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Multiobjective Optimization for Sustainable Groundwater Management in Semiarid Regions

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Abstract: Increasing demands for water by competing users in semiarid regions pose new challenges for water resources managers. Decision makers must understand the interactions between surface water, groundwater, and the environmental system. Additionally, the decisions made with regard to water transfer and allocation must take into consideration the diverse objectives that include water supply, cost efficiency, and ecosystem protection. The work presented herein demonstrates the use of groundwater simulation and optimization to construct a decision support system (DSS) for solving a groundwater management problem associated with the Upper San Pedro River Basin, located in southeastern Arizona. The case is treated as a multiobjective optimization problem in which environmental objectives are explicitly considered by minimizing the magnitude and extent of drawdown within a prespecified region. The approach adopted uses the constraint method to derive the tradeoffs among three competing objectives. Once the proposed algorithm identifies a set of efficient solutions (alternatives), concepts borrowed from fuzzy set theory are applied to rank the alternatives and to assist decision makers in selecting a suitable policy among them, each of which is optimum with regard to its goal and the corresponding consequences.

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Introduction

In an era of increasing demand for water resources, new paradigms of social involvement—as well as better knowledge about the relations among surface water, groundwater, and environmental objectives—make it necessary to devise innovative decision-making tools comprised of sound science, significant amounts of data, and societal preferences. Although the concept of sustainability lacks a concise, agreed-upon definition, in most circumstances sustainable development involves taking care of the needs of the present without compromising the ability of future generations to meet their own needs. Although there is great uncertainty about what future generations would want us to do for them, identifying the tradeoffs among current priorities and our guesses about future generations’ priorities is an important component of any study involving sustainability. Once these tradeoffs are estimated, or at least identified, they can be presented for negotiation and conflict resolution in the political arena. There is no scientific theory to aid in identifying which tradeoffs, if any, are optimum (Task Committee 1998).

Groundwater simulation and optimization techniques have been used together to explore management options. Depending on the particular problem under consideration and the assumptions made in solving it, the optimization problem may be linear, nonlinear, continuous or discrete, or a combination of both. Linear programming has been applied successfully in determining optimal operational policies in water supply systems (Louie et al. 1984; Elmagnouni and Treichel 1994). Quadratic programming has been used when pumping costs depend on drawdown, usually when drawdown magnitude exceeds a small fraction of the saturated thickness (Shafike et al. 1992). Discrete optimization is required in a broad range of design problems. Fixed costs of installing new wells may be a relevant component of cost functions in groundwater planning strategies (Hsiao and Chang 2002). Monitoring network design and several groundwater remediation design projects give rise to combinatorial problems in which decision variables include location of wells and pumping rates (Hsu and Yeh 1989; Ritzel et al. 1994). For this particularly difficult kind of problem, discrete optimization algorithms, such as dynamic programming, branch and bound, local search, and evolutionary algorithms (e.g., genetic algorithms), have been applied successfully. For sites in which complex hydrogeological conditions obscure an obvious intuitive design, simulation-optimization techniques help decision makers in shedding light over alternate feasible options (Ahlfeld and Heidari 1994).

Most of the published works to date on simulation-optimization applications to groundwater management are confined to small- to medium-size sites. In those cases, a single or centralized decision maker is able to define relevant objectives and preferred solutions. When applying systems analysis to a large-scale problem, however, new difficulties arise. First, generally there exists more than one decision maker, and therefore numerous conflicting objectives can be defined. Second, the number of decision and state variables may increase rapidly with the
scale of the problem, increasing the computational burden of obtaining optimal solutions. Third, large-scale systems cannot be treated as lumped systems, and spatial dependence of the problem must be considered when defining objectives and constraints. Furthermore, from a policy perspective, decision makers are faced with the problem of devising management tools to deal with decision variables that may not be under centralized management. For example, hundreds or thousands of small private pumping wells may exert significant stress on the aquifer system, but may be very difficult to manage coherently. When a decision maker can define a problem and articulate the objectives for its solution, it is said that the problem is well structured. In many cases, although an ultimate abstract objective may exist, complex spatial problems are ill- or semistructured and decision makers find it difficult to fully articulate their objectives (Densham 1991). In such circumstances, traditional prescriptive analytical techniques may prove unsatisfactory to decision makers, and therefore more flexible interactive approaches should be sought.

