Sustainable management of a coupled groundwater-agriculture hydrosystem using multi-criteria simulation based optimisation

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ABSTRACT

In this paper we present a new simulation-based integrated water management tool for sustainable water resources management in arid coastal environments. This tool delivers optimised groundwater withdrawal scenarios considering saltwater intrusion as a result of agricultural and municipal water abstraction. It also yields a substantially improved water use efficiency of irrigated agriculture. To allow for a robust and fast operation we unified process modelling with artificial intelligence tools and evolutionary optimisation techniques. The aquifer behaviour is represented using an artificial neural network (ANN) which emulates a numerical density-dependent groundwater flow model. The impact of agriculture is represented by stochastic crop water production functions (SCWPF). Simulation-based optimisation techniques together with the SCWPF and ANN deliver optimal groundwater abstraction and cropping patterns. To address contradicting objectives, e.g. profit-oriented agriculture vs. sustainable abstraction scenarios, we performed multi-objective optimisations using a multi-criteria optimisation algorithm.

Key words | artificial intelligence, density-dependent groundwater flow modelling, integrated water resources management, irrigation, multi-criteria optimisation

INTRODUCTION

The overexploitation of groundwater resources by agriculture is a growing concern worldwide. Coastal regions in arid climates are particularly vulnerable to excessive groundwater mining because declining groundwater levels lead to saltwater intrusion into the aquifer systems. Using this increasingly saline water for irrigation destroys the agricultural resources, which are the economic basis for the farmers and their communities. The worldwide relevance of this mechanism, e.g. at the coasts of Mexico, Australia, Oman, and along the Mediterranean Sea, was discussed by several authors (Cardona et al. 2004; Narayan et al. 2007; Kacimov et al. 2009).

Up to now, three different types of modelling approach have been used in water resources management: (1) employing simplistic optimisation models (e.g. linear programming), (2) replacing the optimisation procedure with the simulation of several – subjectively selected – ‘what if’ scenarios and then selecting the best alternatives that satisfy certain objective criteria (Harou et al. 2009), and (3) simulation-optimisation. While the second approach results in suboptimal solutions, the first approach suffers from inadequate process descriptions. A general shortcoming of current management models is that they do not reliably portray nonlinear, interdependent phenomena of complex hydrological systems and their interdependencies. In addition, the impact of uncertainties of a changing environment associated with global change on the sustainable management of coupled groundwater–agriculture systems cannot be quantified. To overcome these shortcomings, the third approach – which is referred to as simulation-optimisation – was introduced by Gosavi (2003) who suggested a combination of physically based numerical models and (black-box) optimisation methods. Unfortunately, the optimisation of complex water resources systems often becomes computationally intractable when solving simulation-optimisation problems with large numbers of design variables and/or objectives (Loucks & van Beek 2005).
The latest simulation-optimisation modelling approaches extend classical simulation-optimisation strategies by two improvements:

1. customised tuned simulation-optimisation based on surrogate models – these are models which describe the behaviour of process models using only the most relevant features, and
2. the decomposition of complex optimisation problems.

Both improvements are already introduced in management of coastal aquifer systems. Mostly, artificial neural networks (ANN) (Rao et al. 2004; Bhattacharjya & Datta 2009; Dhar & Datta 2009) or piecewise linear transformations (Rejani et al. 2009) are used as surrogate models to emulate the behaviour of groundwater flow models. The resulting surrogate models help to solve mono-criteria optimisation problems, which are represented by a single objective function (Rao et al. 2004), and multi-criteria optimisation problems, if more than one objective function exists (Bhattacharjya & Datta 2009; Dhar & Datta 2009). However, the surrogate models in these studies were designed only for a predefined time period and do not allow for an application of optimisation problems with varying time horizons, which is a major limitation for optimally solving water resources management problems. Another limitation of these studies is that they used detailed model descriptions for the aquifer only, but did not realistically consider the demand side, i.e. the agricultural system and its interdependencies with the aquifer.

