost (R 24-h irrigation^{-1})	12.58

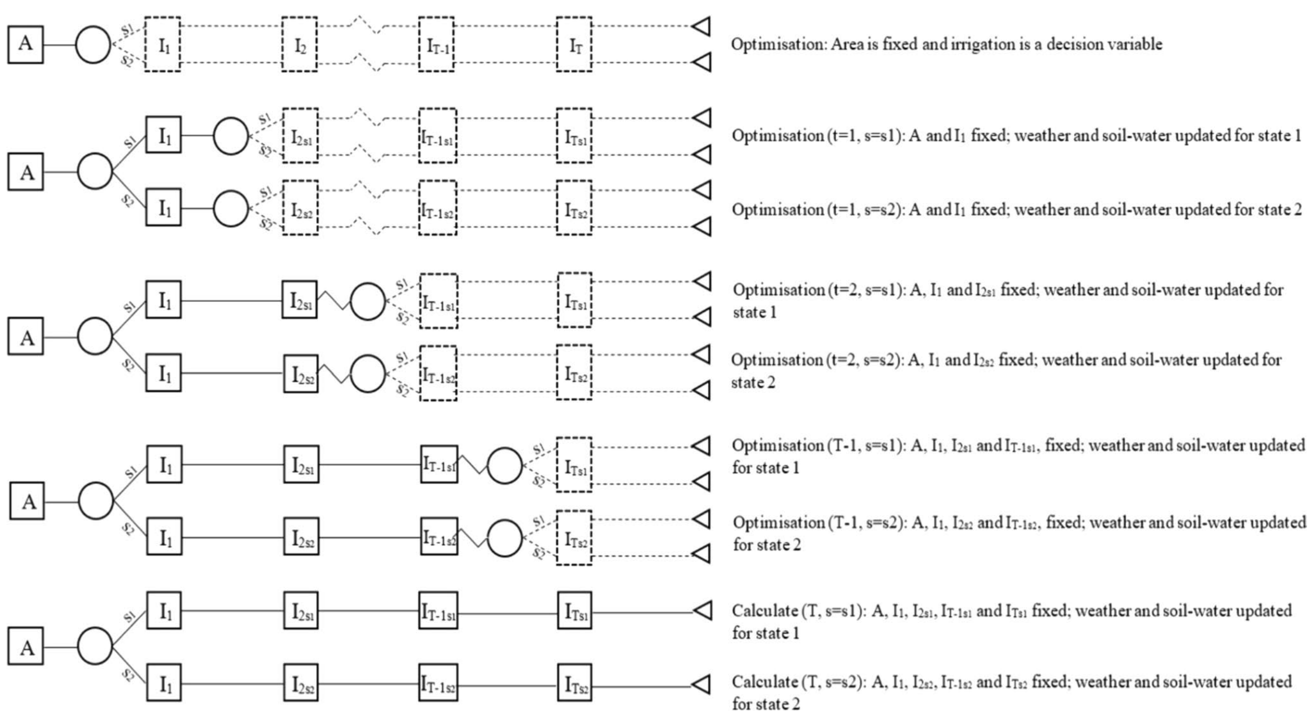

Fig. 3 Schematic representation of decision-making within a single-stage and multi-stage decision framework where; square represents fixed decisions, circle represents possible events to unfold, dotted square represents optimized decisions, left inverted triangle represents the outcome, **A** represents the area, **I** represents the irrigation decisions, **T** represents the decision stage, and **S** represents the possible state of nature to unfold Source: Madende and Grové (2020)

Unfolding information maximization

The unfolding information maximization optimization recognizes that irrigation decisions that maximize expected outcomes irrespective of the state of nature might be suboptimal for a specific state. The second decision tree in Fig. 3 shows that the irrigator can adjust future irrigation decisions based on the expected future state of the soil–crop–atmosphere continuum, given the past state of the soil–crop–atmosphere continuum is known when the adjustment is made. Consequently, the irrigation decision problem must be solved for each unfolding state of nature, exponentially increasing the problem's dimensionality when including more states. The assumption is that the irrigator is allowed to adjust irrigation decisions weekly. Therefore, 20 optimizations are necessary for each unfolding state of nature. After each optimization (i.e., 1 week), the weather file of the SWAP simulation model representing a specific future state of nature is updated with information on the unfolding state of nature. The irrigation amounts are also fixed to correspond with the optimized irrigation decisions of the previous week. As a result, only future irrigation decisions are optimized.