The work presented here focuses on the formulation and construction of a multiobjective management model for groundwater resources on a basin-wide scale, with explicit consideration of environmental objectives. The aim is to estimate the tradeoffs among objectives that represent current needs and objectives representing guesses about priorities of future generations. These objectives are, respectively, the exploitation of groundwater resources and the conservation of ecosystems that depend on the interaction of groundwater and surface water.

The proposed methodology is tested using data collected from the Upper San Pedro River Basin, located in southern Arizona. The San Pedro River is one of the last free flowing rivers in the western U.S., supporting a riparian habitat that harbors hundreds of species of migratory birds, as well as several species of mammals and amphibious, some of which are endangered. The Basin has seen significant population growth, which has increased the demand for groundwater resources that replenish the San Pedro River base flow for much of the year [U. S. Geological Survey (USGS) 1999]. Because of excessive pumping, several reaches of the River have become intermittent. Sound groundwater management policies are required to ensure the sustainability of human development in the Basin, protecting the riparian habitat and the fauna it sustains.

**Case Study**

**General Information**

The Upper San Pedro River Basin is located in the semiarid borderland of southeastern Arizona and the state of Sonora, Mexico. The upper and middle portions of the San Pedro River Basin have a drainage area of 7,610 km² at the USGS gauging station at Redington, Arizona, of which 1,800 km² are located in Mexico (USGS 1999). From an ecological point of view, the Basin, and particularly its upper portion, is an ecosystem of unparalleled importance in the region. The riparian corridor is a key factor in the journey of migratory birds, harboring the richest densest and most diverse inland population—with 385 identified species—in the continental U.S. Additionally, 82 species of mammals, 43 kinds of reptiles and amphibians, and populations of cottonwood-willow and mesquite trees also inhabit this ecosystem (Kingsolver 2000). Of particular relevance is the San Pedro Riparian National Conservation Area (SPRCA). The SPRCA is the United States’ first riparian reserve, established by the U.S. Congress in 1988 in an effort to preserve the rare riparian habitat from damage due to increasing water demands in the surrounding area.

**Hydrogeology**

The San Pedro River Basin is located in the Basin and Range morphologic region, which spans much of the U.S. Southwest. The primary regional aquifer fills the structural depression between the Huachuca Mountains and the Mule Mountains. Groundwater flow is replenished by precipitation occurring mainly in the higher areas of the mountains along the Basin. Recharge occurs in the foothill areas and groundwater flows toward the center of the basin, replenishing the base flow of the San Pedro River. The regional aquifer presents unconfined conditions, although scattered clay lenses may generate confined conditions locally. Near the mountain front, perched water table and steep hydraulic gradients may occur in areas overlying fine-grained sediments.

Groundwater discharges as base flow in the San Pedro and Babocomari Rivers. A significant amount of water is lost due to evapotranspiration through phreatophytes. Pumping occurring up-gradient from the San Pedro and Babocomari intercepts groundwater, and the withdrawal of groundwater from aquifer storage has created a cone of depression in the area near the city of Sierra Vista (USGS 1999). There is widespread concern that this cone of depression, if unchecked, may turn perennial reaches of the San Pedro River into ephemeral, thus jeopardizing the riparian habitat that depends on the base flows of the River.

**Methodology**

The proposed simulation-optimization approach requires two numerical algorithms. The first solves the groundwater flow governing equation. The other seeks an optimal feasible solution to the management problem, given the constraints imposed by the flow system and other physical and institutional constraints.