The decomposition of optimisation problems is aimed at the separation of a complex optimisation problem characterised by a high number of decision variables into smaller, independent optimisation problems which allow for a faster and more reliable solution of the complex optimisation problem. As an example, Schmitz et al. (2007) applied decomposition for optimising furrow irrigation systems by separating the problem of optimal irrigation control from the general problem of optimal irrigation scheduling. More recently, Schütze (2012c) proposed a decomposition solution strategy which allows for the use of numerical process models and Monte Carlo simulations for an optimal water demand management at plot and regional scale.

Within this paper we present key issues of a new simulation-based integrated water management system for sustainable water management in arid zones. We use physically based models to simulate the interacting processes of a fully interacting groundwater–agriculture system, which is affected by water quality due to saltwater intrusion. This model system is linked with multi-criteria optimisation to determine optimal groundwater abstraction schemes and cropping patterns. To get optimal results within reasonable time, surrogate models are introduced which extend the latest approaches by also considering the agricultural water demand, and allow for an application of different time horizons. The combination of a multi-criteria optimisation framework and the derived surrogate models forms a new prototype of a simulation-based integrated water management tool. The functionality of the proposed prototype is demonstrated by a real world example of the Al Batinah coastal region in Oman.

### MATERIALS AND METHODS

Basic components of the simulation-based integrated water management system are shown in Figure 1. This combines coupled simulation models, which are describing the considered hydrological systems, one or more objective function(s) and an adequate simulation-optimisation (S-O) method, which are all to be assumed to be fully interoperable.

In the following, an overview about a real application case is given as well as the three elementary steps which are necessary to apply the simulation-optimisation approach in an extended optimisation framework based on surrogate modelling. These steps are as follows:

1. The setup of process models for simulating the behaviour of the agricultural production as well as the aquifer (see subsection “Data and process model setup”).
2. The development of appropriate surrogate models. These models describe the behaviour of the process models – and at last the behaviour of the natural system. However, the surrogate models only use the most important state and decision variables which are relevant for an optimal management (see subsection “Methods to generate surrogate model”).
The application of the surrogates within a multi-criteria optimisation framework for evaluating Pareto-optimal data sets of the decision variables according to contradicting objectives (see subsection “The optimisation framework for multi-criteria simulation-based optimisation”).

The study site

The study site is located in the north of the Sultanate of Oman in the Al Batinah region. Al Batinah is a roughly 30 km broad coastal plain which extends over 250 km along the coast of the Gulf of Oman north-westward of the capital Muscat. The area comprises the coastal zone of the Wadi Ma’awil catchment, as shown in Figure 2.

Oman’s agricultural production requires irrigation due to arid climate conditions. Most of the farms are located near the coastline and the farmers abstract the water for irrigation from a coastal aquifer by numerous decentralised and often uncontrolled wells (Figure 2). A progressive intensification of the agriculture since the 1980s along with inefficient irrigation practices led to an increasing water demand and to continuously declining groundwater levels. Ongoing overexploitation of the aquifer enforced the intrusion of marine salt water. As a result, this saltwater intrusion caused the closure of numerous coastline farms due to the increasing irrigation water and soil salinities, and therefore it threatens the economic basis for the farmers and their communities.

The coastal aquifer system is replenished mainly by the lateral inflow caused by the rainfall in the upper mountainous part of the catchment. Long-term measurements show mean average precipitation values up to 250 mm/y in the upper mountains and about 50 mm/y along the coastline. The rainfall variability in time and space is extremely high, which means that relatively wet years can be followed by long dry periods over a couple of years.

Data and process model setup

Agricultural production

Local agriculture is practiced by numerous small-scale farms of less than a hectare of land employing irrigation due to local arid conditions. This permits a variety of crops (field crops to fruit trees) to be grown (Sultanate of Oman 2005). According to the aim of the study, the long-term evaluation of the environmental and economical development of a
hypothetical farm – located in the vicinity of the sea – under different management strategies is investigated. For the sake of simplicity the cultivation of two different crops, maize – a salt-sensitive cash crop – and sorghum – a lower priced but more salt-resistant crop, growing in two seasons per year is assumed.

For simulating the agricultural system we used observed daily weather data taken over the last 16 years (1991–2006) from Seeb weather station (International airport, Muscat). A sandy loam soil is typical for the region (50, 36 and 14% sand, silt and clay, respectively) and soil hydraulic properties were taken from Abdelrahman et al. (1993). These data are used to parameterise the Agricultural Production Systems Simulator (APSIM by Keating et al. (2005)) for simulating soil water transport and crop growth.