Results

No consideration of water table uptake

The full irrigation management strategy is a strategy where the irrigator, for each state, uses the previous week's observed evapotranspiration and rainfall levels to schedule irrigation for the current week. Thus, the strategy does not use soil–water information to schedule irrigation and, therefore, ignores the potential contribution of shallow groundwater tables. Each state will have an irrigation schedule as it differs in evapotranspiration and rainfall levels.

Table 5 shows the bio-economic simulation results for the full irrigation strategy. The full irrigation strategy applications vary by 26 mm between a minimum of 557 mm (State 1) and a maximum of 583 mm (State 2), with an expected application of 574 mm. The variation in maize yields was greater when compared to irrigation water applications. Maize yields varied by 3 329 kg ha^{-1} between a minimum of 10 733 kg ha^{-1} (State 2) and 14 062 kg ha^{-1} (State 3) with an expected crop yield of 11 963 kg ha^{-1}. The extent of the crop yield variation is attributed to the ability of SWAP to capture the impact of different states of nature on potential non-stressed crop yields since inspection of the crop results file indicated almost no water stress.

Although the full irrigation strategy achieved state-specific potential crop yields, the water use efficiency of the strategy was low as it varies between a minimum of 1.13 (State 3) and a maximum of 1.28 (State 2) with an expected value of 1.19. The water use efficiency results show that the full irrigation strategy is expected to supply 19% more water (i.e., rainfall, irrigation and shallow groundwater tables) than the crop's evapotranspiration requirement. The mismatch between total water supply and crop evapotranspiration requirements results in an expected drainage loss of 92 mm, which could be as low as 51 mm (State 3) and as high as 143 mm (State 2). The order of magnitude of the drainage losses corresponds with the magnitude of the rainfall. The

Table 5 Economic and biophysical indicators when applying a state-specific full irrigation strategy without considering water table uptake on a 30.1-ha pivot (2021)

Indicators			Units	Full irrigation strategy			
				State 1	State 2	State 3	Expected
Probability of occurrence			fraction	0.23	0.44	0.33	–
Economic	Margin above specified costs		R	132 960	94 006	298 022	170 291
	Production income		R	1 218 329	1 156 890	1 515 716	1 289 433
	Total variable electricity costs		R	34 006	35 720	34 100	34 791
	Active energy charge	Off-peak	R	12 869	13 477	14 211	13 579
		Standard	R	9 030	9 063	8 338	8 816
		Peak	R	1 051	1 617	191	1 016
	Other variable electricity charges		R	11 056	11 564	11 361	11 380
	Other irrigation-dependent costs		R	60 394	63 169	62 064	62 166
	Yield-dependent costs		R	534 893	507 919	665 455	566 110
Biophysical	Irrigation application		mm	557	583	573	574
	Evapotranspiration		mm	657	643	664	653
	Rainfall		mm	146	199	132	165
	Seasonal water table uptake		mm	44	39	45	42
			%	7	6	7	6
	Drainage		mm	54	143	51	92
	Yields		kg ha^{-1}	11 303	10 733	14 062	11 963
	Water use efficiency		fraction	1.14	1.28	1.13	1.19

contribution of shallow groundwater tables to satisfying crop evapotranspiration requirements was less than 7% in all the states.

The MAS of the full irrigation strategy in each state of nature directly results from how the biophysical system responded to the full irrigation strategy. The expected margin above specified costs for the strategy was R170 291, which varied substantially between R298 022 (State 3) and R94 006 (State 2). The substantial variation in the MAS directly results from the yield expectation differences between states of nature and the production income and expenses dependent on crop yield. Expenses dependent on irrigation applications, such as total variable electricity and other irrigation-dependent costs, varied only with R1 714 (R35 720-R34 006) and R508 (R11 564-R11 056), respectively, for the 30-ha pivot.