**Groundwater Model**

The San Pedro River Basin has been studied intensely over the past 20 years and a number of simulation models have been proposed to characterize the groundwater flow regime. A model developed at the University of Arizona (Goode and Maddock 2000) is adopted, which uses a finite difference discretization and MODFLOW (Harbaugh et al. 2000) to simulate steady and transient conditions in the Upper San Pedro River Basin under different extraction scenarios. The simulation model improves previous modeling efforts and uses a four-layered structure with 171 rows and 90 columns in order to represent the real system. The model was calibrated to replicate steady state (prior to year 1960) and transient (period 1940–1997) observations. Goode and Maddock (2000) identified, as of 1997, a total of 3,470 pumping wells with individual pumping rates ranging from 0.0 to 2,761 m³ per day.

**Management Model**

The management model aims to define a set of best groundwater pumping and recharge policies in a basin where groundwater is the main supply source. At a basin-wide scale, spatial variability of the demand motivates the definition of operational sectors (users), \( j = 1 \ldots U \). User \( j \) may receive water from any of the water sources, \( i = 1 \ldots S \). Treatment plants, \( k = 1 \ldots T \), receive effluents.
and return flow from the operational sectors and, afterward, the treated water is discharged or recycled at discharge facilities, \( \ell = 1 \ldots D \). Furthermore, demand at the operational sectors may be offset by the implementation of water conservation projects, \( m = 1 \ldots W \). Three management objectives are considered in the formulation: minimizing the net present value of mitigation costs, maximizing aquifer yield, and minimizing drawdown at selected locations.

**Minimizing the net present value of groundwater depletion mitigation cost.** The goal of preserving the San Pedro River involves acting over groundwater exploitation patterns, as well as searching for alternative sources of water supply for the Basin. Among the many water conservation initiatives that have been proposed to offset water demands in the San Pedro Basin [Upper San Pedro Partnership (USPP) 2003], we have chosen a subset of mitigation projects to serve as an example of how the proposed methodology can be applied to evaluate the tradeoff between cost and sustainability. The net present value of groundwater pumping mitigation is given by the expression

\[
\min Z_1 = \sum_{m=1}^{N} \left( \sum_{j}^{U} \sum_{m}^{M} CC_{j,m} \cdot Do_{j,m,n} \right) + \sum_{j}^{U} \sum_{m}^{M} OM_{j,m} \cdot Sel_{j,m,n} \cdot (1 + r)^{-n}
\]  

(1)

where \( CC_{j,m} \) and \( OM_{j,m} \) = capital and operating and management (OM) costs of implementing mitigation project \( m \) at operational sector \( j \). The binary variable \( Do_{j,m,n} \) is equal to 1 if mitigation project \( m \) is implemented for operational sector \( j \) at management period \( n \); its value is 0 otherwise. In this formulation \( Sel_{j,m,n} \) is a binary variable. A value of 1 indicates that the conservation project \( j \) has been implemented at operational sector \( m \) at management period \( n \); a value of 0 indicates otherwise. In Eq. (1) \( r \) represents the discount rate. It is assumed that once a conservation project is begun, it will continue until the end of the planning period.

**Maximizing aquifer yield.** The total amount of groundwater pumped from the aquifer can be expressed as

\[
\max Z_2 = \sum_{n}^{S} \sum_{i}^{U} \sum_{j}^{N} q_{i,j,n}
\]  

(2)

where \( q_{i,j,n} \) is the quantity of water pumped at well site \( i \) to supply operational sector \( j \) during management period \( n \).

**Minimizing drawdown at selected locations.** The third objective in this formulation acts as a surrogate objective of the ultimate goal, which is to keep critical stretches of the San Pedro River from becoming intermittent. Although the Stream package (Pru diced 1989) allows MODFLOW to simulate the aquifer–stream interaction directly, the estimated base flow rates are highly sensitive to the value of the streambed conductance parameter. Adopting the surrogate objective circumvents the dependence of the management model output on this parameter, therefore increasing the robustness of the model. Furthermore, the interaction between surface and subsurface flows and the dependency of phreatophyte vegetation on these variables remains an open research problem of paramount relevance for the management of the system. In practice, management decisions on the riparian vegetation must take into account the effect of vegetation on base flows, the actual source of water for riparian vegetation (intermediate flow or deeper groundwater), and minimum flow and/or water table requirements for vegetation survival. The objective function selected to represent this goal is the \(^{l}\)-norm of the differences between a target head and the simulated head at a set of selected locations:

\[
\min Z_3 = \frac{1}{H} \sum_{s}^{H} |h_s^t - h_s^s|
\]  

(3)

where \( H \) = number of system states (in space and time) that are being controlled; \( h_s^t \) = simulated head at location \( s \); and \( h_s^t \) = target head at location \( s \). The selected locations are indicators of the state of the recharge from aquifer to stream.