Coastal aquifer

The spatial extension of the considered aquifer system covers the coastal area where agriculture is practiced. The hydrogeology of the study site is characterised by a complex heterogeneous structure of fluviatile, aeolian, and marine deposits, consisting of locally cemented gravels, differently sized sand, silt, loam and clay (Walther et al. 2002). Walther et al. (2012) analysed the available data which were provided by the Ministry of Regional Municipalities and Water Resources and set up a heterogeneous 3D density-dependent groundwater flow model of the alluvial coastal aquifer based on the OpenGeoSys software package (Kolditz et al. 2008) for the study site.

To demonstrate the features of the optimisation framework, a 2D vertical slice of the unconfined 3D alluvial coastal aquifer model was constructed to simulate groundwater flow and to account for saline intrusion and transport. Dimensions and parameters of the model are derived and generalised from the upper layer of a heterogeneous 3D groundwater flow model. The model domain is 6 km long with an aquifer thickness of 57 m at the sea boundary and 73 m at the upstream plain side, respectively. It consists of a single unconfined layer with a hydraulic conductivity $k = 1 \times 10^{-3} \text{ m/s}$ and a porosity of $n = 0.3$. At the upstream boundary a constant flux boundary condition with an estimated inflow $q_0$, which is equal to the replenishment of the aquifer, is used. The sea side boundary condition consists of a constant pressure (sea water level) together with a constant salt concentration. Source terms within the model domain are applied to represent the extraction behaviour of the farmers using constant extraction rates during one cultivation period.

Methods to generate surrogate models

Estimation of 2D crop water production functions for modelling of impacts of water and salt stress on crop yield

The surrogate model for the agricultural production, called 2D-crop water production function (2D-CWPF), is derived by an extension of the OCCASION methodology (Optimal Climate Change Adaption Strategies in Irrigation by Schütze & Schmitz (2010)) as shown in Figure 3(a).

At first, the physically based SVAT (soil, vegetation and atmosphere) model APSIM is coupled with the GET-OPTIS tailor-made evolutionary optimisation algorithm for optimal irrigation scheduling (Schütze et al. 2012a) in order to calculate the maximum yield for a given amount of water and the corresponding optimal irrigation schedule (Loop 1 in Figure 3(a)).

Secondly, the given amounts of water for irrigation are varied (Loop 2 in Figure 3(a)) which results in a single crop water production function (CWPF). The CWPF describes the relationship between the amount of irrigated water and the potential crop yield which can be achieved for each crop and season assuming an optimal water application.

Within a third loop (Monte Carlo Loop in Figure 3(a)) different realisations of local weather characteristics are incorporated in order to derive more robust irrigation schedules. This allows for an agricultural production with a certain reliability. Therefore, 100 synthetic weather realisations were generated by the LARS-WG weather generator (Semenov et al. 1998) on the basis of the aforementioned observed daily weather data from Seeb weather station. Each weather realisation results in a single CWPF. A statistical analysis of the whole set of single CWPFs provides an empirical joint probability function which is referred to as the stochastic crop water production function (SCWPF).

In order to include salinity stress, the SCWPF is extended by a second dimension, namely the salinity of the irrigation water using the salinity tolerance index (Steppuhn et al. 2005). Combining this index with the SCWPF results in a 2D-SCWPF which additionally considers the consequences of the water quality and allows for an appropriate choice of the crop patterns regarding their salinity tolerance. The SCWPF considers climate variability and provides general applicable irrigation schedules which may achieve a certain amount of yield with a given reliability (e.g. 90%), i.e. a given quantile. Once the quantile is defined it is possible to derive a conditional CWPF which is introduced here as 2D-CWPF0.9. The functional relationships of the 2D-SCWPF for defined
Figure 3  Simulation-based integrated water management system consisting of: (a) the estimation procedure for the 2D crop water production function, the surrogate model which describes the agricultural production (2D-CWPF), (b) the procedure of the setup of the surrogate model for describing the aquifer behaviour (ANN-OGS) and (c) the optimisation framework, which links the derived surrogate models with the multi-criteria optimisation algorithm for multi-objective optimisation (AMALGAM) for maximising agricultural profit and aquifer sustainability.
soils, crops and irrigation methods as well as the corresponding optimal irrigation schedules are stored in a database.

