Conjunctive Management of Surface Water and Groundwater Resources under Drought Conditions Using a Fully Coupled Hydrological Model

S. B. Seo, Ph.D.[1]; G. Mahinthakumar, Ph.D., M.ASCE[2]; A. Sankarasubramanian, Ph.D.[3]; and M. Kumar, Ph.D.[4]

Abstract: A conjunctive management model has been developed to obtain optimal allocation of surface water and groundwater under different constraints during a drought. Two simulation models—a fully distributed hydrologic model and a reservoir simulation model—were incorporated in an optimization formulation using a simulation-optimization approach with response functions. The model was tested for the Haw River Basin located in North Carolina. A fully distributed hydrologic model, penn state integrated hydrologic model (PIHM), was used to compute simultaneous depletions in streamflow and groundwater level under pumping. A reservoir simulation model was then incorporated within the optimization framework to determine the optimal allocation of surface water and groundwater resources by minimizing reservoir deficit. A new groundwater sustainability constraint, recovery time for groundwater levels, was introduced in the conjunctive management model. Incorporating the reservoir simulation model within the optimization model resulted in reduced reservoir deficits. Moreover, the recovery time constraint will allow decision makers to evaluate the trade-off between maximizing water availability and preserving groundwater sustainability during a drought. It is envisioned that the management model proposed in this study is a step toward sustainable groundwater withdrawal during a drought. **DOI: 10.1061/(ASCE)WR.1943-5452.0000978.** *© 2018 American Society of Civil Engineers.*

Introduction

Conjunctive use of surface water and groundwater has been considered as an effective approach to mitigate water shortage problems caused by a drought (Cosgrove and Johnson 2005; Liu et al. 2013; Singh et al. 2014, 2015). Conjunctive use involves management of both surface water (e.g., reservoirs, rivers, and canals) and groundwater (aquifer) resources to maximize the efficiency of total water resources utilization (Gupta et al. 1985; Ejaz and Peralta 1995; Shi et al. 2012). Groundwater resources can compensate for diminished surface water availability during a drought. However, because surface water and groundwater are not isolated components of a hydrologic system (Sophocleous 2002; Kumar et al. 2009b), reckless withdrawal of groundwater resources can lead to sustained reduction in groundwater levels and depletion of streamflow during a drought (Rejani et al. 2009; Barlow and Leake 2012). Successful conjunctive management of surface water and groundwater can improve water use efficiency and minimize streamflow depletion during a drought. This can be achieved by using an appropriate optimization model (Barlow et al. 2003; Pulido-Velázquez et al. 2006; Stray et al. 2012; Singh et al. 2015).

In this study, a simulation-optimization (S-O) modeling approach was used to develop a decision model for obtaining optimal allocation of surface water and groundwater for minimizing reservoir deficit during a drought. S-O modeling has been widely used to solve problems in water resources management (Mantoglou et al. 2004; Rao et al. 2004; Katsifarakis and Petala 2006; Safavi et al. 2010; Zekri et al. 2015; Giacomoni and Joseph 2017; Shourian et al. 2017; Zhang et al. 2017). The general concept of S-O modeling is used to develop a decision model in which a simulation model and optimization algorithm are linked. To give a recent example, Giacomoni and Joseph (2017) coupled the stormwater management model (SWMM) with a multiobjective evolutionary optimization algorithm in order to identify the location of stormwater control measures and characterize the tradeoffs between flow regime alteration and implementation costs. Further, Shourian et al. (2017) used a watershed management model (MODSIM) within a particle swarm optimization algorithm to obtain optimal capacities of an interbasin water transfer system.

However, incorporating a standalone simulation model into an optimization model can be complex and may take significant computational time to achieve optimal solutions (Singh 2014a), in particular for a fully coupled distributed hydrologic model. To overcome the limitation of computational burden, a response matrix approach has been used here, which has been used widely to obtain optimal groundwater withdrawals for basin-scale management (e.g., Ejaz and Peralta 1995; Cosgrove and Johnson 2004; Rejani et al. 2009; Salcedo-Sanchez et al. 2013). The response matrix models describe a linear aquifer response to pumping using influence coefficients, which can be computed prior to the application of the S-O model (Singh 2014a, b). Although the response matrix approach has been widely used for management problems in water resources (e.g., Ejaz and Peralta 1995; Barlow et al. 2003; Cosgrove and Johnson 2004; Rejani et al. 2009; Salcedo-Sanchez et al. 2013),

[1]Postdoctoral Scholar, Institute of Engineering Research, Seoul National Univ., 35-217, 1 Gwanak-ro, Gwanak-gu, Seoul 08826, South Korea (corresponding author). ORCID: https://orcid.org/0000-0001-9819-6555. Email: sbseo7@snu.ac.kr

[2]Professor, Dept. of Civil, Construction, and Environmental Engineering, North Carolina State Univ., 2501 Stinson Dr., Raleigh, NC 27695-7908.

[3]Professor, Dept. of Civil, Construction, and Environmental Engineering, North Carolina State Univ., 2501 Stinson Dr., Raleigh, NC 27695-7908.

[4]Assistant Professor, Nicholas School of Environment, Duke Univ., 9 Circuit Dr., Durham, NC 27710.

Note. This manuscript was submitted on June 13, 2017; approved on April 16, 2018; published online on July 16, 2018. Discussion period open until December 16, 2018; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Water Resources Planning and Management***, © ASCE, ISSN 0733-9496.

most studies have used it solely with a groundwater simulation model (e.g., MODFLOW) to compute drawdowns in groundwater level. Some of these studies (Ejaz and Peralta 1995; Cosgrove and Johnson 2004) have also incorporated a simple mass balance model or a routing package to link groundwater flow with surface water processes. In this study, however, a fully coupled hydrologic model is used to simulate the distributed interactions between surface water and groundwater in order to compute simultaneous depletions in groundwater and streamflow under pumping stresses. To reduce modeling complexity and computational cost that are incurred by executing a fully coupled hydrologic model within an optimization approach, a response matrix approach is used. In addition, a reservoir simulation model is used within an optimization model to minimize reservoir deficit (i.e., reduction in reservoir storage below normal operating level) for optimal conjunctive use of water resources. Thus, this study incorporates two simulation models, a fully coupled hydrologic model and a reservoir simulation model, into an optimization model using the S-O approach.

Another advantage of the S-O model is that it can provide a trade-off between groundwater withdrawal rates and depletion of surface water (Barlow et al. 2003) under different constraints. A new sustainability constraint, called the allowable recovery time, is introduced here. The constraint restricts excessive groundwater withdrawal during a drought so that groundwater resources can return to normal within an allowable period. The adjustable constraint enables provision of a trade-off between optimal allocation and sustainable management of water resources. Thus, the objective in this study is to obtain optimal conjunctive allocation to minimize the risk of streamflow depletion, subject to reliable water supply and groundwater sustainability constraints.

Simulation-Optimization Model Formulation

To obtain optimal conjunctive allocation of surface water and groundwater withdrawal subject to reliable water supply and groundwater sustainability, several optimization problems are formulated using the S-O modeling approach with an integrated hydrologic model and reservoir simulation model.

Hydrologic Model

An integrated surface water and groundwater model, Penn State Integrated Hydrologic Model (PIHM), was used to simulate interactions between surface water and groundwater. PIHM is a fully distributed multiprocess model in which surface water, groundwater, and land surface components are coupled using a semidiscrete finite-volume approach (Qu and Duffy 2007). Processes simulated in the model include evaporation, transpiration, infiltration, recharge, overland flow, subsurface flow, and streamflow. More details about the individual process equations have been given by Kumar (2009). Laterally, hillslopes and rivers are discretized using triangular grids and line elements, respectively (Kumar et al. 2009a). Vertically, each triangle element consists of four layers: a surface layer, a 0.25-m-thick unsaturated layer, an intermediate unsaturated layer extending downward from 0.25 m to the groundwater table, and a groundwater layer. Soil moisture in the two unsaturated layers may vary from residual moisture to full saturation. Groundwater pumping in a given triangular grid is incorporated through the sink flux term in PIHM, which has been successfully applied at multiple scales in diverse hydroclimatic regimes in both North America and Europe (Chen et al. 2015; Seo et al. 2016; Shi et al. 2013; Wang et al. 2013; Yu et al. 2015).