The three proposed objectives and their associated tradeoffs are intended to serve as guidelines for decision makers in analyzing future options for development and ecological conservation in the basin. Although for the San Pedro Basin the major current concern is to protect the riparian habitat, the yield objective is useful for assessing the yield potential of the aquifer and the influence of development patterns over the ecosystem. For a given groundwater exploitation pattern, it is expected that drawdown can be mitigated by increasing the cost of recharging the aquifer or by offsetting excess demand with more expensive imported water. Likewise, at any given cost level, the amount of groundwater to be extracted will be linked to the resulting drawdown.

The optimization problem is subject to a set of constraints, which include the capacity constraints:

\[
\sum_{j}^{U} q_{i,j,n} \leq Qs_i^{max} \quad \forall \, i,n
\]  

(4)

\[
\sum_{j}^{U} q_{j,k,n} \leq Qt_k^{max} \quad \forall \, k,n
\]  

(5)

and the demand constraints

\[
\text{Dem}_j \equiv h_c^{min} \quad \forall \, c,n
\]  

(6)

In Eqs. (4)–(6), \( q_{i,j,n} \) = quantity of water pumped at well site \( i \) to supply operational sector \( j \) during management period \( n \); \( q_{j,k,n} \) = rate treated at treatment facility \( k \) from user \( j \) at management period \( n \); \( q_{k,l,n} \) = rate discharged from treatment facility \( k \) to discharge location \( l \) at management period \( n \); \( Qs_i^{max} \), \( Qk_i^{max} \), and \( Qd_i^{max} \) = upper bounds for extraction, treatment, and discharge rates at source \( i \); treatment facility \( k \), and discharge location \( l \), respectively; \( \text{Dem}_j \) = demand rate at operational sector \( j \) and management period \( n \); and \( h_c \) = simulated head at location \( c \) included in the constraint set.

In this formulation, the decision variables are whether or not to implement a mitigation project and the amount of water that should be imported from that source. Therefore, the problem as stated is a mixed-integer nonlinear programming problem.
strained method, but some authors have noted that this method might be rewritten as

\[ \sum_{i} q_{i,j,n} + \sum_{r} \sum_{m} Sel_{j,m,r,n} \cdot q_{m,r,j}^{\text{init}} \geq Dem_{j,n} \quad \forall j,n \]  

or

\[ \sum_{i} q_{i,j,n} + \sum_{m} q_{m,j}^{\text{init}} \geq Dem_{j,n} \quad \forall j,n \]  

The formulation is reduced to a MILP, represented by Eq. (7), or a linear programming problem, represented by Eq. (8), where \( q_{m,j}^{\text{init}} \) is the operational rate of mitigation project \( m \) at operational sector \( j \). Eq. (8) is a special case of Eq. (7) where it is assumed that conservation projects are selected at the beginning of the planning horizon, and where each project’s operational rate, if selected, remains constant for the entire planning horizon.

The tradeoffs among the three selected objectives, and the corresponding nondominated solutions were obtained by the constrained method (Cohon 1978; Louie et al. 1984; Shafike et al. 1992). The noninferior set may also be estimated using a weighting scheme, but some authors have noted that this method might not be able to generate all efficient solutions if the efficient frontier is nonconvex (Watkins and McKinney 1997).