The surrogate model for modelling the aquifer behaviour

For describing the aquifer behaviour, including the phenomena of seawater intrusion, we use an ANN as a surrogate for the numerical groundwater model OpenGeoSys as shown in Figure 3(b). The final surrogate model is referred to as ANN-OGS. The ANN-OGS is set up as follows.

At first, the above outlined model setup of the 2D OpenGeoSys model is used to generate a database containing the responses of the numerical density-dependent groundwater flow model for all realistically feasible abstraction scenarios. As well as the state variables, average salinity concentration $S$ and water levels $h$ before ($t_{i-1}$) and after abstraction ($t_i$), are stored in a scenario database for selected observation points $x_k$. All together, 2,546 scenarios over 20 years are simulated on a PC-cluster with the 2D OpenGeoSys model.

In a second step, the training of an ANN – more specifically a multilayer perceptron net (Nabney 2002) – is performed with a back propagation learning algorithm (Yan & Minsker 2006). The chosen structure of the ANN-OGS comprises input values of water level and values of average salinity at 13 given observation points $x_k$ at the beginning of a cultivation period as well as the abstraction rate over the period (26 input nodes). As output the ANN-OGS provides the values for the same state variables at the end of the cultivation period at 25 output nodes. This state-space ANN architecture makes it possible to simulate the aquifer’s behaviour over different time periods.

The optimisation framework for multi-criteria simulation-based optimisation

The simulation-based integrated water management system, illustrated in Figure 3(c), combines the agricultural and groundwater module within a multi-criteria optimisation framework. It aims to manage both water quality and quantity according to the given objectives. However, the management objectives depend on the interests of the decision maker. The AMALGAM multi-criteria optimisation algorithm which can be seen in Figure 3(c) evaluates Pareto-optimal solutions which allow for identification of best compromises between the given objectives.

Considering a sustainable aquifer management a first objective function ($of_1$) is formulated as sustainability index (Equation (1)) which describes the stability of the water balance and distribution of the salt concentration in the groundwater system:

$$of_1(t_n) = \sum_{k=1}^{end} \frac{abs(S(t_1, x_k) - S(t_n, x_k))}{s_{max}} + \sum_{k=1}^{end} \frac{abs(h(t_1, x_k) - h(t_n, x_k))}{h_{max}}$$  \hspace{1cm} (1)

The index evaluates the change of the aquifer state between the end $t_n$ and the initial state $t_1$ of the simulation period using the average salinity concentration $S$ and the water levels $h$ on the $x_k$ observation points, where a small sustainability index value indicates a high stability of the aquifer system.

The second objective function ($of_2$) is related to the agricultural production and assumes a rational, profit-oriented behaviour of the farmers by evaluating all the revenues minus the costs (Equation (2)).

$$of_2 = \sum_{i=1}^{n} \left[ \left( \sum_{j=1}^{m} P_j Y_j L_j(t_i) - CI_j(t_i) \right) - CP(t_i) \right]$$  \hspace{1cm} (2)

where, $CI_j$ and $CP$ are the fixed and variable costs for the irrigated agriculture and the groundwater pumping respectively, $P_j$ the current prices for the cultivated crops $j = 1 \ldots m$ which are produced from the acreage $L_j$ for the cultivation period $i = 1 \ldots n$, and $Y_j$ the crop yield.

However, both objective functions are contradictory. If the farmers aim at earning high profit – to maximise $of_2$ – they tend to pump as much as possible. But this worsens the aquifer’s situation due to a declining water table and an enforced salt water intrusion which has a negative impact on objective function $of_1$ – the sustainability of the aquifer management.

$$\text{max}(OF^*) = \{-of_1, of_2\}$$  \hspace{1cm} (3)

$$(A_1(t_1) \ldots A_1(t_n), A_m(t_1) \ldots A_m(t_n), L(t_1) \ldots L(t_n), Q(t_1) \ldots Q(t_n)) = \text{arg}(OF^*)$$  \hspace{1cm} (4)

To solve the formulated multi-objective optimisation problem (Equations (3) and (4)) the multi-criteria AMALGAM algorithm (Vrugt et al. 2009) is used which can be seen in Figure 3(c). The AMALGAM algorithm evaluates Pareto-optimal solutions which allow for identification of best compromises between the given objectives.
Decision variables within the optimisation problem (Equation (4)) are: $A_t$ the percentage of the cultivated crops – the cropping pattern, the acreage $L$ and the groundwater pumping rates $Q$ for every cultivation period $i = 1 \ldots n$.