Response Matrix Generation

Response functions represent the influence of a unit pulse of groundwater withdrawal on drawdown/depletion over space and time (Rejani et al. 2009). In other words, response functions are mathematical descriptions of the relationship between a unit stress to an aquifer at a specified location and an impact elsewhere in the system (Cosgrove and Johnson 2004). The impact can be streamflow depletion at a hydraulically connected river segment or change in aquifer depth at a location other than the pumping wells (Cosgrove and Johnson 2004). If the response can be approximated as linear, then the response function can be written in discrete form as (Maddock 1972; Dreizin and Haimes 1977) follows:

$$s_k(n) = \sum_{i=1}^{n} \sum_{j=1}^{\mathrm{NW}} \beta_{j,k}(n-i+1) P_j(i) \tag{1}$$

where $s_k(n)$ = depletion at site k at the end of nth withdrawal period (L^3), and it can be either streamflow [Eq. (2)] or groundwater depletion [Eq. (6)]; $P_j(i)$ = average groundwater withdrawal rate of jth well during the ith period (L^3/T); $\beta_{j,k}(n-i+1)$ = depletion coefficient at site k owing to a unit groundwater withdrawal at the jth well during the $(n-i+1)$th period; i = index for time period; j = index for groundwater withdrawal wells (control points), where the location at which groundwater is withdrawn for water supply is defined as control point; n = total number of periods; k = index for managing points, where the location at which depletion is monitored is defined as managing point; and NW = total number of groundwater withdrawal wells. Site k (managing point) can coincide with the jth well (control point).

The response coefficients $[\beta_{j,k}(n-i+1)]$ in Eq. (1) are generated by repeated runs of PIHM from the first to the last period of a planning horizon by successively imposing a unit withdrawal rate at the jth pumping well for the ith period and zero withdrawal rates for the remaining time periods.

Optimization Formulations

Linear Programming Model for Minimizing Streamflow Depletion

A linear programming model, an inflow-optimization (I-O) model, is constructed to investigate the optimal conjunctive allocation of surface water and groundwater withdrawal. The objective of the linear programming model is to minimize total inflow depletion by the combined withdrawal of surface water and groundwater. The term inflow depletion is defined as an amount of reduced streamflow. The decision variables are the groundwater and surface water withdrawal rates. The objective function of the I-O model is expressed as follows:

$$\min_{P_j(i), W_j(i)} \left\{ \sum_{i=1}^{n} \sum_{j=1}^{\mathrm{NW}} [\mathrm{TW}_j(i) - P_j(i)] + \sum_{i}^{n} \sum_{j}^{\mathrm{NW}} D_j(i) \right\} \tag{2}$$

where $\mathrm{TW}_j(i)$ = total water supply for the jth location during the ith period (known); $P_j(i)$ = groundwater withdrawal at the jth location during the ith period; $D_j(i) = \beta_{j,k}(n-i+1)P_j(i)$ is streamflow depletion by groundwater withdrawal $P_j(i)$ in the jth location during the ith period, represented by the response coefficients shown in Eq. (1); n = total number of months; and NW = total number of groundwater withdrawal locations.

In Eq. (2), the first term on the right-hand side depicts inflow depletion by the direct surface water withdrawal (total demand minus groundwater withdrawal), and second term depicts inflow depletion by groundwater withdrawal. It is assumed that the

amount of inflow depletion by direct surface water withdrawal is equal to the amount of direct surface water withdrawal, $W_j(i)$, itself. Bound constraints on the decision variables, $P_j(i)$ and $W_j(i)$, are $0 \le P_j(\mathrm{i}) \le \mathrm{TW}_j(i)$ and $0 \le W_j(i) \le \mathrm{TW}_j(i)$, respectively, for $\forall\ i = 1, \ldots, n$ and $\forall\ j = 1, \ldots, \mathrm{NW}$. Other constraints are given by Eqs. (3)–(6).

Water Demand Constraint. Total water demand must be satisfied. That is, the sum of surface water and groundwater withdrawals must meet the amount of total water demand for every period

$$\mathrm{TW}_j(i) - (W_j(i) + P_j(i)) = 0 \qquad \forall\ i = 1, \ldots, n \quad \forall\ j = 1, \ldots, \mathrm{NW} \tag{3}$$

where $W_j(i)$ = surface water withdrawal at the jth location during the ith period.

Minimum Inflow Constraint. Inflow depletion by groundwater pumping from the withdrawal locations must be less than or equal to the total amount of groundwater withdrawal for each period

$$\sum_{j=1}^{\mathrm{NW}} D_j(i) - \sum_{j=1}^{\mathrm{NW}} P_j(i) \le 0 \qquad \forall\ i = 1, \ldots, n \tag{4}$$

Groundwater Depletion Constraint. Groundwater depletion due to drawdown induced by pumping must not exceed the maximum allowable value, which is the amount of total water demand for each groundwater withdrawal location

$$d_{cp}(n) = \sum_{i=1}^{n} \sum_{j=1}^{\mathrm{NW}} [\beta'_{j,cp}(n-i+1)P_j(i) - \mathrm{TW}_j(i)] \le 0$$
$$\forall\ i = 1, \ldots, n \quad \forall\ j = 1, \ldots, \mathrm{NW} \tag{5}$$

where $d_{cp}(n)$ = groundwater depletion at control point cp at the end of the nth withdrawal period (L^3/T); $\beta'_{j,cp}(n-i+1)$ = depletion coefficients at control point cp owing to a unit groundwater withdrawal at the jth well during the $(n-i+1)$th period; and cp = index for control points.

Along with the pumping rate constraint, this depletion constraint restricts overexploitation of groundwater withdrawal. The response coefficients $[\beta'_{j,cp}(n-i+1)]$ in Eq. (5) are also generated by repeated runs of PIHM from the first to the last period of the planning horizon as in Eq. (1).

Groundwater Recovery Time Constraint. The groundwater recovery time constraint requires that the groundwater level of each city must return to normal (i.e., recover to equilibrium state) within a prescribed number of periods (rt) after the end of pumping. That is, depletion at the jth location should be less than or equal to zero after the prescribed allowable recovery time, as given in Eq. (6). Although having negative values of depletion would be infeasible (i.e., an increase in groundwater level after pumping), the model can occasionally depict small negative depletions due to uncertainties in initial conditions (Seo et al. 2018)

$$d_{cp}(n+rt) = \sum_{j=1}^{\mathrm{NW}} \sum_{i=1}^{n+rt} [\beta'_{j,cp}(n-i+1)P_j(i)] \le 0$$
$$\forall\ i = 1, \ldots, n+rt \quad \forall\ j = 1, \ldots, \mathrm{NW} \tag{6}$$

Here, the value of rt, which is defined as the maximum allowable recovery time, can be adjusted for multiple cases (e.g., from 1 to any values in rt). Thus, the optimal solutions can vary depending the value of rt. By changing the groundwater recovery time constraint, total inflow depletions during the drought period were minimized.

Nonlinear Programming Model for Minimizing Reservoir Deficit

Although the I-O model minimizes total inflow depletion, it is unclear whether reservoir deficits during drought are efficiently minimized, especially if there is significant seasonality in streamflow. Reservoir deficit is defined as the difference in storage between the operational level and actual level in the reservoir. The reservoir storage optimization (RSO) model is a nonlinear programming model that directly minimizes reservoir deficits during drought conditions, rather than simply minimizing inflow depletions. For this purpose, a reservoir simulation model is newly linked within the optimization model. For minimizing reservoir deficits during the period in which reservoir storage series are below the operational level (i.e., reservoir storage series are positioned in conservation storage), a reservoir simulation model is embedded into the optimization model. Thus, the objective function of the RSO model is calculated as follows:

$$\min_{P_j(i), W_j(i)} \left\{ \sum_{i=1}^{n} [\mathrm{rso} - \mathrm{RM}(I(i) - \mathrm{CD}(i))] \right\}$$
$$\begin{cases} \text{if } \mathrm{RM}(I(i) - \mathrm{CD}(i)) & < \mathrm{rso} \\ \text{otherwise} & 0 \end{cases} \tag{7}$$

where rso = reservoir storage at operational level; $\mathrm{RM}(\cdot)$ = function that represents the reservoir simulation model; $I(i)$ = inflow series during the ith period without any withdrawal; and $\mathrm{CD}(i)$ = depletion in inflow driven by the combined withdrawals of surface water and groundwater during ith period. $CD(i)$ is expressed

$$\mathrm{CD}(i) = \sum_{j=1}^{\mathrm{NW}} [\mathrm{TW}_j(i) - P_j(i) + D_j(i)] \tag{8}$$

Definitions of the variables of $\mathrm{TW}_j(i)$, $P_j(i)$, and $D_j(i)$ were described in the section "Linear Programming Model for Minimizing Streamflow Depletion." The objective function of the RSO model, Eq. (7), was subjected to the same constraints of the I-O model [Eqs. (3)–(6)] as described in the section "Linear Programming Model for Minimizing Streamflow Depletion."

