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A practical planning software program for desalination in agriculture - SPARE:WATER^{opt}

S. Multsch [a,*], D. Grabowski [b], J. Lüdering [c], A.S. Alquwaizany [d], K. Lehnert [e], H.-G. Frede [a], P. Winker [b,c], L. Breuer [a,c]

[a] Institute for Landscape Ecology and Resources Management (ILR), Research Centre for BioSystems, Land Use and Nutrition (IFZ), Justus Liebig University Giessen, Heinrich-Buff-Ring 26, 35392 Giessen, Germany
[b] Department of Statistics and Econometrics, Justus Liebig University Giessen, Licher Strasse 64, 35394 Giessen, Germany
[c] Centre for International Development and Environmental Research (ZEU), Justus Liebig University Giessen, Senckenbergstraße 3, 35390 Giessen, Germany
[d] Research Institute for Water and Energy, King Abdulaziz City for Science and Technology, P.O. Box 6086, Riyadh 11442, Saudi Arabia
[e] IBM Deutschland GmbH, Mainz, Germany

HIGHLIGHTS

- A novel tool for optimizing the use of desalinated water in irrigation agriculture
- Spatial (available land) and temporal (daily water supply) optimization of water utilization
- Balancing water supply and demand made possible using 97% of available water
- Gross margin is maximized by a cropping pattern dominated by cash crops using 77% of available water.
- Irrigation by seawater desalination can be economically feasible for cash crops.

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ABSTRACT

Water shortage limits agricultural production worldwide, and irrigation leads to a rapid depletion of water resources. Using desalinated water for irrigation reduces pressure on local resources but it is expensive. An economically viable utilization for using desalinated water in agriculture is only possible through the optimal planning and management of cropland and irrigation scheduling management. We developed a software program aiming to maximize the gross margin (GM) by optimizing cropping patterns using a site-specific crop water requirement model. We used the simplex algorithm under the boundary conditions of limited water (temporal scale) and available land (spatial scale). In a proof of concept, we tested the software for a desalination plant in Saudi Arabia that produces 60,000 m^3 day^{-1}. A cropping pattern for 4278 ha was derived that maximizes GM (92 Mio US$ yr^{-1}) and uses most (97%) of the constant water supply to the plant. An optimal cropping pattern (4023 ha) solely maximizing GM yields a higher outcome (125 Mio US$ yr^{-1}) and requires even less water for irrigation. This surplus water can be used for leaching soils or other purposes. Both cropping patterns are dominated by cucumber and tomatoes, covering the largest fractions of cropland at 74% and 88%, respectively.

1. Introduction

1.1. Agricultural development by desalination

A vast increase in food prices on the global market has been observed since 2003, and several reasons have been discussed, e.g., weather shocks, increasing oil prices and financial market speculation [1]. Prices for primary commodities, such as rice, wheat, soybean and maize, increased threefold or more until peaking in 2008. After that, the prices dropped again. Investments in agricultural research and development are helpful to prevent food prices from undergoing such severe increases [2]. Because many regions worldwide face an increasing unsustainable use of local

* Corresponding author.
E-mail addresses: sebastian.multsch@umwelt.uni-giessen.de (S. Multsch), Daniel.Grabowski@wirtschaft.uni-giessen.de (D. Grabowski), Jochen.Luedering@zeu.uni-giessen.de (J. Lüdering), aquwaizany@kacst.edu.sa (A.S. Alquwaizany), karl_lehnert@de.ibm.com (K. Lehnert), hans-georg.frede@umwelt.uni-giessen.de (H.-G. Frede), Peter.Winker@wirtschaft.uni-giessen.de (P. Winker), lutz.breuer@umwelt.uni-giessen.de (L. Breuer).

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water resources [3] and increasingly rely on foreign water resources to support their growing populations [4], alternative pathways must be developed to support agriculture with water because the current solutions are often closely associated with local water resource depletion [5,6]. The desalination of seawater provides such an alternative and may be helpful to partly counteract water scarcity [7]. In particular, comprehensive investments in large-scale desalination are needed to ensure a sustainable development as reported for the Gulf Cooperation Council countries (GCC) [8]. The question arises as to how available water resources from new investments, as well as existing ones, can be used optimally. The importance of modelling tools has been recently highlighted to solve such integrated problems regarding the energy, water and food nexus [9] and to ensure a sustainable use of desalinated seawater for agriculture [10]. In this study, a novel spatial decision support system (sDSS) is presented to optimize desalinated water use for agriculture. Because optimal agriculture management is important to successfully utilize desalinated water for irrigation [11], a particular emphasis is given to the factors of irrigation technology, salinity and crop salt tolerance, which have been reported to be major determinants for investigating the potential of agricultural production on the Arabian Peninsula [12]. It has been shown that irrigation technology has a high impact on the national water consumption [13] because changes in cropping pattern as well as the implementation of modern irrigation technology can reduce water consumption by up to 32% in Saudi Arabia [14].

1.2. Desalination technology and cost

Improved desalination techniques [15] may reshape agricultural production. The applicability of different desalination techniques to provide water for irrigation has been recently reviewed [11], and the authors stress the suitability of reverse osmosis (RO) for agriculture purposes. However, Shaffer et al. [16] highlight the potential of forward osmosis technology coupled with RO for agriculture purposes compared to the sole application of RO because of its better water quality at lower costs. Efforts have been made to use renewable energy for running plants, e.g., by photovoltaic power, wind power or solar energy, and the feasibility of the application of desalination with renewable energy has been discussed widely [17,18].

The costs for desalinated water are still high compared to the utilization of surface or groundwater for irrigation because the latter ones have no or only low prices in most countries. In most cases, only pumping costs are incurred. Generally, it is often unclear whether the cost for desalination includes capital and investment costs or the planned lifespan of the desalination plant [19–21], which makes difficult a general comparison of literature data on desalination costs. For example, the price for desalination using RO ranges between 0.5 and 1.2 US$ m^{-3} [19], which is high compared to the water costs of 0.05 € m^{-3}, as reported for an irrigation district in Spain [22] using surface water resources for irrigation. The key question is as follows: how much are farmers willing to pay? Barron et al. [23] conducted a nationwide study in Australia based on various datasets of water availability, quality and economic aspects and stated that farmers a likely to spend no > 1.2 AU$ m^{-3} (1.0 AU$–0.7 US$). In contrast, a water price between 0.14 and 0.35 US$ m^{-3} has been reported for an irrigation district in Jordan [24]. Overall, desalinated water remains an expensive resource, and its consumption should be managed properly to avoid wasting precious water and to ensure an economically feasible utilization.

1.3. Optimization of water allocation

To optimize water resource use, different scales and factors must be considered, i.e., (i) the spatial allocation of water (e.g., between districts) [22,25,26], (ii) the crop selection and cropping patterns [26] and (iii) the timing of the crop irrigation schedule [27], in addition to the amount of available irrigation water. The optimization of cropping pattern is often conducted by coupled crop water economic optimization models, assuming a fixed water supply. The optimization is often performed in a hierarchical way, e.g., Garcia-Vila and Fereres [22] derived crop productivity functions for site-specific conditions with a dynamic crop model (AquaCrop [28,29]) under various supplies. These functions are then used in a second step in an economic model to optimize management. Reca et al. [30] used a three-step hierarchical system to optimize water use: on the field level for single crops, on the district level for cropping pattern and on a hydrological system scale for complete land cover. Pandey et al. [31] used the Cropwat model [32] in a three-phase approach to optimize the field level water use as well as the cropping pattern. Shanguuan et al. [33] applied in their hierarchical approach three layers with different objectives in order to maximize crop yields, the benefit of the cropping pattern and the benefit at the basin scale. The objective functions that are commonly optimized is the gross margin [22,25], the water use efficiency, or a combination of both. Others optimize the gross income, net income, irrigation water productivity or labour use [26], as well as crop yield [34]. Net farm income, minimization of waterlogging and minimization of groundwater depletion are listed in another review [35]. Most optimization approaches are restricted by limitations, e.g., maximum and minimum percentages for each crop to prevent optimization for favouring only high-value crops [25], land and water availability [31] and irrigation depth [30]. Such limitations are implemented by penalty functions [25] or limited parameter ranges as is often the case for cropping patterns [30].