Consideration of water table uptake

Optimal expected outcome irrigation strategy

The DE algorithm uses information on the expected state of the soil–crop–atmosphere continuum to devise an irrigation schedule that is the best-performing profit-maximizing schedule irrespective of the state of nature. Consequently, the algorithm also considers shallow groundwater tables as a water source to satisfy crop evapotranspiration requirements.

Table 6 shows the bio-economic simulation results when the optimized irrigation schedule is applied to each state of nature. The optimal expected outcome irrigation strategy applied only 148 mm of irrigation, which is 426 mm less than the expected irrigation application of the full irrigation strategy. The substantial reduction in irrigation application did not impact crop yields in each state of nature much, with absolute deviations from the full irrigation strategy being less than 102 kg ha^{-1} across the states of nature.

Reducing irrigation applications of the optimal expected outcome strategy improved the expected water use efficiency by 15 percentage points, showing that the strategy uses rainfall and shallow groundwater tables more efficiently. Drainage losses associated with overirrigation and ineffective rainfall were reduced to zero in State 1 and State 3, while the drainage losses in State 2 were reduced by 86 mm. The optimal expected outcome irrigation strategy increased the contribution of shallow groundwater tables to satisfying the crop evapotranspiration requirements substantially across all states of nature. Compared to full irrigation, the water table uptake increased by a minimum of 42 percentage points (State 2) and a maximum of 46 percentage points (State 3), with an expected increase of 45 percentage points. When applying the optimal expected outcome irrigation strategy, shallow groundwater tables contributed about 51% to satisfy the expected crop evapotranspiration requirement.

The expected MAS for the optimal expected outcome irrigation strategy is R 243 553, which is R73 262 higher than that of the full irrigation strategy. The reason for the increase in the expected MAS is that the reduction in irrigation application decreased total variable costs and other irrigation-dependent costs, while crop yields were not affected much. The optimal expected outcome irrigation strategy did, however, increase the crop yields in State 2 while compromising crop yield in the other states. The variable electricity costs decreased by a minimum of R25 509 (State 1) and a maximum of R27 223 (State 2), with an expected reduction of R26 294. The other irrigation-dependent costs decreased by a minimum of R44 353 (State 1) and by a maximum of R47 128 (State 2), with an expected decrease in R46 125. Expected production income and expected yield-dependent costs did not change much because crop yields were not affected much by the optimal expected outcome irrigation strategy. Expected production income increased by R1 503 while expected yield-dependent cost increased by R660 compared to the full irrigation strategy.

Optimal sequential irrigation strategy

The optimal sequential irrigation strategy allows the irrigator to adjust the optimal expected outcome irrigation strategy weekly for the rest of the season based on the unfolding state of nature. The results of the optimal sequential irrigation strategy are given for each state of nature in Table 7.

Table 7 shows that, contrary to expectation, no substantial adjustments were made to the optimal expected outcome irrigation strategy when the irrigator had the chance to react to unfolding information regarding the soil–crop–atmosphere continuum. In absolute terms, the optimal sequential irrigation strategy does not deviate more than 18 mm from the optimal expected outcome irrigation strategy in any state of nature. Irrigation adjustments in all states of nature resulted in higher crop yields. Interestingly, the total irrigation application was increased in State 2 while the applications were reduced in the other two states to increase crop yield. The increases were small, with the highest increase (i.e., 100 kg ha^{-1}) in State 1. The relatively small changes in irrigation applications resulted in an increased shallow groundwater table contribution in State 1 and State 3 of 14 mm and 17 mm and a decrease of 7 mm in State 2. Accordingly, the water use efficiencies changed by one percentage point in absolute terms.

The MAS increased with R8 007 and R3 340 in State 1 and State 3 because irrigation applications were reduced, and crop yields increased in these states of nature. The results for State 2 seem non-optimal because the MAS of the optimal sequential irrigation strategy reduced the MAS of the optimal expected outcome strategy with R510.