S-O Modeling Framework

Based on the S-O modeling approach, two different management models are formulated: (1) a linear programming I-O model (PIHM is solely incorporated with the optimization model), and (2) a nonlinear programming RSO model (both PIHM and a reservoir simulation model are incorporated with the optimization model). The overall S-O modeling framework is shown in Fig. 1. For the I-O model, the simplex linear programming solver (in MicroSoft Excel) was used because the objective and constraints listed in section "Linear Programming Model for Minimizing Streamflow Depletion" are all linear. Because the embedded reservoir model in the RSO model implies a nonlinear problem with discontinuous derivatives, the evolutionary algorithm solver (in MicroSoft Excel) was used to obtain the optimal solutions.

Case Study

Application Site and Data Sets

Haw River Basin, which makes up the northern portion of the Cape Fear River on the East Coast of the United States (36°00′ N; 79°30′ W) was used as an application watershed in this study (Fig. 2). The headwaters of Haw River run into the Jordan Lake Reservoir, and the drainage area of the basin is 3,945 km^2. The 177-km-long

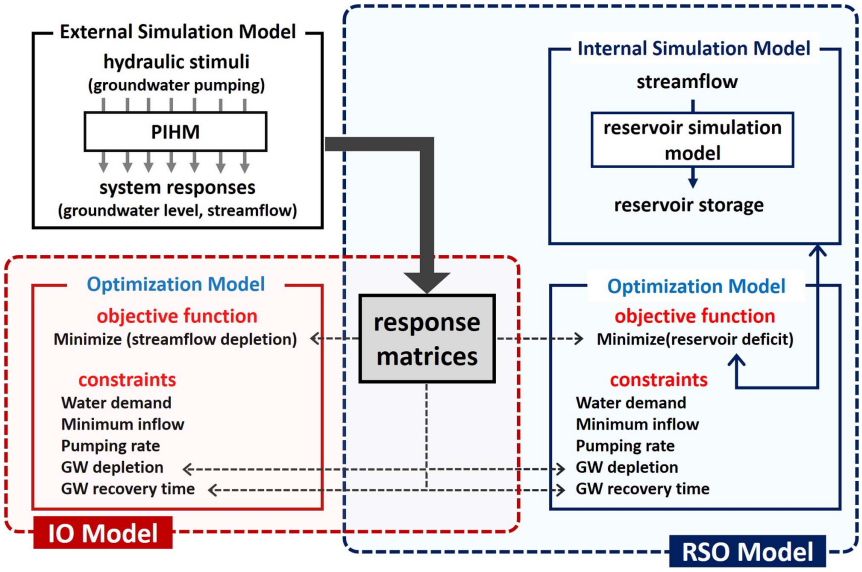

Fig. 1. Simulation-optimization modeling framework for the conjunctive management models: I-O model and RSO model.

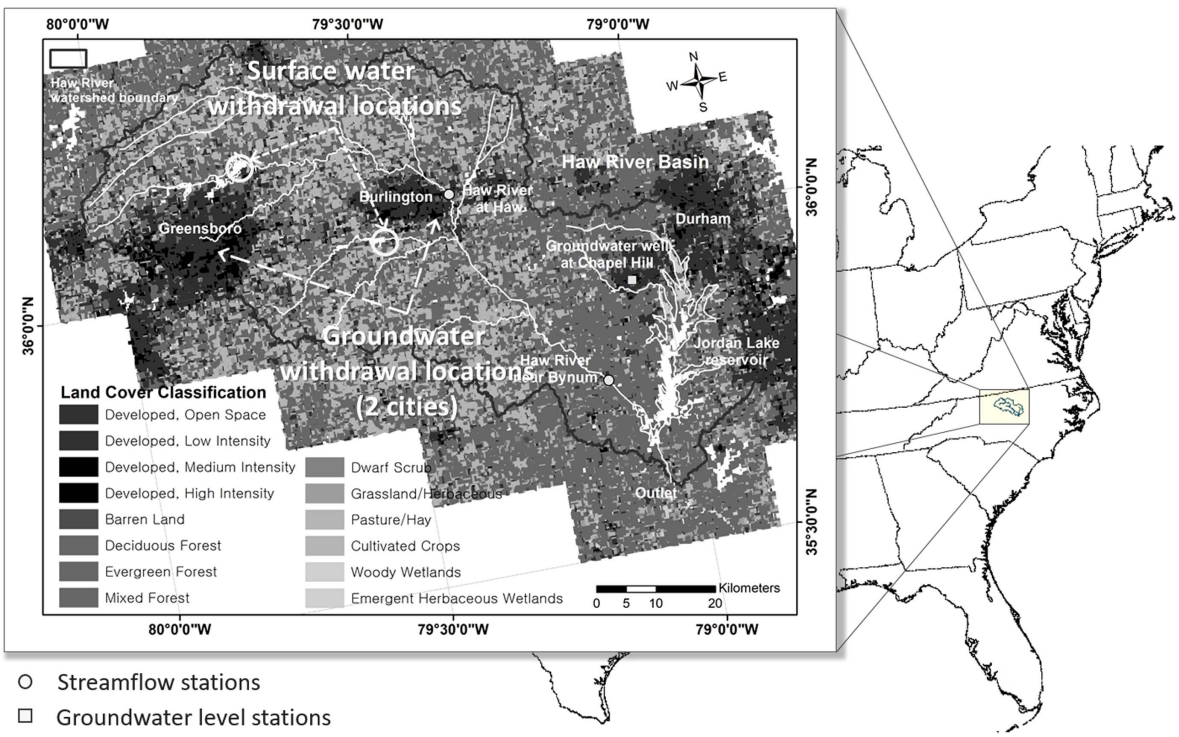

Fig. 2. Application site: Haw River Basin with land cover information.

river and its 1,481-km-long tributaries provide freshwater for residential/industrial/recreational use and transportation and serve as a habitat for irreplaceable wildlife. The Haw River Basin is characterized by a humid subtropical climate, which mean annual precipitation is 1,138 mm. Land cover information in Fig. 2 indicates that forest covers more than half of the entire watershed. The land-use distribution in the watershed is 35% deciduous forest, 22% agricultural land, and 20% developed urban area.

The water supply source for the two biggest cities in the basin, Greensboro and Burlington, North Carolina, is mostly surface water withdrawal. Average daily withdrawals for the two cities were approximately 1.10 and 0.53 m^3/s [97 and 45 million of liters per day (MLD)] in 2012 (North Carolina Division of Water Resources 2012). Surface water sources for the cities are from local lake/reservoirs, which are adjacent to the urban areas. In drought, however, lake/reservoir levels drop quickly, and restrictions are enforced (City of Greensboro 2010). Thus, demand for alternative sources such as groundwater withdrawal is rising. There is a pumping well previously built by the city of Burlington to transfer water to neighboring lakes/reservoirs in a drought. Besides, during an actual drought in 2001–2002, the city of Greensboro worked with regulatory agencies to determine how the pumping wells could

benefit the city in the event of a drought of long duration (City of Greensboro 2010). Thus, both the cities are aware of potential benefit from the pumping wells in a drought.

Aquifers of the Piedmont region—in which the Haw River Basin is located—are localized, complex fractured metamorphic, igneous, and sedimentary rocks. The rocks are covered almost everywhere by regolith, and most of the groundwater is stored in the shallow, porous regolith (Lindsey et al. 2006; Heath 1984). The aquifer averages approximately 10–20 m in thickness (i.e., depth to bedrock) and may be as much as 100 m thick on some ridges (Heath 1984). On average, however, the combined thickness of soil, saprolite, and the transition zone of regolith has been estimated to be less than 20 m in the Piedmont region (Daniel 1989).

Observed Meteorological Data Sets

Daily 1/8° gridded (roughly 12 × 12 km) meteorological data were used to drive the hydrological model. The data are now available from 1951 up to 2010 for the contiguous United States. Maurer et al. (2002) have provided details regarding these data and a downloadable link, which is originally from the Computational Hydrology Group at the University of Washington.

Observed Streamflow and Groundwater Data Sets

Streamflow and groundwater level data sets for the Haw River Basin were downloaded from the USGS (2015) water data. Haw River at Haw Station (USGS HUC8-02096500) provides daily streamflow data from 1928 to the present, and the Haw River near Bynum Station (USGS HUC8-02096960) has daily streamflow data available from 1973 to the present. The groundwater level data were recorded as weekly series at Chapel Hill Station (USGS OR-069 355522079043001). Because there is less variability in daily groundwater level series than streamflow, monthly groundwater data were obtained by aggregating weekly series to a monthly scale.