Mathematical algorithms are used to solve the optimization problem. Four methods, i.e., linear, non-linear and dynamic programming and a genetic algorithm, have been recently discussed in the context of irrigation management optimization [35]. To solve nonlinear problems, simulated annealing (SA) comes into play. The simulated annealing approach has been recently reviewed for conjunctive water use management, and the practicability of combining optimization approaches and simulation models has been highlighted [36]. Brown et al. [37] used such a coupled approach to optimize irrigation scheduling using simulated annealing and the FarmWi$e/APSIM model. They showed that pasture yields could be increased by 10% through optimal irrigation scheduling in Canterbury (New Zealand). In the case of multi-objective optimization problems, which are limited by several constraints, linear programming is an often-applied method. A popular linear programming optimization method is the simplex algorithm [38,39]. This algorithm enables an effective and straightforward implementation of boundary conditions, which is important in the case of planning land use under a limited water supply and other constraints. Sadeghi et al. [40] optimized the management of a watershed in Iran using the simplex method, showing that soil erosion could be reduced and the net benefits increased through the optimal planning of orchards, irrigation and dryland farming. Khare et al. [41] utilized an economic engineering optimization model based on the simplex algorithm. They derived optimal cropping patterns supplied by either surface or groundwater for a planned canal system in India. The results indicate potential water saving through inter-basin water trade. Chen et al. [42] applied the Conversion of Land Use and its Effects (iCLUE) program, which implements the simplex method for optimizing land-use pattern for an area in Northern China. The authors highlight the practicability of the proposed method to ensure ecological security at the regional scale.

1.4. Study objective

Countries experiencing food price shocks as observed in the last decade [1] require measures to increase resilience. This leads to the need for further investments in research and development in the agricultural sector [2]. As part of Saudi Arabia's strategy to cope with limited water resources, desalination is proposed as one measure to address water shortage [8]. Given that agriculture is the largest water-consuming sector in Saudi Arabia, constituting > 90% of the total water use [43], there is greater potential to improve irrigation management in order to make the best use of this expensive resource. Potential strategies to improve desalinated seawater use in agriculture include the spatial reallocation of crops, the diversification of cropping patterns and the optimization of water use over time by balancing supply and demand. A new sDSS for planning and optimizing desalinated water use in agriculture has been developed because the importance of modelling tools in such a context has been recently highlighted [10]. A software package has been implemented called SPARE:WATER^{opt} aiming at the temporal and spatial economic optimization of cropping patterns according to limited water and land availability. The newly developed software SPARE:WATER^{opt} is an extension to the previous published software tool SPARE:WATER [5]. A case study was presented of a RO desalination plant in eastern Saudi Arabia along the Arabian Gulf with a daily water production of 60,000 m^3 day^{-1}. The irrigated fields near the desalinated plant sum to 84,753 ha, which is considered the total potential area for irrigation agriculture in this study. The simplex algorithm [38,39] was used to plan cropping patterns by maximizing the gross margin under limited water and available land. The site-specific monthly crop water needs for 19 major crops grown in Saudi Arabia and their different sowing dates were taken from a database calculated using SPARE:WATER in a previous study (Multsch et al., 2016b). Two strategies are addressed in order to determine the optimal cropping patterns for the irrigation with desalinated water.

2. Methods and materials

2.1. Modelling framework

The framework "SPARE:WATER^{opt}" proposed in this study(Fig. 1) aims to support the planning of cropping patterns in arid and semi-arid regions, where land and water resources limit agriculture. The software was made for various stakeholders, such as farmers, engineers, authorities and private companies (Fig. 1a), but can of course be used for further research. The software was implemented with VB·NET for Windows computers with a graphical user interface (GUI). The GUI enables the configuration of the model, e.g., selection of region, crops, scenario settings and boundary conditions (Fig. 1b). The user can set up the software step by step in order to define the scenario, regions and available crops or can load a pre-defined setup from .csv files in batch run mode. Optimization with the simplex algorithm was conducted with a script written in the Python programming language. We used the SciPy package and its linear programming features (Fig. 1c). The GUI and the script use of a database in SQLite, which contains information on arable land, prices, crop water needs and the results of the optimization, i.e., the cropping pattern and the related costs, revenues and GM (Fig. 1d).

In the first step, the user creates a scenario. This contains the definition of the water supply, water cost and objective function, as well as the irrigation management parameters (salinity control, efficiency and technology). The second step is the definition of the regions that should be supplied and the crops that can be grown according to a given irrigation technology. In the third step, the user sets boundary conditions related to minimum and maximum available arable land for specific crop types. By running this setup, the simplex algorithm determines the optimal cropping pattern in relation to the objective function and boundary conditions. The results are stored in the database, and three graphs in the GUI show the annual water demand and GM, as well as the monthly water needs of each crop per month in relation to the monthly water supply.

2.1.1. Water balance

The cropping patterns to be developed consider the limited monthly water supply and available land in each region. For this reason, the user must provide data on the monthly net irrigation requirements, i.e., the productive amount of irrigation that actually contributes to crop growth (IRR_{prod}) for each crop and region. These data can be derived by field experiments or by simulation models [5,29]. These simulation models require input information on the management, soil and climate, which are available, for example, from public datasets from the FAO (soil: [44]; climate: [45]) or local authorities. IRR_{prod} is the amount of water needed to allow full crop growth considering no limitations through pests, diseases, or nutrient or water stress. Nevertheless, irrigation losses can occur through deep percolation (i.e., water flow to deeper soil layers or groundwater) [46]. Thus, IRR_{prod} is adjusted by the irrigation efficiency (IRR_{eff}) to include these water losses. In our study, water losses are related to on-farm processes. Off-farm losses, such as those through canal cracks, are neglected.