The optimisation framework (Figure 3(c)) works as follows. At first, estimates of the decision variables are provided by the optimisation algorithm. Secondly, the consequences, in terms of water level and salinity changes, of the given decision variable, i.e. the pumping rates, are evaluated by the groundwater surrogate model ANN-OGS (Equation (5)). Afterwards, the calculated salinity value of the pumped water for irrigation and the pumping rate are used to calculate the crop yields using the irrigation module (i.e. the 2D-CWPF$^{0.9}$ surrogate model) according to the given values of crop pattern and acreage (Equation (6)).

$$h(t_i, x), S(t_i, x) = \text{ANN-OGS}(h(t_{i-1}, x), S(t_{i-1}, x), Q(t_i))$$  \hspace{1cm} (5)

$$Y_f(t_i) = A_f(t_i) \cdot \text{2D-CWPF}^{0.9}(Q(t_i), S(t_i, x_p))$$ \hspace{1cm} (6)

Finally, by incorporating regional specific cost models for the irrigated agriculture and the groundwater abstraction (Malik & Al-Zubeidi 2006), the net profit (Equation (2)) is calculated at the end of the simulation period as well as the sustainability index (Equation (1)). Iterative simulations over improved estimates of the decision variables – given by the optimisation algorithm according to the multi-objective problem (Equations (3) and (4)) – allow for a successive approximation of the true Pareto front.

RESULTS AND DISCUSSION

Generation of surrogate models

The derived surrogate model for the agricultural production (i.e. the database of 2D-CWPF$^{0.9}$, see Figure 3(a)) contains water demand functions for a yield reliability of 90% assuming an irrigation efficiency of 100%. The functions indicate that sorghum achieves a higher yield for a given amount of water and has a higher salt tolerance than maize (9.9 t/ha vs. 7.1 t/ha at 400 mm irrigation volume). However, the price per ton for maize is higher than for sorghum (US$150/t vs. US$100/t), which offers a higher profit, if the water quality is good. To account for different irrigation methods, the water demand has to be divided by the irrigation efficiency of the applied irrigation method (for more details see Schütze et al. 2012b and Grundmann et al. 2012).

To validate the results of the groundwater surrogate ANN-OGS, 625 of the simulated scenarios are used to calculate the root mean square error (RMSE) between simulation results of the surrogate model and the numerical simulation model. The very low RMSE values of 0.0042 m for the groundwater levels and 44 $\mu$S/cm for the salinity values demonstrate the high ability of the derived surrogate model to simulate the aquifer behaviour instead of the physically based 2D OpenGeoSys model. Furthermore, the ANN-OGS operates approximately 1,000 times faster than the physically based OpenGeoSys model, which allows for multi-criteria optimisation within a reasonable time (a couple of hours instead a couple of months).

Application of the multi-criteria optimisation framework

Figure 4 shows results for multi-criteria optimisation run where the ‘Sustainability Index ($of_1$)’ is plotted over the ‘Profit ($of_2$)’ for all solutions which are evaluated during the optimisation procedure. Therefore, the dark dots represent all solutions found by the optimisation algorithm. The crosses comprise the Pareto-optimal data set, i.e. the Pareto front. In addition, the circles represent specific optimal solutions assuming certain weights assigned to the single objective functions $of_1$ and $of_2$. Varied solutions along the Pareto front are of multi-objective type and represent potential compromises between contradicting objectives, depending on the relationship or weighting between both objectives.