Watershed Data Sets

To account for the spatial heterogeneity in topography, hydrogeology, and land cover, watershed data sets such as watershed boundary, digital elevation, and land-cover/soil classification for the Haw River Basin were obtained from USGS National Map Viewer (2015). Land cover/soil classification data sets were obtained from the geospatial data gateway of the Natural Resources Conservation Service (NRCS 2015). Ecological and hydrogeological parameters and meteorological forcings were automatically extracted from the data sets using an integrated model/geographic information system (GIS) framework, PIHMgis (Bhatt et al. 2014), and mapped onto the unstructured discretization of the model domain. In this study, average size of triangular cells was 5 km^2.

PIHM Parameter Calibration

PIHM parameters were calibrated by comparing monthly streamflow and groundwater level driven by observed forcing data (daily observed precipitation and temperature time series at 1/8th degree) to observed streamflow and groundwater data sets from 1956 to 1980 (Seo et al. 2016). Hydrogeological parameters—such as soil hydraulic conductivity, macroporosity, and soil retention parameters—were adjusted uniformly across the model domain to ensure that modeled streamflow and groundwater variations were captured well. Figs. 3(a and b) present a comparison of monthly series of simulated streamflow and groundwater level, respectively, for the calibration period from 1956 to 1980, along with observations. For evaluation of the PIHM simulation performance, correlation coefficient (CC) and Nash-Sutcliffe efficiency (NSE) were computed for the calibration period and the validation period (from 1981 to 2005) for each season (Table 1). Performance of streamflow and groundwater level was reasonably good enough given that the parameters were manually adjusted to maintain the physical characteristics on all the parameters.

Reservoir Simulation Model

The primary source of surface water for the cities located downstream of the Haw River Basin, such as Cary, Apex, and Durham,

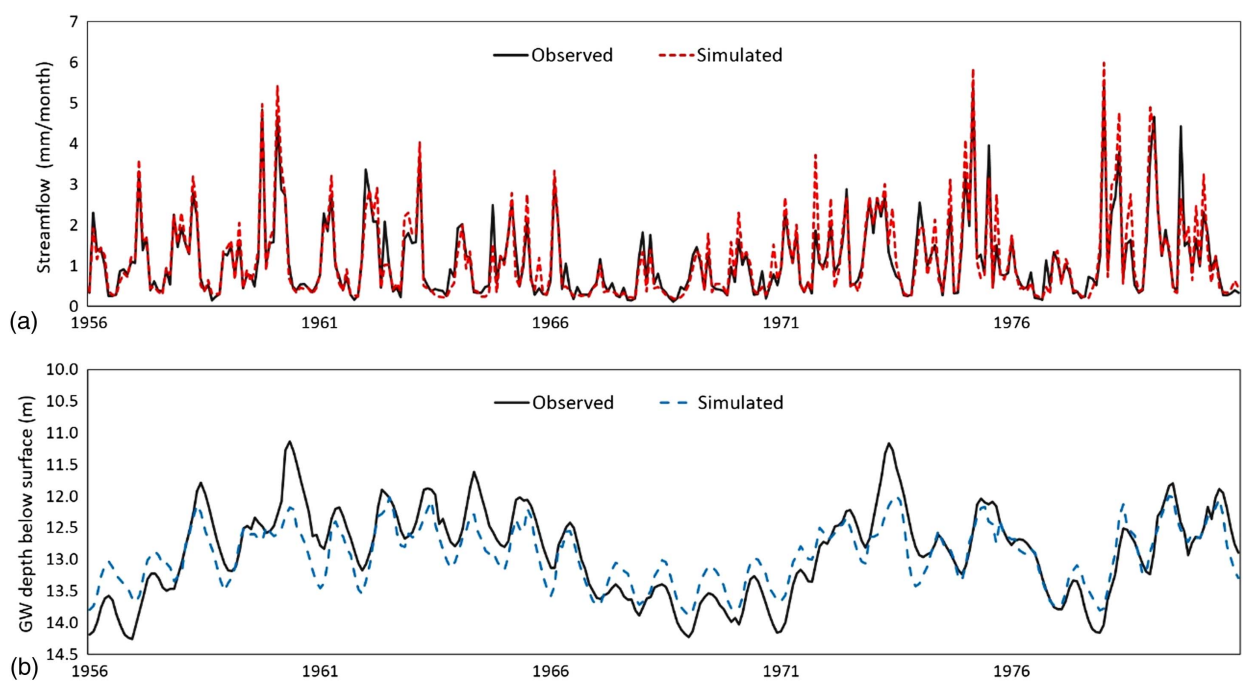

Fig. 3. Simulated streamflow and groundwater level series driven by PIHM with the calibrated parameters during the calibration period (1956–1980): (a) monthly streamflow series at Haw River at Haw Station; and (b) monthly groundwater level series at Chapel Hill Station (without pumping).

Table 1. Evaluation of the PIHM simulation performance for each season: correlation coefficient and Nash-Sutcliffe efficiency values on monthly streamflow and groundwater level for the Haw River Basin

		Calibration (1956–1980)								Validation (1981–2005)							
		CC				NSE				CC				NSE			
Measurement	Station name/number	DJF	MAM	JJA	SON	DJF	MAM	JJA	SON	DJF	MAM	JJA	SON	DJF	MAM	JJA	SON
Streamflow	Haw USGS 02096500	0.95	0.93	0.94	0.97	0.84	0.82	0.86	0.92	0.94	0.86	0.88	0.94	0.77	0.74	0.73	0.86
Groundwater level	USGS OR-069 355522079043001	0.82	0.80	0.77	0.77	0.63	0.59	0.56	0.57	0.70	0.69	0.68	0.67	0.48	0.47	0.45	0.45

Note: DJF = December-January-February; MAM = March-April-May; JJA = June-July-August; and SON = September-October-November.

North Carolina, is Jordan Lake. To obtain optimized allocation of water withdrawals to reduce risk in reservoir storage, a reservoir simulation model for Jordan Lake is used in this study. Net inflow series driven by PIHM are used with the Jordan Lake Reservoir model to simulate reservoir storage series based on the US Army Corps of Engineers (USACE) guidelines for operating Jordan Lake Reservoir. The reservoir model was initially developed by Sankarasubramanian et al. (2009) and has been used to develop storage forecasts and assessment of the impacts of near-term climate change within a year on the Jordan Lake Reservoir system (Singh et al. 2014). Most of the reservoirs in North Carolina partition the conservation storage for downstream water quality and water supply. The sum of the previous month's storage and inflow is allocated by using the fraction of 0.64 and 0.36 for downstream water quality and water supply, respectively. The water releases for downstream water quality and water supply are then allocated according to the operation rule based on the current storage. Detailed equations in the Jordan Lake Reservoir simulation model have been given by Singh et al. (2014). The simulated reservoir storage series were validated with the recorded reservoir levels. The R^2 value was 0.74 between simulated monthly reservoir storage series and observations. The time-series plot for simulated monthly reservoir storage, along with observed storage, is presented in Fig. 4.

Conjunctive Management Model Formulation

A planning horizon of 21 months (January 2001–September 2002, which was actually a drought period in the Haw River Basin) was considered for the management model (i.e., $n = 21$). During drought, it is assumed that municipal water supply for the two cities, Greensboro and Burlington, are withdrawn from either surface water or groundwater rather than only from surface water. Thus, the combined withdrawals are set to meet the monthly total water demand, fixed at 97 and 45 MLD for the cities of Greensboro and Burlington, respectively. A total 25 of wells were randomly distributed in each city, and these wells were considered to be control points to minimize dimensions of response matrices on spatial domain (e.g., Psilovikos 2006). For this purpose, after optimizing the total groundwater withdrawal for each city, the amount of withdrawals was equally divided and applied to all the wells in each city.

The response coefficients $[\beta_{j,k}(n-i+1)]$ were generated by repeated runs of PIHM from the first month to the last month by successively imposing the pumping wells of each city to a withdrawal of 97 MLD (45 MLD) minus the unit pulse for Greensboro (Burlington) for the ith month and zero withdrawal for the rest of the months. Consequently, groundwater depletions at two managing points (the two cities, i.e., NW = 2) and streamflow depletions at one managing point (inflow into Jordan Lake Reservoir, i.e., $M = 1$) were recorded over a 30-month period (January 2001–June 2003). An additional 9 months of depletions responses after pumping were needed for the estimation of recovery time for groundwater level at the two pumping regions (managing points). Thus, the size of the response matrices was extended from 21 to 30 months by running 9 more months of PIHM simulation without any groundwater withdrawal (i.e., $rt = 9$). The recovery time variable was used as a constraint in the management model.