Salinization is another important process to be considered. When water evaporates from the soil, salts remain in the rooting zone, limiting plant water uptake, decreasing crop yields and impacting soil structure

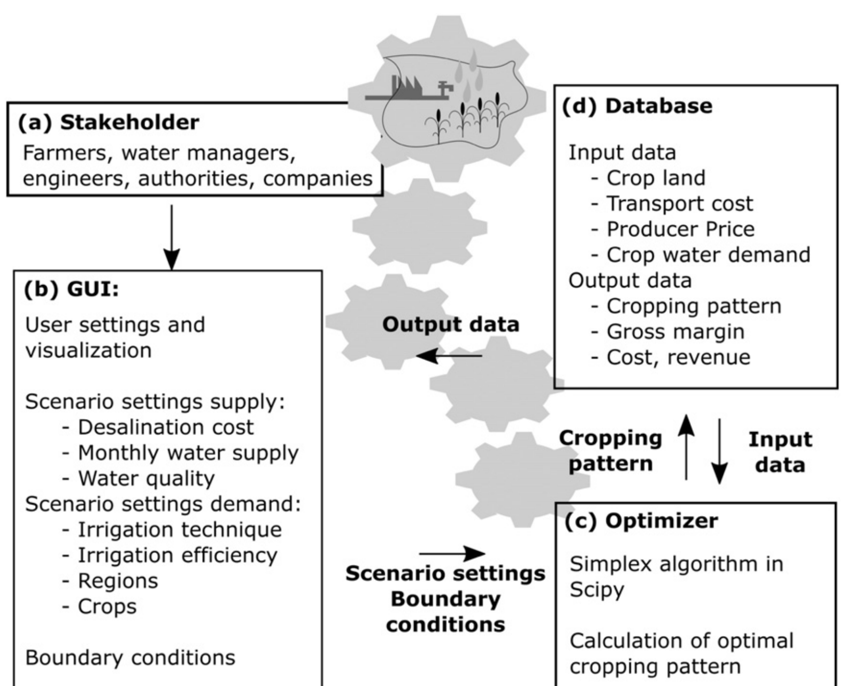

Fig. 1. Components of the newly developed optimization framework within the spatial decision support system (sDSS) SPARE:WATER^{opt}: (a) Stakeholders (b), Graphical User Interface (GUI) written in VB·Net for Windows Systems, (c) Optimization algorithm (scientific programming tool SciPy), and (d) SQLite database with all input and output data.

[47]. In the worst case, salt crusts seal the soil surface, making crop cultivation impossible. Therefore, salinity management plays a major role when water of lower quality (i.e., with a high salt content) is used for irrigation. Desalinated water is of high quality and may not lead to salinization, but in case of blending or partially desalinated water, this problem becomes particularly evident. Hence, management by means of additional irrigation (leaching requirement, *LR*) to wash out the salt from the rooting zone is an important task [48–51]. Based on these assumptions, the gross irrigation requirement (IRR_{gross}) is derived as follows:

$$IRR_{gross} = \frac{IRR_{prod}}{IRR_{eff}} + LR \tag{1}$$

with IRR_{gross}, IRR_{prod} and *LR* in cubic metres per hectare ($m^3\ ha^{-1}$) and IRR_{eff} in percent (%). The losses from inefficient irrigation, which do not contribute to crop growth (IRR_{unprod}), are assumed to percolate. These water losses can fully or partly cover *LR* [50]. Thus, *LR* refers only to the additional leaching requirement when IRR_{unprod} cannot cover the potential *LR*. The potential leaching requirement is calculated according to Ayers and Westcot [51] based on the crop's tolerable salt concentration in the rooting zone (EC_e), the salinity of the irrigation water (EC_w) and IRR_{prod} [5].

2.1.2. Economic balance

The economic balance is determined for a cropping pattern, which is planned for one year. Costs refer to desalination (c_{desal}) costs and the costs to pump water from the desalination plant to the fields (c_{trans}). The costs refer to units of water per cubic metre multiplied by the gross irrigation (IRR_{gross}) per crop and region. The revenue is calculated by multiplying the crop yield per hectare (*CY*) by the harvest area (*x*) and the producer price (*Price*). GM is calculated as follows for each region (*r*) and crop (*c*):

$$gm_{r,c} = \overbrace{\left[Price_c \times CY_{r,c} \times x_{r,c}\right]}^{\text{Revenue}} - \overbrace{\left[IRR_{gross\,r,c} \times (c_{trans} + c_{desal})\right]}^{Cost} \tag{2}$$

with c_{desal} and c_{trans} in US dollars per cubic metre (US\$ m^{-3}), IRR_{gross} in cubic metres per hectare ($m^3\ ha^{-1}$), *Price* in US dollars per tonne (US\$ t^{-1}), *CY* in tonnes per hectare ($t\ ha^{-1}$), harvest area *x* in hectares per year ($ha\ yr^{-1}$) and *gm* in US dollars per hectare (US\$ ha^{-1}). The total GM is derived by summing $gm_{r,c}$.

2.1.3. Optimization algorithm

The goal of this study is to identify the cropping patterns that make the best use of limited water resources for irrigation agriculture. Hence, a cropping pattern needs to maximize the GM and makes the best use of the water supply by desalination. Transport costs may limit the GM of fields far from the water source. Available cropland restricts the extent of irrigation areas in each region. Furthermore, the harvest area of some crops may be restricted to adjust the algorithm to specific objectives, e.g., limit the maximum area of cash crops or define the minimum areas for staple foods. This algorithm maximizes the objective function by selecting the optimal cropping pattern as follows:

$$\max(GM) = \sum_{r=1}^{R} \sum_{c=1}^{C} gm_{r,c} \cdot x_{r,c} \tag{3}$$

with the total *GM* (US\$ yr^{-1}), *gm* (US\$ ha^{-1}), and harvest area *x* ($ha\ yr^{-1}$) for all regions *r* and all crops *c*, as well as the total number of regions *R* and the total number of crops *C*. In order to consider the boundary conditions, such as limited available arable land or limited available water, the objective function is subjected to a set of boundary conditions (i.e., inequality and equality constraints):

$$\left.\begin{array}{lll} a_{inequality} & \times x \leq b_{inequality} & (i) \\ a_{equality} & \times x = b_{equality} & (ii) \end{array}\right\} \tag{4}$$

with (i) the upper bound inequality constraint $a_{inequality}$ in harvest area *x* and the upper boundary value $b_{inequality}$, as well as (ii) the upper bound equality constraint $a_{equality}$ in harvest area *x* and the values of each equality $b_{equality}$. Eq. (4) represents the general form and is solved for three constraints, which limit the selection of the possible cropping pattern. The first boundary condition relates the monthly irrigation water requirement per crop and region to the total monthly water supply. This boundary condition ('monthly water supply limit') is obligatory:

$$\begin{pmatrix} IRR_{gross1,1,1} & IRR_{gross1,1,2} & \cdots & IRR_{gross1,R,C} \\ IRR_{gross2,1,1} & IRR_{gross2,1,2} & \cdots & IRR_{gross2,R,C} \\ \cdots & \cdots & \cdots & \cdots \\ IRR_{grossM,1,1} & IRR_{grossM,1,2} & \cdots & IRR_{grossM,R,C} \end{pmatrix} \times \begin{pmatrix} x_1 \\ \cdots \\ x_c \\ \cdots \\ x_{R,C} \end{pmatrix} \leq \begin{pmatrix} WS_1 \\ WS_2 \\ \cdots \\ WS_M \end{pmatrix} \tag{5}$$

where $IRR_{gross\ M,R,C}$ is the irrigation requirement per hectare for all crops and regions in all months *M* and for the water supply *WS* ($m^3\ month^{-1}$).