**Linkage between Simulation and Optimization**

In this methodology, a first-order Taylor series expansion is used to express head as a linear function of pumping and recharge rates

\[ h_j(q) = h_j(q^0) + \sum_{v} \frac{\partial h_j}{\partial q_v} (q^1 - q^0) \]  

From Eq. (9), it can be seen that the key elements in linking simulation and optimization are the influence coefficients \( \delta h_j/\delta q_v \), where \( h_j \) is the hydraulic head of groundwater at location \( s \). In Eq. (9), \( q^1 \) and \( q^0 \) are two feasible values of the vector \( q \) of pumping or recharge decision variables; and \( q_v \) is the \( v \)th element. The influence coefficients are computed using the simulation model. If the perturbation method or the sensitivity equation method are used, \( N+1 \) simulation runs are required to obtain the coefficients for \( N \) decision variables (Yeh 1986). Because the response of the system is nonlinear for an unconfined aquifer, an iterative procedure is carried out for convergence. The procedure begins with an initial guess of the values of the decision variables, \( q = q^0 \). The influence coefficients are computed and an optimal solution, \( q^1 \), is obtained. Sequentially the influence coefficients are updated using the optimized \( q^1 \) and the procedure is repeated until convergence takes place. Obviously, treating the pumping rate at each time period—at each of the 3,470 pumping wells identified in the original San Pedro simulation model—as an independent decision variable is both impractical and computationally prohibitive. Therefore, preprocessing the field data to bring the management model to a moderate size becomes important.

The first step is to differentiate those wells that may be subject to management from those that, due to legal or practical constraints, would be very difficult to manage. In the previous section, it was noted that water use types listed for the San Pedro River Basin wells in the ADWR databases are public supply, irrigation, domestic, stock, industrial, and commercial. Wells selected for management purposes are those classified as public, irrigation, and industrial. Public wells are owned by municipal or private water supply utilities, and industrial wells are owned by a few entities. In both cases, it was assumed that management could be reached through negotiation between user organizations, cities, and the well owner. In the case of irrigation wells, management options are more limited, generally consisting of land purchases that permit a change in the use of land and hence the shut-off of the wells. Irrigation wells are included in the management model in order to evaluate the ecological yield of certain land purchases. Domestic, stock, and commercial wells, although included in the simulation model, are not subject to optimization in the management model for diverse reasons. Domestic wells are intended for water supply in individual homes or subdivisions. Therefore, their management would require difficult negotiations with multiple homeowners. Stock, industrial, and commercial wells are not abundant in the Basin, so their influence on the overall decision is negligible from the point of view of water consumption.

After this first selection process 507 irrigation wells, 32 industrial wells, and 112 public wells are left for consideration as decision variables. Further clustering follows in order to associate the pumping rates from several wells to a single pumping parameter (Hill et al. 2000). Pumping variables were grouped according to use, owner, and location, yielding 128 well decision variables. Preliminary tests serve to identify those pumping variables that are more influential over drawdown values. Only these values are retained in the management model, resulting in a total of 48 pumping well parameters.

**Stakeholder Involvement**

Sustainable water resources management is an interdisciplinary problem that requires the coordinated effort of a wide range of specialists, decision makers, and stakeholders. For this reason, generating alternatives becomes an iterative process in which simulation and optimization provide information to decision makers. At the same time, decision makers drive the analysis through expressing their views in terms of objective functions and constraints. Because sustainable management is necessarily a multi-objective problem, no optimal solution in the traditional sense can be found, and decision makers should express their preferences within a set of nondominated solutions. This preference could be for a single alternative or for a range of values of each objective function. In the latter case, further refinement of the alternative space could be accomplished by rerunning the algorithm described in the previous sections, limiting the range of each objective to prespecified values.

This research benefits from stakeholders’ participation by the existence of the USPP (http://www.usppartnership.com), consisting of 20 agencies and organizations with interest in the San Pedro River and its future. The writers participated in meetings with USPP representatives where input regarding priorities and Basin particularities was obtained. Additional data required to
The presented methodology has been applied to the Upper San Pedro River Basin. The main goal is to visualize the tradeoffs between sustainability of groundwater use and economic and development considerations. For the sake of conciseness and clarity, this section includes aggregated results as opposed to individual efficient pumping or recharge rates for each well. In order to evaluate the influence of different basic assumptions on the results, two policy-analysis options are tested: One in which pumping rates are assumed to be constant over the entire planning horizon and one in which pumping rates are allowed to vary within the planning horizon. In both cases, it was assumed that mitigation projects are implemented at the beginning of the planning horizon and that they continue to operate throughout the planning horizon.