Optimal Allocation of Surface Water and Groundwater Withdrawals

The conjunctive management model was developed for maximizing surface water availability by changing the groundwater withdrawal plan during a drought. The I-O model finds optimal allocation of surface water and groundwater withdrawal during a

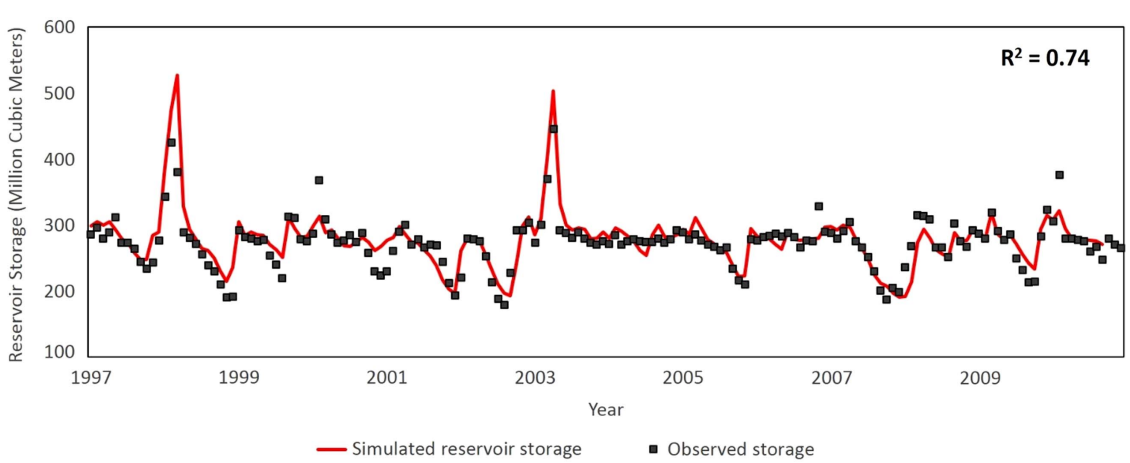

Fig. 4. Monthly reservoir storage series simulated by the Jordan Lake Reservoir model developed in this study during the period from 1997 to 2010 (14 years).

drought for minimizing depletions in inflow. Thereafter, the optimized inflow series are loaded into the reservoir model to assess the corresponding changes in reservoir storage of the Jordan Lake. On the other hand, the RSO model finds the optimal allocation for directly minimizing reservoir deficit because the reservoir simulation model is linked with the optimization model.

Results

Optimal Conjunctive Withdrawals

Optimal conjunctive withdrawals corresponding to the varying groundwater recovery time constraints from 1 to 9 months were obtained. Figs. 5(a and b) shows the monthly mean inflow depletions and reservoir deficits, respectively, along with corresponding fraction of groundwater withdrawals to the total withdrawal for both management models. Markers represent monthly mean inflow depletion by optimal conjunctive withdrawals, and bars indicate the corresponding fractions of the groundwater withdrawal to the total withdrawal according to different values of groundwater recovery time constraint (1, 3, 5, 7, and 9 months). It shows that increasing the allowable recovery time increases the fraction of groundwater withdrawal, resulting in decreased depletion of inflow. This implies that more water can be withdrawn from groundwater to reduce inflow depletion, even though it will increase groundwater recovery time. This is justified geophysically because there is a lagged impact on groundwater recharge and base flow processes. That is, lagged reduction in inflow depletion can occur when some of the surface water withdrawal is replaced with groundwater withdrawal that is not adjacent to the river reach. Thus, there is a trade-off between minimizing inflow depletion and groundwater recovery time. As seen in Fig. 5(a), the I-O model results in lower inflow depletions than the RSO model (solid markers below diagonal striped markers) because the objective in the I-O model is to minimize inflow depletion. Conversely, the RSO model leads to lower reservoir deficits than the I-O model (diagonal striped markers below solid markers in Fig. 5(b) because its objective is to minimize reservoir deficit. In both cases, the RSO model requires a lower fraction of groundwater withdrawal than the I-O model. This is associated with groundwater withdrawal timing during the management period.

Fig. 6(a) shows the monthly series of the fractions of groundwater withdrawals for both the management models under a 1-month recovery time constraint. Under the I-O model, most of the groundwater was withdrawn during the first 5 months (January–May 2001) which is just before the beginning of the dry spell. In contrast, the RSO model withdrew most of the groundwater during the dry spell (May–November 2001). Thus, groundwater withdrawals during normal/wet period were minimized when the RSO model was adopted. This is because the reservoir usually maintains the operational storage level unless drought occurs. The RSO model increases inflow series when reservoir storage is below the operation level, whereas the I-O model focuses only on maximizing inflow series, regardless of reservoir condition. In this regard, the RSO model outperforms the I-O model for minimizing of reservoir deficit, with lower amounts of groundwater withdrawals.

Fig. 6(b) shows the changes in inflow series when using the I-O and RSO models under the 1-month recovery time constraint. The I-O model increases inflow more than the RSO model during the first 4 months. However, during the first 2 months of the first dry spell (May and June 2001), the RSO model was able to increase inflow series more than the I-O model. This is associated with the fact that all the water demand was met by groundwater [i.e., groundwater withdrawal fraction = 1 during these 2 months, as seen in Fig. 6(a)]. Thus, the RSO model obtained a more efficient groundwater withdrawal plan for maximizing water availability in the reservoir during the drought by directly linking the reservoir model into the optimization model.

Next, the changes in reservoir storage due to the I-O and RSO models are presented in Fig. 6(c) under the 1-month recovery time constraint. It shows the impact of increased inflow series on reservoir storage. During the first dry spell, although both the models increase reservoir storage, the RSO model outperforms the other. However, during the second dry spell (April–September 2002), both the models yield lower values than the baseline storage (simulated reservoir storage without pumping). This is because of a lagged inflow depletion caused by groundwater withdrawals during the first dry spell and no additional groundwater withdrawals during the second dry spell. Above all, the reason there is no groundwater withdrawal allowed during the second dry spell is due to the short recovery time constraint (i.e., 1 month). To meet this constraint, groundwater storage should come back to normal right after the end of the drought (October 2002). Consequently, both the models restrict groundwater withdrawals during the second dry spell because there is no time for groundwater to be restored.

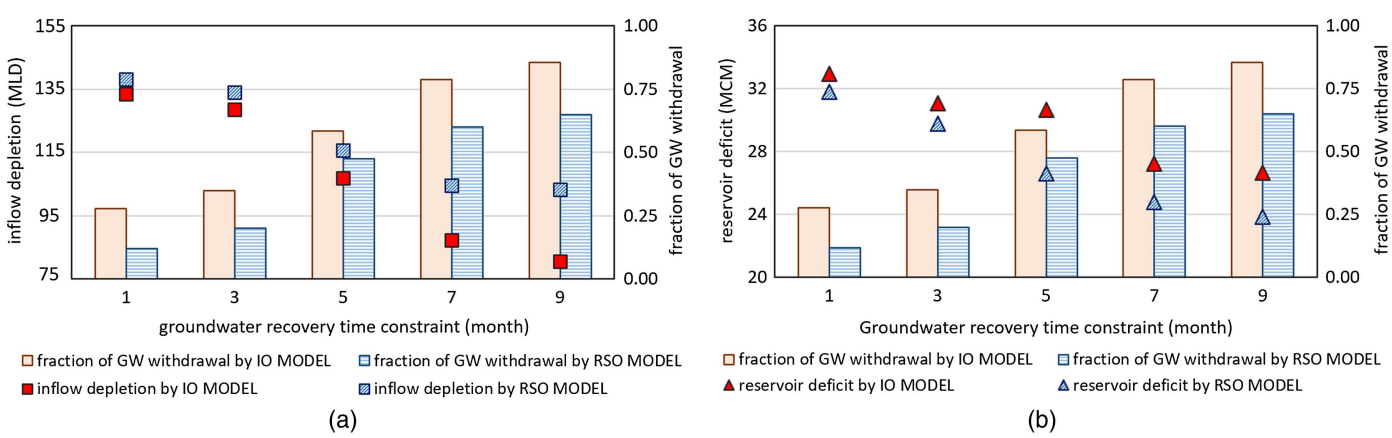

Fig. 5. Inflow depletion and reservoir deficit driven by the conjunctive withdrawals obtained by RSO model and comparison with I-O model: (a) monthly mean inflow depletions corresponding to varying groundwater recovery time constraints; and (b) monthly mean reservoir deficit corresponding to varying groundwater recovery time constraints.