The second boundary condition is optional (Eq. (6)) ('use all available water'). If activated, it forces the algorithm to use at least a minimum fraction of the available water WU_{min}, $0 \leq WU_{min} \leq 1$. WU_{min} was set to 0.95 in this study in order to account for a small deviation from the boundary conditions. For higher WU_{min}, the optimization algorithm has difficulty finding an optimal solution. This boundary condition is optional:

$$\begin{pmatrix} IRR_{gross1,1,1} & IRR_{gross1,1,2} & \cdots & IRR_{gross1,R,C} \\ IRR_{gross2,1,1} & IRR_{gross2,1,2} & \cdots & IRR_{gross2,R,C} \\ \cdots & \cdots & \cdots & \cdots \\ IRR_{grossM,1,1} & IRR_{grossM,1,2} & \cdots & IRR_{grossM,R,C} \end{pmatrix} \times -1 \times \begin{pmatrix} x_1 \\ \cdots \\ x_c \\ \cdots \\ x_{R,C} \end{pmatrix} \leq \begin{pmatrix} WS_1 \\ WS_2 \\ \cdots \\ WS_M \end{pmatrix} \times -1 \times WU_{\min} \tag{6}$$

The third boundary condition (Eq. (7)) ('limited available cropland') restricts the sum of the harvest area of all crops in a region to the available cropland in each region, whereby the upper bound inequality constraint *a* has a Boolean value (0 or 1), which indicates whether or not the restriction is applied to the combination of crop and region:

$$\begin{pmatrix} bool_{1,1,1} & bool_{1,1,2} & \cdots & bool_{1,R,C} \\ bool_{2,1,1} & bool_{2,1,2} & \cdots & bool_{,2R,C} \\ \cdots & \cdots & \cdots & \cdots \\ bool_{R,1,1} & bool_{R,1,2} & \cdots & bool_{R,R,C} \end{pmatrix} \times \begin{pmatrix} x_1 \\ \cdots \\ x_c \\ \cdots \\ x_{R,C} \end{pmatrix} \leq \begin{pmatrix} CL_1 \\ CL_2 \\ \cdots \\ CL_R \end{pmatrix} \tag{7}$$

with *bool* between 0 and 1 and potential cropland *CL*. Moreover, the software provides the ability to implement boundary conditions for the upper and lower limits of the harvest area of certain crops, i.e., to limit the area of cash crops or to produce at least the minima of staple foods. The objective function (3) and all of the inequality constraints (4–7) are linear functions. As such, the problem can be solved using a linear optimization method. One common method is the simplex algorithm [38,39], which has been implemented in many scientific programming tools, including the Python package SciPy [52]. This linear optimization problem is convex, and the simplex algorithm is guaranteed to find the global optimum, i.e., the best possible cropping pattern satisfying all of the selected constraints.

2.2. Database and study site

As a proof of concept, we applied our method in a case study for a desalination plant close to Al-Khafjy (Saudi Arabia). Table 1 gives a summary of the input data and sources. The information of the geographic location of irrigated areas was derived from the Global Map of Irrigated

Areas [53]. The cropland is ~200 km from south and south-west of Al-Khafjy and covers an area of 240 km (E-W) × 130 km (N-S). The climate conditions follow a W-E trend (Appendix Fig. A2). The average temperature slightly decreases from west to east (25–27 °C), and the average humidity and wind speed increase from west to east (30–42% and 1.86–2.28 m s^{-1}, respectively). No change is observed for sunshine hours when western and eastern areas are compared. This leads to an overall increasing W-E trend of reference evapotranspiration (2160–2400 mm yr^{-1}). Rainfall is highest in the W and lowest in the E (108–132 mm yr^{-1}). Data on the monthly crop irrigation requirements (IRR_{prod}) are available from a nationwide dataset of 3758 irrigated sites in Saudi Arabia for 19 major crops and various planting dates (www.uni-giessen.de/cms/hydro/download, "SPARE:WATER/Plot-scale irrigation requirements KSA") [14]. In detail, this database holds values on IRR_{prod} on the basis of high resolution gridded environmental data (0.063°) and long term climatic observations averaged from 1986 to 2006. The data shows a good fit in comparison to other modelling studies and field information in Saudi Arabia [14]. IRR_{eff} and the irrigation technology are uniform in space, but with varying values among crop types. We have assumed modern irrigation technology, i.e. sprinkler irrigation for cereals and fodder crops as well as drip irrigation for vegetables and fruits. The respective efficiencies are 0.70 and 0.85 for sprinkler and drip systems [54,55]. The data on crop yields were taken from statistics for each province in Saudi Arabia derived from the Ministry of Agriculture for the year 2011. Prices of the crops were taken from the FAOSTAT database [56] for Saudi Arabia, derived from the global average, or taken from other open-access sources if national prices were missing for specific crops (Fig. A4). Transport costs were derived from the vertical and horizontal pumping cost of water, i.e., 0.05 US$ m^{-3} 100 km horizontal and 100 m vertical [20] (Appendix Fig. A1). The desalination cost for RO was recently reported to be 0.5 to 1.2 US$ m^{-3} for RO [19]. Thus, we assumed desalination costs of 0.75 US$ m^{-3}. The daily production of Al-Khafjy was assumed to be 60,000 m^3 day^{-1} (21,900,000 m^3 yr^{-1}) with an electric conductivity of 1.0 dS m^{-1} (1.0 dS m^{-1}–640 mg L^{-1}).

We address two strategies to derive GM maximized cropping patterns. With Strategy I, we aim to maximize the GM and to use 95% of the available water from the desalination plant. Such a strategy may be important, particularly when no capacity for storing surplus water is available. All three of the boundary conditions in Eqs. (5)–(7) are considered. Strategy II aims to solely maximize the gross margin and refers to Eqs. (5) and (7) only.

3. Results

3.1. Monthly irrigation demand and gross margin

A cropping pattern was derived for Strategy I, i.e., maximizing GM by using most of the available water given the limited available cropland. The annual water consumption of the resulting cropping pattern sums to 21.318 Mio m^3 yr^{-1} for one year (92% of the annual water supply from the desalination plant) (Fig. 2a,c). This represents the optimal solution with a GM of 92.071 Mio US$ yr^{-1} (Fig. 2b). Tomatoes share have a GM of 88.03 Mio US$ yr^{-1}, the highest fraction of GM, and are highly productive (~30,000 US$ ha^{-1}) (Table 2). They are grown on 71% of the cultivated land (Fig. 2d). The total area cultivated sums to 4278 ha (Table 2). Tomatoes are planted throughout most of the year, from October to February. Sesame covers 11.3% of the remaining cropland, and millet, maize, cucumber and barley the rest of it. Most of the water is consumed by tomatoes (49%), followed by sesame (25%) and millet (13%) (Fig. 2a, c). Notably, 10% of the cropland (sesame) consumes 25% of the available water. The production of sesame is economically not feasible, with a negative GM of −3732 US$ ha^{-1} (Table 2). This is also the case for barley (−3877 US$ ha^{-1}) and maize (−8287 US$ ha^{-1}). The boundary condition that all of the available water should be consumed (Eq. (5)) leads to the cultivation of these economically unproductive crops. Hence, we investigated a second strategy without needing to use all of the available water.

The sole maximization of the GM under limited land and water availability in Strategy II leads to total an annual water consumption of 16.945 Mio m^3 yr^{-1} (Fig. 3a,c). This is 77% of the available water from desalination, providing a total GM of 125.131 Mio US$ yr^{-1} (Fig. 3b). Tomatoes (43%), cucumbers (56%) and a small fraction of millet (2%) constitute the majority of the GM (Table 2). The distribution of water demands across cultivated crops shows a different partitioning compared to that of Strategy I as reported in Table 2. A high fraction of IRR_{gross} is attributed to millet (25%), despite its low share (12%) of the total harvested area. In contrast, tomatoes require the same portion of IRR_{gross} but cover 45% of the harvest area. Cucumber and tomatoes are grown on 4022 ha (almost 90% of the cultivated cropland) (Fig. 3d). Cultivating cucumber achieves the highest economic yield of approximately 39,000 US$ ha^{-1} compared to that of tomatoes (~30,000 US$ ha^{-1}), but this is associated with a nearly two-times-higher water demand (4734 m^3 ha^{-1}) compared to that of tomatoes (2604 m^3 ha^{-1}). The lowest economic yield is achieved with millet (4754 US$ ha^{-1}), paired with the highest water demand (9053 m^3 ha^{-1}) of all crops in Strategy II (Table 2). Nevertheless, the GM is still positive, which is not the case for millet in Strategy I.