Table 6 Economic and biophysical indicators for a state-specific sequential strategy considering water table uptake and the changes relative to the optimal expected outcome irrigation strategy for a 30.1-ha pivot (2021)

Indicators			Units	Optimal expected outcome irrigation strategy				Change relative to full irrigation strategy			
				State 1	State 2	State 3	Expected	State 1	State 2	State 3	Expected
Probability of occurrence			fraction	0.23	0.44	0.33	–	0.23	0.44	0.33	–
Economic	Margin above specified costs		R	196 655	174 222	368 680	243 553	63 694	80 216	70 658	73 262
	Production income		R	1 207 335	1 167 345	1 513 992	1 290 936	− 10 994	10 455	− 1 725	1 503
	Total variable electricity costs		R	8 497	8 497	8 497	8 497	− 25 509	− 27 223	− 25 603	− 26 294
	Active energy charge	Off-peak	R	4 197	4 197	4 197	4 197	− 8 672	− 9 280	− 10 014	− 9 382
		Standard	R	1 363	1 363	1 363	1 363	− 7 667	− 7 699	− 6 974	− 7 453
		Peak	R	0	0	0	0	− 1 051	− 1 617	− 191	− 1 016
	Other variable electricity charges		R	2 937	2 937	2 937	2 937	− 8 119	− 8 627	− 8 425	− 8 443
	Other irrigation-dependent costs		R	16 042	16 042	16 042	16 042	− 44 353	− 47 128	− 46 022	− 46 125
	Yield-dependent costs		R	530 066	512 510	664 698	566 770	− 4 827	4 590	− 757	660
Biophysical	Irrigation application		mm	148	148	148	148	− 409	− 435	− 425	− 426
	Evapotranspiration		mm	557	566	620	582	− 100	− 78	− 43	− 71
	Rainfall		mm	146	199	132	165	0	0	0	0
	Seasonal water table uptake		mm	273	286	329	297	229	248	284	255
			%	49	51	53	51	42*	45*	46*	45*
	Drainage		mm	0	56	0	25	− 54	− 86	− 51	− 67
	Yields		kg ha^{-1}	11 201	10 830	14 046	11 977	− 102	97	− 16	14
	Water use efficiency		fraction	1.02	1.12	0.98	1.05	− 0.12	− 0.16	− 0.15	− 0.15

*The relative change is measured in percentage points

Table 7 Economic and biophysical indicators for a state-specific sequential strategy considering water table uptake and the changes relative to the optimal expected outcome irrigation strategy for a 30.1-ha pivot (2021)

Indicators			Units	Optimal expected outcome irrigation strategy				Change relative to full irrigation strategy			
				State 1	State 2	State 3	Expected	State 1	State 2	State 3	Expected
Probability of occurrence			fraction	0.23	0.44	0.33	–	0.23	0.44	0.33	–
Economic	Margin above specified costs		R	204 662	173 712	372 020	246 272	8 007	−510	3 340	2 719
	Production income		R	1 219 299	1 170 902	1 514 746	1 295 502	11 964	3 557	755	4 566
	Total variable electricity costs		R	8 069	9 376	7 531	8 467	−428	879	−965	−30
	Active energy charge	Off-peak	R	3 970	4 616	3 568	4 122	−227	419	−628	−75
		Standard	R	1 220	1 480	1 384	1 388	−144	117	20	25
		Peak	R	101	46	0	43	101	46	0	43
	Other variable electricity charges		R	2 778	3 234	2 775	2 978	−159	298	−162	41
	Other irrigation-dependent costs		R	15 174	17 667	14 091	15 914	−867	1 626	−1 951	−128
	Yield-dependent costs		R	535 319	514 071	665 029	568 774	5 253	1 562	331	2 005
Biophysical	Irrigation application		mm	140	163	130	147	−8	15	−18	−1
	Evapotranspiration		mm	567	574	623	589	11	8	3	7
	Rainfall		mm	146	199	132	165	0	0	0	0
	Seasonal water table uptake		mm	288	280	347	304	14	−7	17	6
			%	51	49	56	51	2	−2	3	0
	Drainage		mm	0	56	0	25	0	0	0	0
	Yields		kg ha^{-1}	11 312	10 863	14 053	12 019	111	33	7	42
	Water use efficiency		fraction	1.01	1.12	0.98	1.05	−0.01	0.00	−0.01	0.00