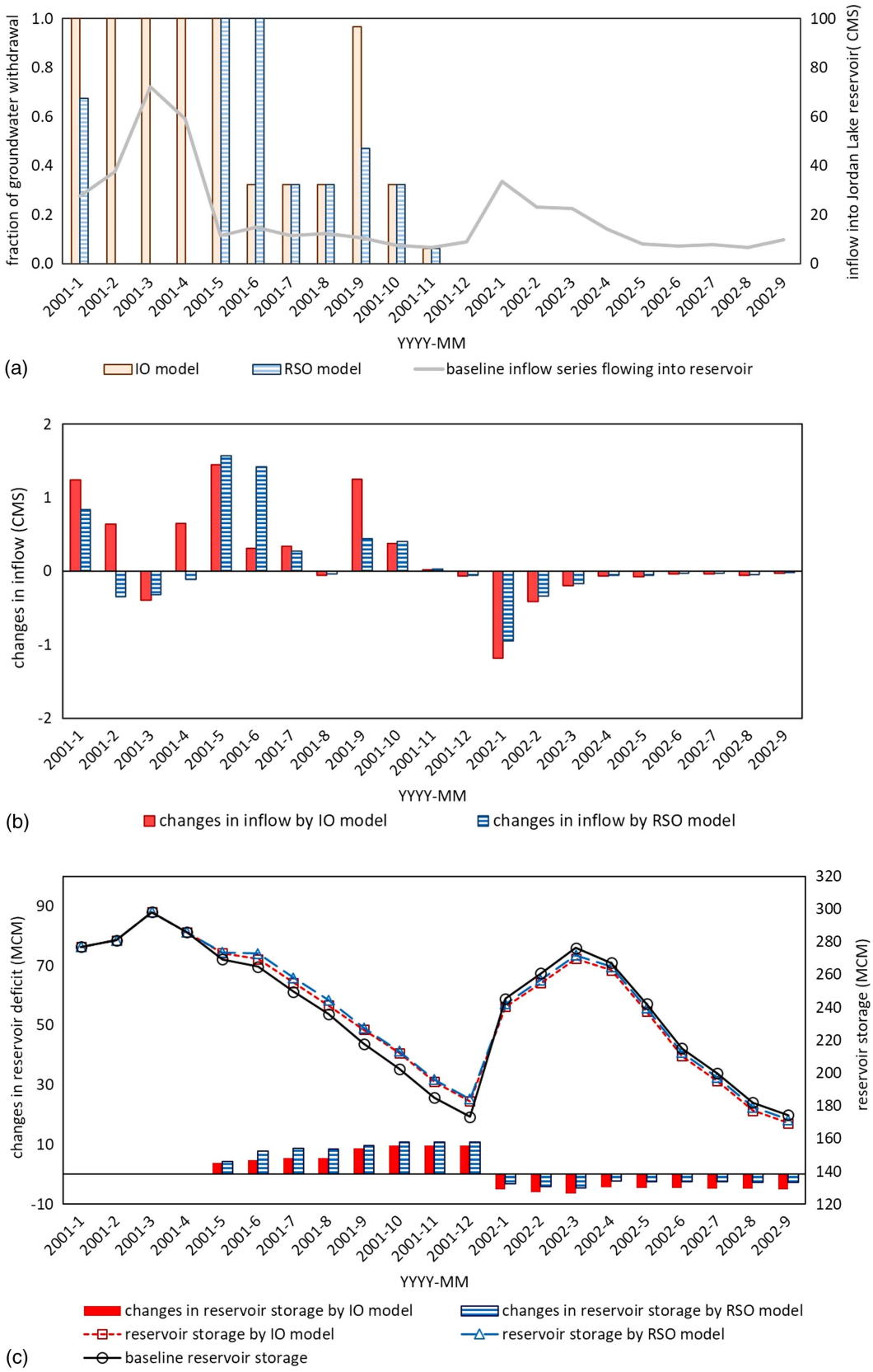

Fig. 6. Optimal groundwater withdrawals obtained by the both I-O and RSO models and changes in inflow and reservoir storage corresponding to the optimal withdrawals under 1-month recovery time constraint: (a) fraction of optimal groundwater withdrawals obtained by I-O and RSO models under 1-month of recovery time constraint; (b) changes in inflow driven by optimal groundwater withdrawals obtained by I-O and RSO models under 1-month recovery time constraint; and (c) changes in reservoir storage driven by optimal groundwater withdrawals obtained by I-O and RSO models under 1-month recovery time constraint.

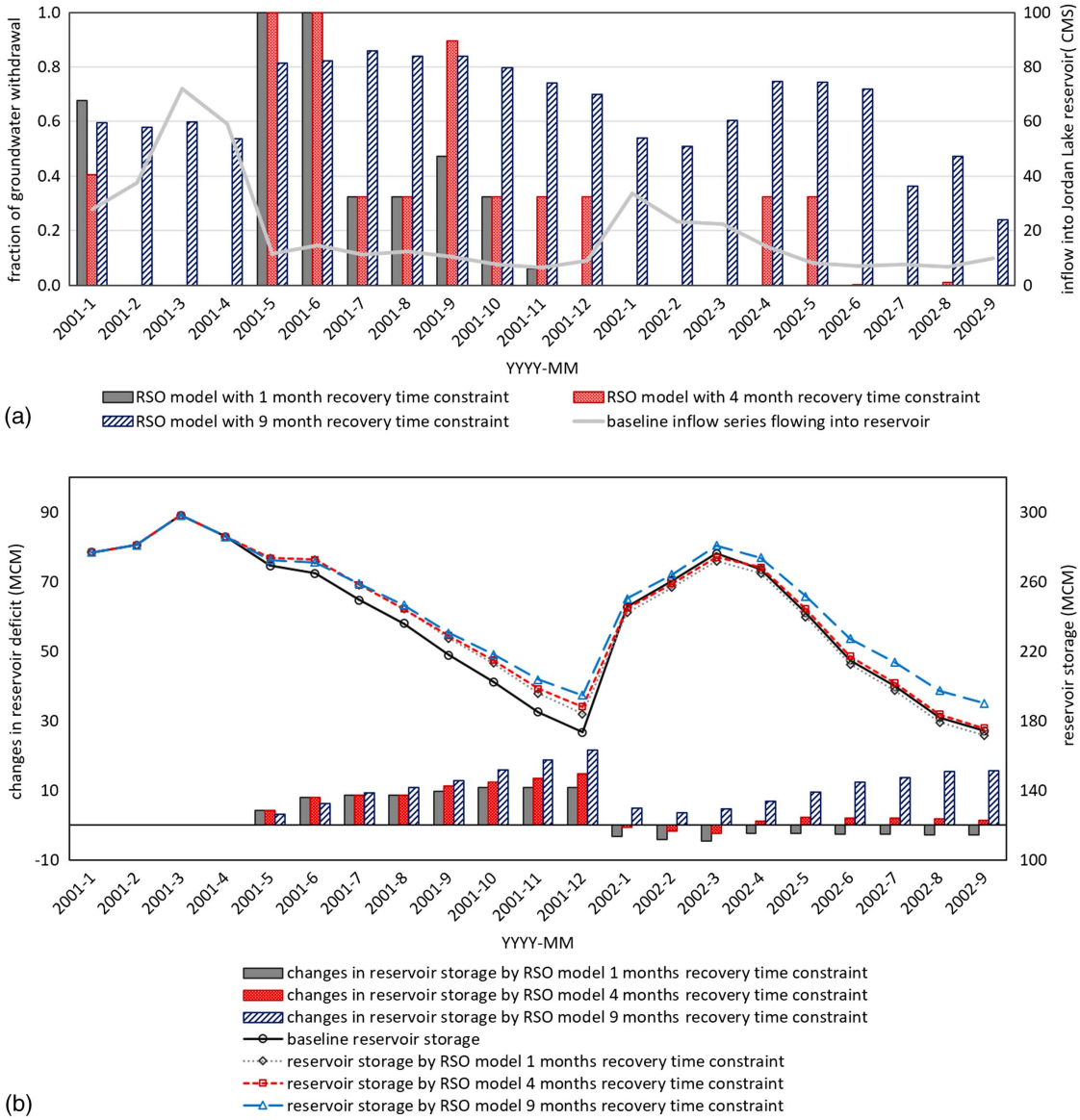

Fig. 7. Optimal groundwater withdrawals obtained by the RSO model and changes in reservoir storage corresponding to the optimal withdrawals under 1, 4, and 9 months of recovery time constraints: (a) fraction of optimal groundwater withdrawals obtained by the RSO model under 1, 4, and 9 months of recovery time constraints; and (b) changes in reservoir storage driven by optimal groundwater withdrawals obtained the RSO models under 1, 4, and 9 months of recovery time constraint.