3.2. Regional allocation and comparative advantages

The regional distribution of the cropping pattern for Strategy I is shown in Fig. 4a. The crops are cultivated along the edges of the available cropland in the NW, W and SE. The boxplots in Fig. 4b illustrate the span of IRR_{gross} on all of the potentially cultivated cropland (grey shaded area in Fig. 4a). Asterisks indicate the average IRR_{gross} of the actually cultivated areas as allocated by the simplex algorithm. Some crops are cultivated in fields, which have a higher IRR_{gross} compared to the average IRR_{gross} of the entire cropland, as shown in Fig. 4b by the asterisks that are outside of the boxplots to the right. This is the case for barley, maize, millet and sesame, where the average IRR_{gross} of cultivated crops is higher than the average of the potential areas by 54, 12, 26 and 46%, respectively. These crops are cultivated on less productive areas regarding irrigation demand. Other crops, such as cucumber and tomatoes, are in most cases grown in comparable productive areas, as shown by the low average IRR_{gross} of the cultivated areas, which lies within the limits of the IQR of all potential areas or which is even lower than the average of the potential areas, such as for cucumber.

A likely reason for the heterogeneous spatial allocation of the crops is the producer price. Cucumber and tomatoes are cash crops with the highest profit compared to that of cereals, such as millet. These crops are allocated to the areas with the best growing conditions as determined by the simplex algorithm. Another reason is the boundary condition 'use all available water.' This condition may lead to situations where a better location for crop growth (i.e., lower IRR_{gross}) is not selected for a specific crop because it would not be in agreement with the boundary condition. To test this hypothesis, the impact of WU_{min} on the regional

Table 1
Model input data.

Data	Reference	Description
Net irrigation requirements	[5,14]	3758 sites, 19 major crops, different sowing dates
Irrigated fields	Siebert et al. [53]	Gridded map, 0.083°, ~10 × 10 km
Crop yields	Ministry of Agriculture, Saudi Arabia	19 major crops, average values between 2000 and 2011
Prices	FAOSTAT [56]	Country specific for Saudi Arabia and global average prices (Fig. A3)
Desalination costs	Ghaffour et al. [19]	0.5–1.2 US$ m^{-3}, reverse osmosis
Water transport costs	Zhou and Tol [20]	0.05 US$ m^{-3} 100 km horizontal and 100 m vertical (Fig. A1)

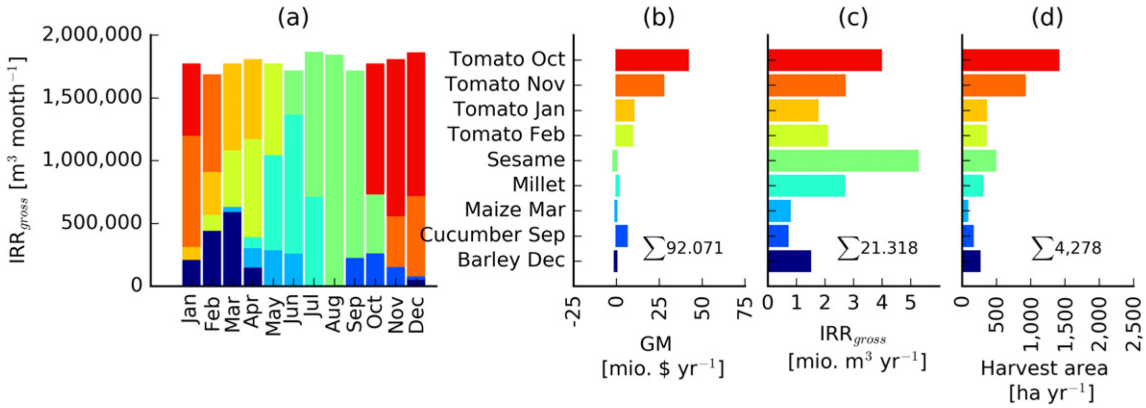

Fig. 2. Optimization of the GM and water supply according to Strategy I ('maximize gross margin and water use'; 'use all available water'; and 'limited available cropland'). The monthly water demand of crops is shown in (a). The annual gross margin GM, gross irrigation IRR_{gross}, and harvest area are depicted in (b), (c) and (d), respectively.

distribution of crops was investigated. We set $WU_{min} = 0.85$ in a second model run with all other parameters fixed (results not shown). In this case, tomatoes were also grown on fields with a lower IRR_{gross} than the average of the potential arable areas. This supports our interpretation, and we conclude that maximizing water utilization can lead to the cultivation of crops in comparable marginal arable fields in order to maintain the boundary conditions.

The second strategy shows a different result regarding the spatial distribution of actually cultivated areas. These areas are concentrated towards the W and NW of the available cropland (Fig. 5a). The fields selected by the algorithm also provide the best growing conditions. This is represented by the low average IRR_{gross} (asterisks in Fig. 4b and Fig. 5b) of the actually cultivated areas (cucumber Feb.: 5068 m^3 ha^{-1}, cucumber Sep.: 4352 m^3 ha^{-1}, tomato Nov.: 2428 m^3 ha^{-1}, tomato Oct.: 2772 m^3 ha^{-1}) compared to the IRR_{gross} of all of the potentially cultivated cropland (represented by the boxplots in Fig. 4b and Fig. 5b). An exception is millet, which is sown in areas where the average IRR_{gross} is 25% higher than the average of all regions. This finding for millet is similar to Strategy I, where cereals with a lower economic value are sown in the less productive areas.

Another interesting aspect is the general preference of cropland in the W and NW. These areas have nearly the highest cost for pumping water from the desalination plant in Al-Khafjy to the cropland (Appendix Fig. A1). However, the reason for the preferable cultivation is the better environmental conditions, i.e., higher rainfall rates and lower potential evapotranspiration (Appendix Fig. A2) that compensate for these costs.

Table 2
Per hectare results and percentage of total.

Crop	Gross margin GM [US$ ha^{-1}]	IRR_{gross} [m^3 ha^{-1}]	Harvest area [ha yr^{-1}]	IRR_{gross} [%]	Harvest area [%]
Strategy I: Maximize gross margin and water use on limited available land					
Barley Dec	-3877	5825	254	6.9%	5.9%
Cucumber Sep	39,405	4494	154	3.2%	3.6%
Maize Mar	-8287	10,386	74	3.6%	1.7%
Millet	4720	9039	295	12.5%	6.9%
Sesame	-3732	10,830	485	24.6%	11.3%
Tomato Feb	26,400	6016	344	9.7%	8.0%
Tomato Jan	28,322	4963	351	8.2%	8.2%
Tomato Nov	29,847	2939	914	12.6%	21.4%
Tomato Oct	29,656	2813	1406	18.6%	32.9%
Strategy II: Maximize gross margin on limited available land					
Cucumber Feb	38,622	5068	784	23.5%	19.5%
Cucumber Sep	39,361	4401	1001	26.0%	24.9%
Millet	4754	9053	461	24.6%	11.5%
Tomato Nov	30,015	2432	1568	22.5%	39.0%
Tomato Oct	29,648	2775	208	3.4%	5.2%

4. Discussion

By comparing irrigation Strategies I and II, we show that economically productive cropping patterns can be identified using desalinated seawater at costs of 0.75 US$ m^{-3}. However, using all of the available water for irrigating cropland does not necessarily lead to a higher GM, as shown in Strategy I, which contains crops that are economically unproductive. Thus, it is preferable to focus on a cropping pattern, which only maximizes the GM as presented in Strategy II. In this case, surplus water can be stored, used for domestic supply and industrial use, or applied to agricultural land to leach salts from the root zone to maintain soil quality.