*The relative change in the water table uptake is measured in percentage points

Discussion

The bio-economic simulation results confirm the claims by Barnard et al. (2021) that farmers who irrigate to satisfy crop evapotranspiration requirements will have low water use efficiencies. The bio-economic optimization results estimated that 51% of maize's crop evapotranspiration could originate from shallow groundwater tables using optimal irrigation management, reducing the irrigation requirements substantially without impacting crop yields. This contribution is in line with findings by Jovanovic et al. (2004), who found that the shallow groundwater tables can potentially contribute about 40% or more to the crop water demand under near-optimal irrigation schedules. Liu et al. (2022) estimated the contribution to be 49%. Huo et al. (2012) showed with field lysimeters and simulations with SWAP that the contribution from shallow groundwater not only depends on crop type, soil texture, etc., but that irrigation volumes and frequency should be determined according to the groundwater table depth.

The bio-economic analyses assume the area limiting case (i.e., 30-ha irrigated irrespective of water application rates per hectare). Consequently, the analyses only consider changes in irrigation water use at the intensive margin (i.e., irrigation water applications per hectare) (Graveline 2016). According to Graveline (2016), intensive margin changes will create the opportunity to increase the irrigated area (i.e., extensive margin changes) if the production area is not limited. The intensive margin changes in irrigation water use using shallow groundwater tables are substantial; therefore, the extensive margin change, if possible, would also be substantial. However, widespread use of shallow groundwater tables and extensive margin changes in water use may result in unintended hydro-ecological consequences as well as consequences for the revenues of the irrigation supplier.

The economic benefit of adapting irrigation management decisions was small, contrary to the findings of Madende and Grové (2020), who did not consider shallow groundwater tables and included water scarcity in their analyses. The risk of a short supply of irrigation water is reduced in the presence of a shallow groundwater table. Consequently, conjunctive water use strategies considering shallow groundwater tables provide substantial economic benefit at the farm level (i.e., optimal expected outcome irrigation strategy), leaving less potential to decrease risk through adaptive decision-making (i.e., optimal sequential irrigation strategy) because a shallow groundwater table neutralizes the impact of insufficient water.

The bio-economic optimization models used a probabilistic representation of the state of the soil–plant–atmosphere when optimizing irrigation water applications. Consequently, when optimizing irrigation application decisions, the optimization procedure has access to all information (i.e., weather states and the cause-and-effect interactions in the SWAP simulation model).

Conclusions

This paper aimed to approximate the profitability of conjunctively using irrigation water and root-accessible shallow groundwater tables to satisfy crop evapotranspiration. The results provided some biophysical and new economic lessons from South Africa into why farmers do not consider shallow groundwater tables when scheduling irrigation.

Inconsistent irrigation water use efficiencies, indicating suboptimal management, were found with an irrigation strategy of using the previous week's observed evapotranspiration and rainfall levels to schedule irrigation for the current week (full strategy). The margin above specified costs varied substantially (> 200%) among states of nature, this variation is attributed to differences in yield expectations across states and the corresponding impact on production income and expenses.

Improved irrigation water use efficiencies (15 percentage points) compared to the full irrigation strategy were found when an optimized irrigation schedule based on expected states of the soil–crop–atmosphere continuum was employed. This reduction in irrigation had minimal impact on crop yields, confirming the successful utilization of rainfall and shallow groundwater tables as additional water sources to satisfy crop evapotranspiration. The margin above the specified costs increased by R73 262 compared to the full irrigation strategy, primarily attributed to reduced irrigation applications. This led to decreased total variable costs and other irrigation-dependent costs.

Surprisingly, the optimal sequential irrigation strategy, designed to allow weekly adjustments based on unfolding information about the soil–crop–atmosphere continuum, did not result in substantial deviations from the optimal expected outcome irrigation strategy. This indicates that the initial optimized strategy was already nearly optimal for various unfolding conditions. The margin above specified costs varied across states of nature and highlighted the complex interplay between irrigation adjustments, crop yields and economic performance in different states, emphasizing the need to carefully consider context-specific factors in irrigation management decisions. Future research is needed to devise an information dissemination strategy to facilitate irrigation management considering shallow groundwater tables.

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Data availability The data that support this study cannot be publicly shared due to ethical or privacy reasons and may be shared upon reasonable request to the corresponding author if appropriate.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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