Trade-Off between Optimal Management and Environmental Sustainability

As briefly mentioned in the previous section, the groundwater recovery time constraint can restrict excessive groundwater withdrawals from an environmental sustainability point of view. However, the recovery time can be subjective according to regional factors such as the hydrogeological characteristics, climate regimes, and regulatory policies. By changing the value of recovery time constraint (i.e., by tightening or loosening the restriction of groundwater withdrawal), the optimal groundwater withdrawals would also change in accordance with the extent of restriction. Thus, the groundwater management plan can account for the sustainability of groundwater resources.

Fig. 7(a) presents three different series of fractions of groundwater withdrawals obtained by the RSO model, with three different cases of recovery time constraints: 1, 4, and 9 months. It clearly shows that a larger quantum of groundwater withdrawals was permitted under the 9-month recovery time constraint than during the others. Moreover, most of the groundwater withdrawals occurred during the very dry spell for the cases of 1 month and 4 months, whereas groundwater was withdrawn across all the months under the case of 9 months. Nonetheless, fraction of groundwater withdrawal was greater during the drier periods for all three cases. This is because the RSO model focuses on increasing inflow during drier conditions to preserve reservoir storage at the highest.

Fig. 7(b) shows corresponding changes in reservoir storage under the three different cases. Contrary to the 1-month case, the 4-month and 9-month cases increase reservoir storage in both the dry spells. In addition, the 9-month case obviously outperforms the 4-month case because a longer time was allowed for groundwater to recharge back to normal level after the management period. Not surprisingly, by loosening the restriction on recovery time, water availability in the reservoir was increased by the RSO model. As discussed previously, the recovery time constraint

enables one to see a trade-off between maximizing surface water availability and preserving sustainability of groundwater resources.

Concluding Remarks

Two different management models for the optimal allocation of surface water and groundwater withdrawals during a drought were developed using an S-O modeling approach. Both models used a response matrix approach to improve computational efficiency. A fully distributed and coupled hydrological model, PIHM, was used to generate response functions on streamflow and groundwater levels. The first management model, the I-O model, formulated an optimization function using a simple linear programming. The RSO model, on the other hand, incorporated two different models: (1) PIHM, and (2) a reservoir simulation model, with the optimization function using a nonlinear programming with discontinuous derivatives by coupling the response matrix approach with the S-O modeling framework. Whereas the I-O model minimized inflow depletion, the RSO model directly minimized reservoir deficit to obtain optimal allocations of surface and groundwater withdrawals. Moreover, the recovery time constraint provided insights into the trade-off between maximizing conjunctive water use efficiency and ensuring sustainability of water resources during a drought.

It is hoped that the proposed modeling framework has shed light on a new perception of sustainable management of groundwater withdrawal during a drought. Given that water resources management is principally directed at optimal allocations with respect to cost, sustainability of water resources can be easily overlooked. In this regard, a recovery time constraint was embedded in the management model to successfully address the trade-off between minimizing inflow depletion and groundwater recovery time. Thus, this study focused more on how a water resources system could come back to normal under a transient conjunctive water withdrawal during a drought, rather than merely providing the optimal solutions for conjunctive use of surface water and groundwater.

The trade-off between maximizing water use efficiency and preserving sustainability of water resources on a local-scale watershed can vary depending on its geophysical characteristics and climatic conditions followed by a drought. A watershed with different geophysical conditions and climate regime (e.g., located in arid climate such as the southwestern United States) may lead to different decisions. Thus, the use of a fully distributed and coupled hydrological model, as used in this study, is necessary for a local-basin-scale study because of its ability to incorporate heterogeneity of geographical data and simulate the interaction between surface water and groundwater simultaneously. Notably, any given climate scenario can affect the resiliency of the water resources system (Seo et al. 2018). In this regard, application of multiple climate forcing scenarios may be able to provide uncertainty induced by potential climate forcing. Further, the proposed modeling approach can be extended to a long-term conjunctive management plan for a watershed in an arid climate regime, in which groundwater resources constitute the primary source of water supply.

For this approach to be adopted for real-time drought management, extended-period forecasts (e.g., for periods longer than 1 year) of climate forcing (i.e., precipitation and temperature) with good skill are required for generating reliable inflow series. Besides, even though the cost aspect was not considered in the proposed management model, it can be incorporated if reliable cost information is available with regard to water withdrawals. In this case, a mixed integer optimization model, such as turning groundwater withdrawals on/off for each month, may be more appropriate.

Acknowledgments

This research was supported in part by the National Science Foundation under Grant No. 1204368. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

References

Barlow, P. M., D. P. Ahlfeld, and D. C. Dickerman. 2003. "Conjunctive-management models for sustained yield of stream-aquifer systems." *J. Water Res. Plann. Manage.* 121 (1): 35–48. https://doi.org/10.1061/(ASCE)0733-9496(2003)129:1(35).

Barlow, P. M., and S. A. Leake. 2012. *Streamflow depletion by wells—Understanding and managing the effects of groundwater pumping on streamflow.* US Geological Survey Circular 1376, 84. Reston, VA: US Geological Survey.

Bhatt, G., M. Kumar, and C. J. Duffy. 2014. "A tightly coupled GIS and distributed hydrologic modeling framework." *Environ. Model. Software* 62 (Dec): 70–84. https://doi.org/10.1016/j.envsoft.2014.08.003.

Chen, X., M. Kumar, and B. L. McGlynn. 2015. "Variations in streamflow response to large hurricane-season storms in a southeastern US watershed." *J. Hydrometeorol.* 16 (1): 55–69. https://doi.org/10.1175/JHM-D-14-0044.1.

City of Greensboro. 2010. "2010 water supply master plan." Accessed June 1, 2016. http://www.greensboro-nc.gov/modules/showdocument.aspx?documentid=3700.

Cosgrove, D. M., and G. S. Johnson. 2004. "Transient response functions for conjunctive water management in the Snake River Plain, Idaho." *J. Am. Water Resour. Assoc.* 40 (6): 1469–1482. https://doi.org/10.1111/j.1752-1688.2004.tb01599.x.

Cosgrove, D. M., and G. S. Johnson. 2005. "Aquifer management zones based on simulated surface-water response functions." *J. Water Resour. Plann. Manage.* 131 (2): 89–100. https://doi.org/10.1061/(ASCE)0733-9496(2005)131:2(89).

Daniel, C. C. 1989. "Statistical analysis relating well yield to construction practices and siting of wells in the Piedmont and Blue Ridge provinces of North Carolina." Rep. No. 2341-A. Raleigh, NC: US Geological Survey.

Dreizin, Y. C., and Y. Y. Haimes. 1977. "A hierarchy of response functions for groundwater management." *Water Resour. Res.* 13 (1): 78–86. https://doi.org/10.1029/WR013i001p00078.

Ejaz, M. S., and R. C. Peralta. 1995. "Maximizing conjunctive use of surface and ground water under surface water quality constraints." *Adv. Water Resour.* 18 (2): 67–75. https://doi.org/10.1016/0309-1708(95)00004-3.

Giacomoni, M. H., and J. Joseph. 2017. "Multi-objective evolutionary optimization and Monte Carlo simulation for placement of low impact development in the catchment scale." *J. Water Res. Plann. Manage.* 2 (9): 1–15. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000812.

Gupta, C. P., S. Ahmed, and V. V. S. Gurunadha. 1985. "Conjunctive utilization of surface water and groundwater to arrest the water- level decline in an alluvial aquifer." *J. Hydrol.* 76 (3–4): 351–361. https://doi.org/10.1016/0022-1694(85)90142-8.

Heath, R. C. 1984. *Ground-water regions of the United States*. Washington, DC: US Government Printing Office.

Katsifarakis, K. L., and Z. Petala. 2006. "Combining genetic algorithms and boundary elements to optimize coastal aquifers' management." *J. Hydrol.* 327 (1–2): 200–207. https://doi.org/10.1016/j.jhydrol.2005.11.016.

Kumar, M. 2009. "Toward a hydrologic modeling system." Ph.D. thesis. Pennsylvania State Univ.

Kumar, M., G. Bhatt, and C. J. Duffy. 2009a. "An efficient domain decomposition framework for accurate representation of geodata in distributed hydrologic models." *Int. J. Geog. Inf. Sci.* 23 (12): 1569–1596. https://doi.org/10.1080/13658810802344143.

Kumar, M., C. J. Duffy, and K. M. Salvage. 2009b. "A second-order accurate, finite volume–based, integrated hydrologic modeling (FIHM)

framework for simulation of surface and subsurface flow." *Vadose Zone J.* 8 (4): 873–890. https://doi.org/10.2136/vzj2009.0014.