In our study, costs refer to desalination, water transport and revenues to producer prices without considering potential subsidies. The assumption is that the user of the proposed model knows the target salinity level of the desalination plant, the daily production and the related costs per cubic metre. These parameters and the producer price of field crops have a significant impact on the determination of the cropping pattern in view of maximizing the GM. Moreover, local environmental conditions alter the irrigation requirement of field crops as well as the irrigation management (i.e., irrigation technology, efficiency, and salinity level). Due to the complexity of the GM estimation, a comparison with other literature data is difficult. Nevertheless, a rough evaluation of the economic productivity of irrigation with desalinated seawater can be made and is helpful to put the results of our study into context. This evaluation was performed for a cash crop (tomatoes) and a cereal with a lower economic value (barley).

The cropping patterns that we calculated are dominated by the harvest area of tomatoes and cucumber. Both have a high GM of approximately 30,000 and 39,000 US$ ha^{-1}, respectively. These results emphasize the economic preference of specific vegetables. Similar results have been reported by others within a modelling study growing tomatoes with desalinated brackish water from RO in Brazil [57]. The irrigation demand was assumed to be 5 mm day^{-1}, and the authors assumed an initial yield of 40 t ha^{-1}, resulting in an economic value between 42,440 (1 dS m^{-1}) and 28,590 US$ ha^{-1} (6 dS m^{-1}) for the different salinity levels. In the study of an irrigation district in Spain, it was shown that the GM of barley varies from 245 to 327 € ha^{-1} (0.10–0.12 € m^{-3}) [58] at costs of 0.06–0.15 € m^{-3} for water distribution, extraction and storage from a regional groundwater store. The authors highlight that maximum benefits are achieved when using water efficiently considering deficit scheduling rather than focusing on maximum yield production because the relative productivity of additional irrigation decreases with higher yields. This GM is high compared to that of our study, as we found a negative GM (−3877 US$ ha^{-1}). This large difference can be attributed to a 1.7-fold-higher IRR_{gross} irrigation in our study as well as the lower costs for

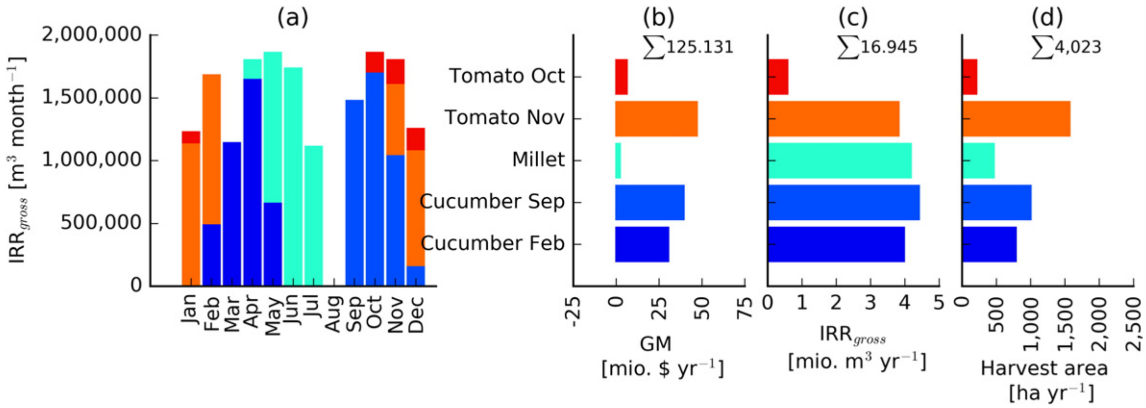

Fig. 3. Optimization of the GM and water supply according to Strategy II ('maximize gross margin' and 'limited available cropland'). The monthly water demand of crops is shown in (a). The annual gross margin GM, gross irrigation IRR_{gross}, and harvest area are given in (b), (c) and (d), respectively.

irrigation water and subsidies of 220 € ha^{-1} in Spain. The crop yield of barley is comparable between both studies, at 5.8 and 6.5 t ha^{-1} in Saudi Arabia and Spain, respectively. This value is similar for similar crops, such as wheat. In particular, low water costs lead to an economically valuable production of barley in Spain. This is not possible using rather expensive desalinated water, as is available in Saudi Arabia. We acknowledge that the environmental conditions and economic boundary conditions (subsidies, cost for irrigation water, prices, crop yield, etc.) are not comparable to those of our study, but this comparison emphasizes the general applicability of optimization models to solve water allocation problems.

We also acknowledge that we did not consider other costs related to farming practice, e.g., pesticides, fertilization, labour, machinery, harvesting, and seeding and irrigation techniques, which may alter our results. In particular, fertilization might play a major role because most minerals are removed through the RO process. The additional minerals (Mg and Ca) that need to be added to the irrigation water may cost approximately 0.09 US$ m^{-3} [59]. Alternatively, water blending with brackish water has been reported as a method to add missing minerals [59,60]. However, such a strategy could in turn increase the salt load to the rooting zone. Crop selection, in particular that of salt-tolerant crop types [61], could then become important.

As with all modelling studies, the quality of our results depends on the input data, parameter uncertainty and model structural errors. For example, different model structures and parametrizations can vary the prediction of the irrigation demand of fields crops [62]. This is likely to feed back into the results of the optimization algorithm and could be addressed in future work by ensemble modelling and model-averaging techniques [62–64]. The cropping patterns derived by our optimization process are unique. However, they could be biased by only slight advantages in the model outputs of a target variable, e.g., a certain crop gains a minimal additional GM compared to that of another crop and will be therefore selected by the algorithm. Solutions with a slightly less favourable GM are not considered, even though they might be more robust in view of other model uncertainties. Such changes have been denoted as parameter perturbations [65], and it is important to find 'robust' solutions that are independent of such perturbations. Robust optimization [66] has been highlighted in the frame of water resource planning to address such uncertainties, e.g., for designing optimal groundwater remediation systems [67]. Overall, a comprehensive uncertainty assessment, including a fuzzy-based selection of non-perfect cropping patterns, is needed and should be considered in future model development.

The production of desalinated seawater remains expensive, and its application for irrigation is justified considering other aspects of sustainability in addition to the solely economic balance.