**Case 1. Constant pumping policy.** In this case, it is assumed that the entire planning horizon is represented by a single management period, in such a way that the optimal pumping rates obtained for existing wells subject to management are constant. For the same reason, mitigation projects are always assumed to start at the beginning of the planning horizon. Therefore, linear variables can characterize the operational rates at which these projects are implemented.

Table 1 shows the payoff matrix for this scenario. The range between the lower and upper bounds of objective functions 1 and 2 (cost and yield) is discretized into 36 points that are introduced as constraints to generate the nondominated set. Figs. 1 and 2 illustrate the two-way tradeoff between the drawdown objective and the yield and cost objectives, respectively. Less than 36 points are visible in each nondominated set because some points overlay others. From Fig. 1, it can be seen that the drawdown objective is independent from the amount of water pumped from the system as long as mitigation projects such as artificial recharge are implemented accordingly. Therefore, three levels of satisfaction are observed: (1) Average drawdown is 6.9 m when mitigation cost is $7.6 \times 10^3$ or above; (2) average drawdown is around 8.8 m when mitigation cost is equal to $2.9 \times 10^3$; and (3) average drawdown is around 10.8 m when mitigation cost is less than $4.0 \times 10^3$. All of these states occur regardless of the overall amount of water being extracted from the aquifer, within the feasible range. The values in the boxes in Fig. 1 indicate the parameterized values of mitigation costs to which each series of points correspond. When more than a cost value appears in the box, it is because alternatives corresponding to those parameterized cost values lay over the same projected position in the plane formed by the “yield” and “drawdown” objectives. A closer inspection of the results (not shown here for space reasons) reveals that below certain levels, artificial recharge does not affect the long-term drawdown objective. Fig. 2 shows the tradeoff between the drawdown objective and mitigation costs. This figure is a cross section of Fig. 1, and the independence from aquifer yield can be seen here as well. This independence stems from the configuration of the recharge wells for this test problem. All recharge wells are positioned closely to the locations at which drawdown is evaluated, therefore “shielding” these locations from effects caused by pumping in farther away locations. This situation could change if feasibility constraints limited the amount of recharge that could be applied in the field, or the location of recharge wells.

**Case 2. Dynamic pumping policy.** In Case 2 pumping rates at existing wells subject to management are allowed to vary with time, thus creating a more flexible policy that can react to future changes in forcing conditions such as water demands or natural recharge. The planning horizon (20 years) is divided into five four-year management periods during which pumping rates remain constant. No scheduling of mitigation projects was allowed. This implies that, if selected, a mitigation project will start at the beginning of the planning horizon.

Table 2 presents the payoff matrix obtained when applying the simulation-optimization scheme under the Case 2 scenario. Comparison between Tables 1 and 2 shows that there are no major
changes in the drawdown objective in terms of the best and worst values when allowing pumping rates to change with time. A difference between both tables lies in the lower bound of aquifer yield. Greater flexibility in the pumping policy allows distributing pumping in a way that results in a slightly better drawdown objective while at the same time more water is being extracted from the aquifer. The tradeoff figures corresponding to Case 2 are in all aspects quite similar to those corresponding to Case 1 and therefore are not shown here. In Cases 1 and 2, water demand at each operational sector is treated as a constraint, and its right hand side value was adopted by supposing that pumping rates in 1997 are representative of the total demand.

Each point of the nondominated sets computed for Cases 1 and 2 represents a specific policy alternative that is to be compared with the others in order to decide management actions. These alternatives have in common the fact that they are efficient; this is, that no improvement can be achieved for a particular objective without diminishing the satisfaction associated with the other objectives. The problem of selecting which alternative remains open because all alternatives are equivalent from an efficiency point of view. This remaining issue is discussed subsequently, and a graphical methodology for ranking the alternatives is proposed.