Within this application the Pareto-optimal data set consists of 1,743 solutions. The shape of the Pareto front may be divided into two different ranges between specific optimal solutions (circles). Part one comprises the range between the single solution, where only $of_1$ is considered, and the solution labelled as ‘multi-objective scenario’. In this range, only a moderate change in the hydrological system stability occurs if the profit of the agricultural production increases. Within the second part – between the solutions labelled as ‘multi-objective scenario’ and ‘the long-term profit scenario’ ($of_2$), respectively – an increase of the agricultural production yields to a stronger change in the groundwater system’s stability, which means a higher risk for damaging the groundwater system.

Figure 5 presents the temporal variability in profit, crop pattern percentages, and the irrigation water salinity for the specific solutions ‘multi-objective scenario’ and ‘the
long-term profit scenario’ (circles in Figure 4). The ‘long-term profit scenario’ shows an increase in profit during the first 15 years and then diminishes with time, necessitating changes in the crop pattern caused by steadily increasing aquifer salinity. In contrast, the ‘multi-objective scenario’ generates relatively smoother graphs. In this scenario, maize is grown consistently, but on a smaller relative acreage than in the first years of the profit scenario. As a result, the salinity in irrigation water rises only slightly and a modest, sustainable profit is achieved over the entire 20-year time frame. Due to smaller acreage and pumping rates of the ‘multi-objective scenario’, the fixed initial costs for pumping and irrigation equipment are lower than for the long-term profit scenario. This is shown by different initial values of the profit graphs for the given configuration of the prototype application. Nevertheless, the cumulative profit over the time of 20 years is more than two times higher for the ‘long-term profit scenario’ as displayed in Figure 4. However, a comparison of the gradients of the profit and salinity graphs at the end of the 20-year period between the selected scenarios indicates that under the ‘long-term profit scenario’, the farmer will no longer find agricultural production to be profitable due to increased salinity values. In contrast, for the ‘multi-objective scenario’, the farmer can work sustainably for further years because of a more sustainable aquifer management.
In general, multi-objective optimisation problems can be solved either by means of a multi-criteria optimisation shown in this paper or in a simplified manner by a weighted sum of the objective functions using a mono-criteria optimisation algorithm. Grundmann et al. (2022) applied the latter approach and evaluated solutions for the ‘long-term profit scenario’ and the ‘multi-objective scenario’. A comparison of the results achieved by Grundmann et al. (2022) with those of this study shows similar results for both scenarios. Especially the objective function values are in agreement with the corresponding points on the Pareto front. This indicates that the multi-objective solution converges to the true Pareto front. However, the multi-criteria optimisation approach provides a larger set of Pareto-optimal solutions, which allows for identification of best compromises between the given objectives. Therefore, the Pareto-optimal data sets can potentially serve as tools for stakeholders and decision makers in order to evaluate management decisions according to their management goals. As shown in this study, these goals may include sustainable environmental and socio-economic development parameters or criteria.

CONCLUSION AND OUTLOOK

The presented prototype of a simulation-based integrated water management model allows for the management of both water quality and quantity of a coupled, dynamic agriculture–groundwater system. Thereby, the modelling of the density-driven groundwater flow is mandatory for calculating crop yield damages due to aquifer overpumping and irrigation with salty water. The application, dealing with a typical management problem in coastal arid regions, shows that farm operation focusing exclusively on profit maximisation leads sooner or later to further progress of the saltwater front. Therefore, the objective of sustainability must explicitly be considered as a second optimisation objective to provide sustainable solutions both in an environmental and social sense. The performed multi-criteria optimisation run helps to understand the interplay and feedback mechanisms between a groundwater management and the agricultural production in terms of water quantity and quality. With the application of a multi-criteria optimisation algorithm we demonstrate the capability of Pareto-optimal solutions to find best compromises between contradicting management objectives. To find the true Pareto front within reasonable time a rigorous application of artificial intelligence methods is necessary in order to speed up the simulations. Along these lines, the presented prototype forms the basis for the development of a large-scale management and planning system focusing on a sustainable arid-zone water resources management. Nevertheless there is still a need for a careful evaluation of the results and preselection of appropriate management scenarios (e.g. due to large number of members of the Pareto-optimal data set). In this context further efforts are necessary to analyse and formulate the optimisation problem and its constraints as well as to compare appropriate optimisation algorithms which are able to solve the multi-criteria optimisation problem.

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