1. Irrigation agriculture in Saudi Arabia currently relies on pumping fossil, non-renewable groundwater [43]. This results in a highly unsustainable groundwater depletion [6].
2. The pumping of groundwater is energy demanding and costly. We therefore analysed a nationwide dataset of groundwater depths (Ministry of Agriculture) to quantify the total pumping cost. Assuming a pumping cost of 0.05 US$ m^{-3} [20] for 100 m of vertical transport, the national average cost is approximately 0.16 US$ m^{-1} given an average well depth of 311 m (Fig. A3). These costs need to be

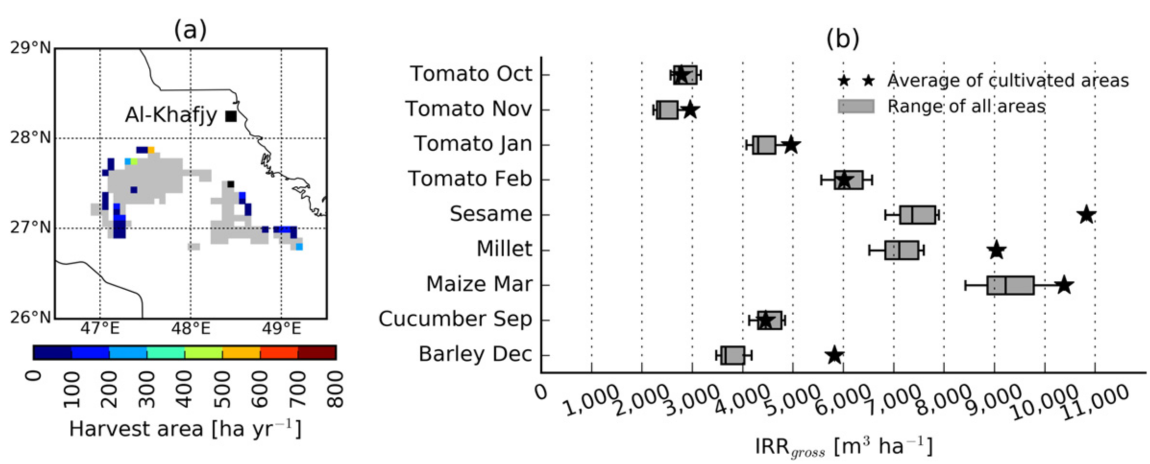

Fig. 4. Harvest area (a, grey area not cultivated) and gross irrigation (IRR_{gross}) (b) for the cropping pattern according to Strategy I. Boxes indicate the interquartile range (IQR), and whiskers represent 1.5 times the IQR of the calculated IRR_{gross} for all potentially cultivated cropland. Black stars specify the average IRR_{gross} of the actually cultivated areas as allocated by the simplex algorithm.

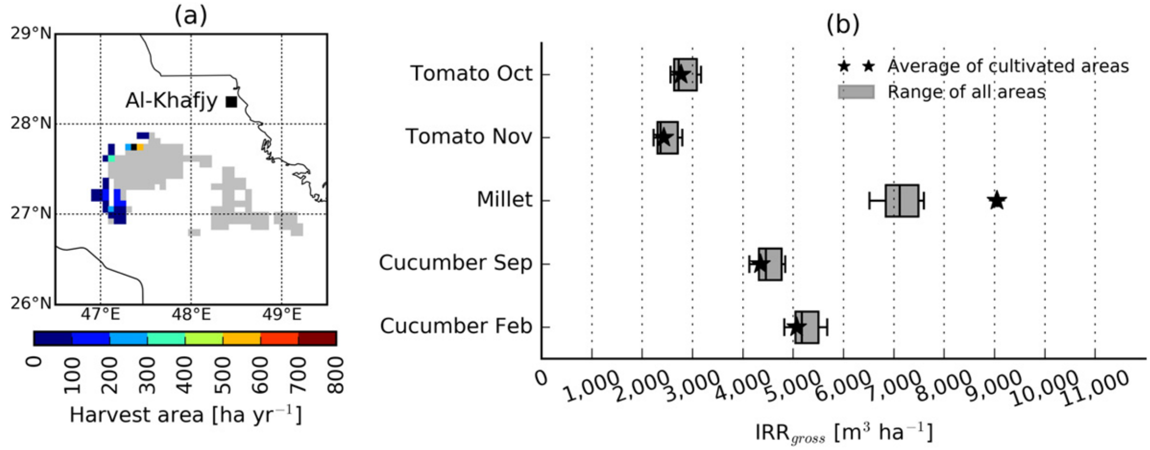

Fig. 5. Harvest area (a, grey area not cultivated) and gross irrigation (IRR$_{gross}$) (b) for the cropping pattern according to Strategy II. Boxes indicate the interquartile range (IQR), and whiskers represent 1.5 times the IQR of the calculated IRR$_{gross}$ for all potentially cultivated cropland. Black stars specify the average IRR$_{gross}$ of the actually cultivated areas as allocated by the simplex algorithm.

considered when comparing desalinated water use with pumping groundwater for irrigation.

3. The production of agricultural commodities for local markets can increase self-sufficiency and foster independence from the global food market and resilience against price shocks. For example, the national food consumption of tomatoes sums to approximately 790,000 t yr^{-1} [56] in Saudi Arabia. According to Strategy II, an area of 1776 ha can be cultivated with tomatoes, equal to 7% of the national consumption but only approximately 0.2% of the total cultivated area (0.75 Mio ha in 2011). Hence, facilitating at least a partial self-sufficiency for some cash crops and staple food commodities may be viable using desalinated seawater. Such developments are important because Saudi Arabia relies on foreign water resources. Mekonnen and Hoekstra [68] estimated that 66% of the national water footprint of consumption (i.e., water consumed by goods and services inside and outside of the country) is related to the import of services and goods (1995–2001). Such a combined analysis of desalination in the frame of the water-food nexus has been highlighted for irrigation agriculture in Australia [23] and might be of importance for Saudi Arabia and other countries.

In this study, the focus was on the determination of optimal cropping patterns, i.e., crop selection. The importance of the latter has been recently highlighted for Gulf Cooperation Council countries in order to improve the efficiency of domestic food production [69], demonstrating the need for optimization tools for planning cropping patterns based on environmental and economic aspects as presented here.

5. Conclusions

The proposed sDSS represents a newly developed tool to maximize GM by optimizing cropping patterns under limited land and water availability for desalinated water use in agriculture. This model is driven by data on local crop water requirements, and the user can set specific parameters regarding irrigation management, i.e., irrigation technology, efficiency, salinity control and crop salt tolerance. All of these parameters are important when managing agriculture and water use in the Arabian Peninsula [12].

A desalination plant is defined by its daily water production, water price and water quality. Using a straightforward approach, our tool can be easily adapted to other desalination plants and may be useful to investigate the optimal water use of other systems. Optimization has shown that crops could be cultivated even far from the desalination plant. Hence, spatial aspects and distances should be considered when optimizing desalinated seawater use in agriculture. This concept can be further extended to any irrigation problem for which a number of boundary conditions are given (e.g., legally fixed allocation of the amount of irrigation water, total available water from reservoirs or surface waters, or reduced water resource availability due to climate change).

Currently, the costs for desalination vary with different systems, plant size and many other factors [19–21]. The increasing use of solar energy will further alter these costs. Vast solar energy investments are, for example, planned in Saudi Arabia [70], aiming at a high capacity of 41 GW. A global perspective of the applicability of solar desalination indicated that MENA countries are highly amenable to such systems [71]. This will likely decrease desalination costs and therefore change optimal cropping patterns. Spatial decision support systems, such as SPARE:WATER [5], in combination with economic optimization methods as proposed in this study, are helpful for evaluating the feasibility of solar-driven seawater desalination and for use in irrigation agriculture in the future.

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Appendix A. Appendix

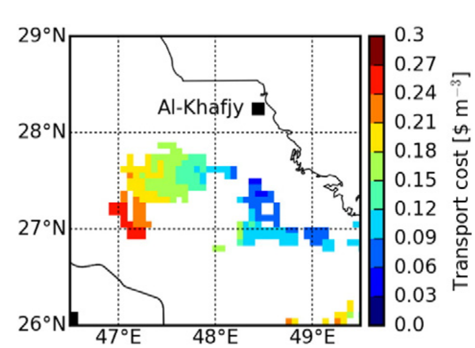

Fig. A1. Transport costs for pumping water from the Al-Khafjy desalination plant to agricultural fields.