**Visualization of Results and Decision Making**

For the so-called generating techniques—in which many possible alternatives are generated and proposed to decision makers—the challenge is to express decision makers’ preferences in a consistent manner so that after a systematic comparison process, a single alternative is selected. Several techniques that apply different comparison algorithms in order to rank a set of alternative projects have been proposed in the literature. Shafike et al. (1992) compared distance-based methods, Q-Analysis and Electre III in the context of a groundwater remediation problem. It turns out that the analysis algorithm used plays an important role in the final outcome of the multicriterion selection process. On the other hand, in the context of multiple stakeholders the process of preference structuring and final selection is an interactive process that usually involves negotiation and conflict resolution (Thiessen and Loucks 1992; Cai et al. 2004).

For these reasons, a different approach to the problem of alternative selection is proposed. This approach is based on the premise that a final decision on management policies must arise only after a negotiation process that may be too complex to be appropriately described by conventional multicriterion analysis techniques. Therefore, the aim is to provide stakeholders with as much information as possible at the beginning of such a negotiation process. In this context, visualization of results is paramount for discriminating between preferable and undesirable alternatives.

The proposed methodology borrows concepts from fuzzy set theory (Zadeh 1965) to assess qualitatively each one of the available efficient solutions, based on the level of satisfaction attained for the optimized objectives and on additional criteria. A similar methodology has been presented to aid in the process of turbine design (Roy et al. 1996). An advantage of this approach is that quantitative data can be integrated with qualitative indicators to provide a more substantial and meaningful information to decision-makers and stakeholders.

The main concept can be summarized as follows. Once the nondominated set is generated based on an initial set of objectives, additional criteria are used to define a fuzzy set that represents a qualitative characteristic of interest. These criteria may have not been included in the original optimization problem. By evaluating the additional criteria for each efficient solution, a membership value is obtained and thus the degree of membership of the entire nondominated set can be mapped. This approach allows incorporating complex criteria (e.g. nonlinear and discontinuous) into the analysis without explicitly considering them in the optimization process, thus keeping the computing requirements at a moderate level. Furthermore, the use of fuzzy sets enables the modeler to incorporate linguistic variables and smooth transitions between acceptable and unacceptable states of the system. These characteristics are highly desirable in a context of conflict resolution.

To illustrate the methodology, assume that together with objectives 1, 2, and 3 (mitigation cost, aquifer yield, and $l^1$-norm of head-target deviations, respectively), the decision makers consider the standard deviation and the maximum value of simulated-target heads differences in the protected area as the most relevant characteristics that define the sustainability of any given management alternative.

The degree of “desirability” of each alternative is computed based upon the degree of satisfaction associated with the objectives included in the multiobjective optimization as well as with the satisfaction associated with the additional criteria. By adopting the concept of membership function from fuzzy set theory, the degree of membership of each optimized objective in the fuzzy set “satisfactory” is equal to the reciprocal of the normalized distance to the upper bound in the payoff matrix. For the additional, nonoptimized criteria, the membership functions can be defined arbitrarily based on decision makers’ preferences and problem characteristics. For this example, “not pronounced” and “moderate” membership functions are devised to be applied to the maximum and standard deviation of the simulated-target heads differences. The membership functions are presented in Fig. 3.

Once all criteria have been selected and membership values assigned, an aggregation function is required to assign a single desirability value to each alternative. Ordered weighted averaging (OWA) (Yager 1988) works by assigning normalized weights to the components of a sorted vector of criteria. Formally, a mapping \( F : P \rightarrow I \) (where \( I = [0, 1] \)) is an OWA operator if there exists a weighting vector \( W=(W_1, W_2, \ldots, W_n) \), associated with \( F \), such that

\[
W_i \in (0, 1)
\]

\[
\sum_i W_i = 1
\]  

(10)

where

\[
F(a_1, a_2, \ldots, a_n) = W_1 b_1 + W_2 b_2 + \cdots + W_n b_n
\]  

(11)

In Eq. (11) \( b_i \) is the largest element in the collection \( a_1, a_2, \ldots, a_n \). The degree of membership of each alternative from the nondominated set in the fuzzy sets corresponds to the \( a_i \) elements in the definition of OWA given above. For the objectives