Lindsey, B. B. D., W. F. Falls, M. J. Ferrari, T. M. Zimmerman, D. A. Harned, E. M. Sadorf, and M. J. Chapman. 2006. "Factors affecting occurrence and distribution of selected contaminants in ground water from selected areas in the Piedmont Aquifer System, Eastern United States, 1993–2003." US Geological Survey Scientific Investigation Rep. 2006-5104. Reston, VA: US Geological Survey.

Liu, L., Y. Cui, and Y. Luo. 2013. "Integrated modeling of conjunctive water use in a canal-well irrigation district in the lower Yellow River Basin, China." *J. Irrig. Drain. Eng.* 139 (9): 775–784. https://doi.org/10.1061/(ASCE)IR.1943-4774.0000620.

Maddock, T. 1972. "Algebraic technological function from a simulation model." *Water Resour. Res.* 8 (1): 129–134. https://doi.org/10.1029/WR008i001p00129.

Mantoglou, A., M. Papantoniou, and P. Giannoulopoulos. 2004. "Management of coastal aquifers based on nonlinear optimization and evolutionary algorithms." *J. Hydrol.* 297 (1–4): 209–228. https://doi.org/10.1016/j.jhydrol.2004.04.011.

Maurer, E. P., A. W. Wood, J. C. Adam, D. P. Lettenmaier, and B. Nijssen. 2002. "A long-term hydrologically based dataset of land surface fluxes and states for the conterminous United States." *J. Clim.* 15 (22): 3237–3251. https://doi.org/10.1175/1520-0442(2002)015<3237:ALTHBD>2.0.CO;2.

Natural Resources Conservation Service. 2015. "Geospatial data gateway." Accessed June 10, 2015. http://datagateway.nrcs.usda.gov/.

North Carolina Division of Water Resources. 2012. "Local water supply plan." Accessed June 1, 2016. http://www.ncwater.org/Water_Supply_Planning/Local_Water_Supply_Plan/.

Psilovikos, A. 2006. "Response matrix minimization used in groundwater management with mathematical programming: A case study in a transboundary aquifer in northern Greece." *Water Resour. Manage.* 20 (2): 277–290. https://doi.org/10.1007/s11269-006-0324-5.

Pulido-Velázquez, M., J. Andreu, and A. Sahuquillo. 2006. "Economic optimization of conjunctive use of surface water and groundwater at the basin scale." *J. Water Res. Plann. Manage.* 132 (6): 454–467. https://doi.org/10.1061/(ASCE)0733-9496(2006)132:6(454).

Qu, Y., and C. J. Duffy. 2007. "A semidiscrete finite volume formulation for multiprocess watershed simulation." *Water Resour. Res.* 43 (8): W08419. https://doi.org/10.1029/2006WR005752.

Rao, S. V. N., S. M. Bhallamudi, B. S. Thandaveswara, and G. C. Mishra. 2004. "Conjunctive use of surface and groundwater for coastal and deltaic systems." *J. Water Res. Plann. Manage.* 130 (3): 255–267. https://doi.org/10.1061/(ASCE)0733-9496(2004)130:3(255).

Rejani, R., M. Jha, and S. Panda. 2009. "Simulation-optimization modelling for sustainable groundwater management in a coastal basin of Orissa, India." *Water Resour. Manage.* 23 (2): 235–263. https://doi.org/10.1007/s11269-008-9273-5.

Safavi, H. R., F. Darzi, and M. A. Marino. 2010. "Simulation-optimization modeling of conjunctive use of surface water and groundwater." *Water Resour. Manage.* 24 (10): 1965–1988. https://doi.org/10.1007/s11269-009-9533-z.

Salcedo-Sanchez, E. R., M. V. Esteller, S. E. Garrido Hoyos, and M. Martinez-Morales. 2013. "Groundwater optimization model for sustainable management of the Valley of Puebla aquifer, Mexico." *Environ. Earth Sci.* 70 (1): 337–351. https://doi.org/10.1007/s12665-012-2131-z.

Sankarasubramanian, A., U. Lall, F. A. Souza Filho, and A. Sharma. 2009. "Improved water allocation utilizing probabilistic climate forecasts: Short-term water contracts in a risk management framework." *Water Resour. Res.* 45 (11): 1–18. https://doi.org/10.1029/2009WR007821.

Seo, S. B., K. Mahinthakumar, M. Kumar, and A. Sankarasubramanian. 2018. "Assessing the restoration time of surface water and groundwater systems under groundwater pumping." *Stochastic Environ. Res. Risk Assess.* 1–19. https://doi.org/10.1007/s00477-018-1570-9.

Seo, S. B., T. Sinha, K. Mahinthakumar, A. Sankarasubramanian, and M. Kumar. 2016. "Identification of dominant source of errors in developing streamflow and groundwater projection under near-term climate change." *J. Geophys. Res. Atmos.* 121 (13): 7652–7672. https://doi.org/10.1002/2016JD025138.

Shi, F., C. Zhao, D. Sun, D. Peng, and M. Han. 2012. "Conjunctive use of surface and groundwater in central Asia area: A case study of the Tailan River Basin." *Stochastic Environ. Res. Risk Assess.* 26 (7): 961–970. https://doi.org/10.1007/s00477-011-0545-x.

Shi, Y., K. J. Davis, C. J. Duffy, and H. Yu. 2013. "Development of a coupled land surface hydrologic model and evaluation at a critical zone observatory." *J. Hydrometeorol.* 14 (5): 1401–1420. https://doi.org/10.1175/JHM-D-12-0145.1.

Shourian, M., Y. Raoufi, and J. Attari. 2017. "Interbasin water transfer capacity design by two approaches of simulation-optimization and multicriteria decision making." *J. Water Res. Plann. Manage.* 143 (9): 1–12. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000818.

Singh, A. 2014a. "Conjunctive use of water resources for sustainable irrigated agriculture." *J. Hydrol.* 519 (Nov): 1688–1697. https://doi.org/10.1016/j.jhydrol.2014.09.049.

Singh, A. 2014b. "Simulation and optimization modeling for the management of groundwater resources. II: Combined applications." *J. Irrig. Drain. Eng.* 140 (4): 1–9. https://doi.org/10.1061/(ASCE)IR.1943-4774.0000689.

Singh, A., S. N. Panda, C. K. Saxena, C. L. Verma, V. N. E. Uzokwe, P. Krause, and S. K. Gupta. 2015. "Optimization modeling for conjunctive use planning of surface water and groundwater for irrigation." *J. Irrig. Drain. Eng.* 142 (3): 04015060. https://doi.org/10.1061/(ASCE)IR.1943-4774.0000977.

Singh, H., T. Sinha, and A. Sankarasubramanian. 2014. "Impacts of near-term climate change and population growth on within-year reservoir systems." *J. Water Res. Plann. Manage.* 141 (6): 04014078. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000474.

Sophocleous, M. 2002. "Interactions between groundwater and surface water: The state of the science." *Hydrogeol. J.* 10 (1): 52–67. https://doi.org/10.1007/s10040-001-0170-8.

Stray, B. J., J. H. van Vuuren, and C. N. Bezuidenhout. 2012. "An optimisation-based seasonal sugarcane harvest scheduling decision support system for commercial growers in South Africa." *Comput. Electron. Agric.* 83 (Apr): 21–31. https://doi.org/10.1016/j.compag.2012.01.009.

USGS National Map Viewer. 2015. "Data download and visualization services." Accessed August 15, 2015. https://viewer.nationalmap.gov/.

USGS Water Data Webpage. 2015. "USGS water data for the nation." Accessed March 5, 2015. http://waterdata.usgs.gov/nwis/.

Wang, R., M. Kumar, and D. Marks. 2013. "Anomalous trend in soil evaporation in a semi-arid, snow-dominated watershed." *Adv. Water Resour.* 57 (Jul): 32–40. https://doi.org/10.1016/j.advwatres.2013.03.004.

Yu, X., A. Lamčová, C. J. Duffy, P. Krám, J. Hruška, T. White, and G. Bhatt. 2015. "Modelling long term water yield effects of forest management in a Norway spruce forest." *Hydrolog. Sci. J.* 60 (2): 174–191. https://doi.org/10.1080/02626667.2014.897406.

Zekri, S., C. Triki, A. Al-Maktoumi, and M. R. Bazargan-Lari. 2015. "An optimization-simulation approach for groundwater abstraction under recharge uncertainty." *Water Resour. Manage.* 29 (10): 3681–3695. https://doi.org/10.1007/s11269-015-1023-x.

Zhang, C., B. Xu, Y. Li, and G. Fu. 2017. "Exploring the relationships among reliability, resilience, and vulnerability of water supply using many-objective analysis." *J. Water Res. Plann. Manage.* 143 (8): 4017044. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000787.