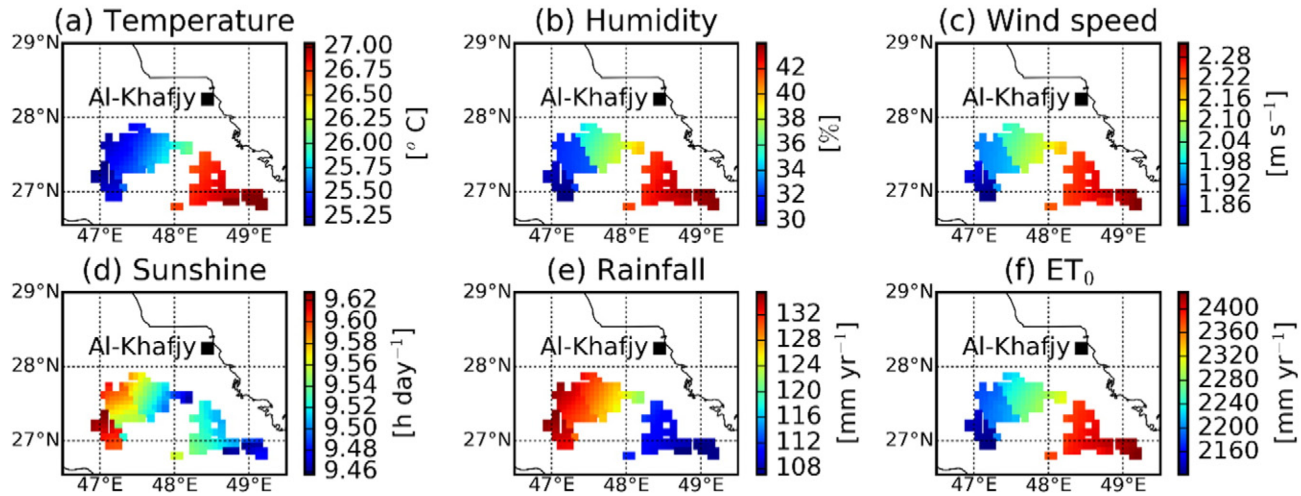

Fig. A2. Annual climatic conditions at irrigated fields close to Al-Khafjy (ET_o = reference evapotranspiration; data from the Presidency of Meteorology & Environment, PME, Saudi Arabia).

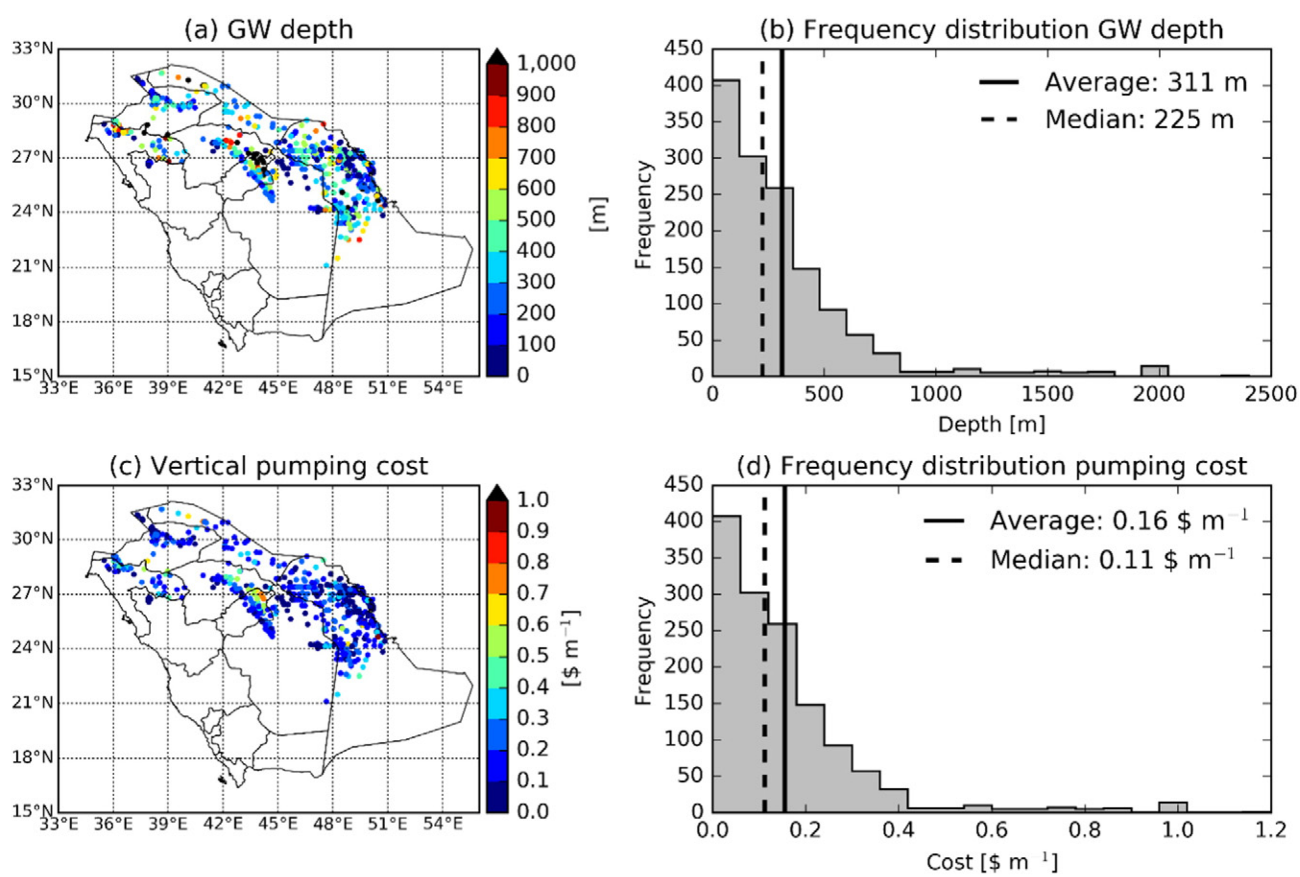

Fig. A3. Groundwater (GW) depths and associated pumping costs in Saudi Arabia. The pumping costs were calculated according to costs of 0.05 US$ m^{-1} for vertical transport [20] [data source for groundwater depths: Ministry of Agriculture, Saudi Arabia].

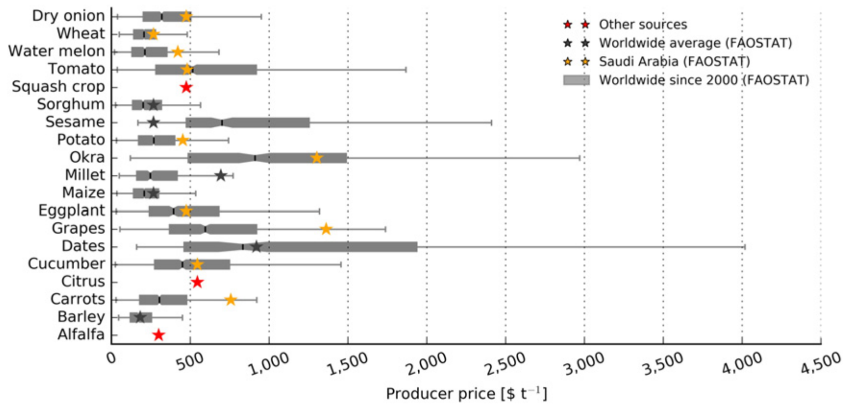

Fig. A4. Producer prices of crops according to information given by FAOSTAT [56].

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