<table>
<thead>
<tr>
<th>Objective being optimized</th>
<th>Drawdown [m]</th>
<th>Cost ($)</th>
<th>Yield (m$^3$/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drawdown</td>
<td>6.88</td>
<td>3.10E+08</td>
<td>−28,050</td>
</tr>
<tr>
<td>Cost</td>
<td>11.04</td>
<td>0.0</td>
<td>−135,289</td>
</tr>
<tr>
<td>Yield</td>
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<td>0.0</td>
<td>−135,857</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Objective being evaluated</th>
<th>Drawdown</th>
<th>Cost</th>
<th>Yield</th>
</tr>
</thead>
<tbody>
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<td>−135,857</td>
</tr>
</tbody>
</table>
included in the multiobjective optimization, membership is equal to the normalized value of the objective function in the interval $[0, 1]$, where 0 and 1 correspond to the lower and upper bounds obtained, respectively. For the two additional criteria, the membership value results from the membership functions shown in Fig. 3.

By using different weighting ($W$) vectors, different mappings are reached. Figs. 4(a and b) show a few examples of the desirability (here, denoted by $FF_1$) mapping obtained over the set of nondominated solutions given a particular $W$ vector. The continuous mapping is presented for visualization purposes only, and it is convenient to note that it was obtained from interpolation of the discrete alternatives generated from the simulation-optimization algorithm. Also note that the range of values for each objective is $[0, 1]$, where 0 and 1 represent the worst and best values of each objective, respectively, as obtained from the payoff matrix.

Fig. 4(a) corresponds to the case in which the weighting vector $W$ equals $(0,0,0,0,1)$. The overall value of the desirability function $FF_1$ is equal to the degree of membership of the best-performing objective in its corresponding “fuzzy set.” Higher values of $FF_1$ in the nondominated set of Fig. 4(a) are located along the axes where each objective attains its best value (1.0). Fig. 4(b), on the contrary, shows the mapping that results by assigning utmost importance to the worst-performing objective $[W = (1,0,0,0,0)]$. In this case, the OWA operator is equivalent to the “min” operator (or the logical operator “and”) and preferable alternatives are those located towards the “center” of the nondominated set. Additional conclusions can be extracted from the absolute values of the membership functions. If these were to be deemed unacceptable by decision makers or stakeholders, it could be concluded that the basic assumptions upon which the simulation-optimization process is being performed are inadequate and that a reformulation of policy strategies should be considered.

Conclusions

The framework of a DSS has been developed to aid decision makers in evaluating groundwater pumping and recharge policies in semiarid regions. The proposed DSS explicitly considers environmental objectives in its mathematical formulation. The constraint method is used to generate nondominated solutions for a multiobjective optimization problem involving economic, environmental, and development objectives. The methodology is applied to a real case, the Upper San Pedro River Basin, in Arizona. The results provide two important kind of information. First, the payoff matrix allows decision makers to know, given the current state of knowledge of the system and the simulation tools applied to the problem, what are the best and worst values of the objectives considered. Second, the tradeoffs are quantified, therefore providing direction in terms of desirable and attainable management policies.

Once a set of efficient alternatives is identified, decision makers face the task of selecting among them the one that best reflects their preferences. This process is highly complex when multiple decision makers and stakeholders participate. Although this work does not address the problem of negotiation and conflict resolution, the aim is to create a tool that will provide insights with respect to the sustainable management of the system. The proposed methodology borrows concepts from fuzzy set theory to enrich the information pool available to decision-makers. By mapping a desirability function onto the nondominated set, two goals are achieved. First, discrimination among efficient alternatives can include additional criteria that otherwise would be difficult to include in the formal mathematical programming process, like nonlinear functions. Second, the absolute values of the desirability function provide useful information regarding the suitability of basic assumptions for performing sustainability planning.
The proposed methodology relies heavily on the input from decision makers and stakeholders, and can be combined with more interactive methods for generating weights and planning scenarios.

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