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Research papers

Assessing the effects of water restrictions on socio-hydrologic resilience for shared groundwater systems

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A R T I C L E I N F O

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A B S T R A C T

Groundwater resources are shared across management boundaries. Multiple management units that differ in scale, constraints and objectives may manage a shared resource in a decentralized approach. The interactions among water managers, water users, and the water resource components influence the performance of management strategies and the resilience of community-level water supply and groundwater availability. This research develops an agent-based modeling (ABM) framework to capture the dynamic interactions among household-level consumers and policy makers to simulate water demands. The ABM is coupled with a groundwater model to evaluate effects on the groundwater table. The framework is applied to explore trade-offs between improvements in water supply sustainability for local resources and water table changes at the basin-level. A group of municipalities are simulated as agents who share access to a groundwater aquifer in Verde River Basin, Arizona. The framework provides a holistic approach to incorporate water user, municipal, and basin level objectives in evaluating water reduction strategies for long-term water resilience.

1. Introduction

Water management is a major challenge for growing urban water systems. Sustainable human water use practices should balance the continued capacity to meet water demands for an increasing population and the protection of groundwater and surface water resources from over-exploitation (Elshafei et al., 2015). While urban water management is based on the science of hydrologic processes to address depletion of water resources, human activities that alter the natural processes are of scientific interests as well. Anthropogenic activities that influence the hydrologic cycle range from direct interactions, such as withdrawals and return flows, to indirect actions, such as land cover change, dam construction, hydropower generation, and anthropogenic climate change (Eslamian and Eslamian, 2017; Shahid et al., 2017; Weiskel et al., 2007). A limited characterization of the dynamics between human and natural systems can hinder the predictive capabilities of models to capture emergent behaviors and system performance (Elshafei et al., 2015). The field of socio-hydrology focuses on characterizing and integrating hydrologic processes and human interactions within a changing biophysical environment with the objective of understanding co-evolving dynamics, feedbacks, and threshold behaviors that are present across multiple scales (Sivapalan et al., 2012; Sivapalan, 2015). Research has advanced our understanding of socio-hydrology systems by exploring the co-evolution of humans and water systems (Liu et al., 2014) and characterizing the aspects of social systems, including norms, economics, regulations, and infrastructure choices on water security and community-level resilience (Yu et al., 2017; Scott et al., 2016; Srinivasan et al., 2017; Solander et al., 2016).

To better incorporate the concepts of socio-hydrology in managing water systems for improved resilience and sustainability, further research is needed to develop realistic simulations of human-water systems that can be used for decision-making (Di Baldassarre et al., 2016). Water resources are managed by multiple decision makers that share a common resource and differ in their access to water and supply constraints, and simulation frameworks are needed represent the co-evolution of policies, behaviors, and water resources as an emergent outcome due to the interactions among a set of managers within a human-water system. Both the behavioral response of human populations and organizations and the performance of managers in achieving their goals have a hydrologic impact on water systems. This study develops a simulation framework to represent independent water management units to realistically assess the effectiveness and feasibility of long-term basin-level water management strategies. We extend the field of socio-hydrology by developing a modeling framework to explicitly represent the interconnections of population, policy, and hydrology to quantify the sustainability of alternative management practices in a shared

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groundwater system. Real world water restriction policies are assessed based on their impacts on the demand reduction of communities, city-level water supply performance, and groundwater improvements at a basin-level. Cities are simulated to enact mandatory water restrictions as a proactive or reactive mechanism to protect groundwater when demands grow beyond a permitted yield.

To facilitate the heterogeneity, complexity, and adaptive behaviors of stakeholders that are involved in shared water management, we use an agent-based modeling (ABM) approach. ABM represents a set of autonomous and heterogeneous actors that act and interact to produce system-level emergent behavior. ABM has been used to simulate the complexity of consumer water demands in which consumer behaviors are influenced by interactions with other consumers, water suppliers, meteorological information, water pricing, educational conservation campaigns, innovation diffusion, and opinion dynamics (Downing et al., 2000; Moss and Edmonds, 2005; Athanasiadis et al., 2005; Galán et al., 2009; Berglund, 2015; Al-Amin et al., 2015; Mashhadi Ali et al., 2017). In our study, water users and water managers in each city are represented as agents.

The ABM approach provides an approach to simulate water use based on indoor water consumption data available through surveys and historical local weather data. Local data allows simulation of heterogeneous actions and reactions to water restrictions. The ABM approach also facilitates simulation of the dynamic interactions among water user agents, manager agents, and water resources to simulate city and basin level emergent groundwater level responses. This framework is applied for an illustrative case study in the Verde River Basin, Arizona, where eight cities are represented using population agents and manager agents to capture the complexity of a human-water system at a basin level. The ABM is coupled with a regional groundwater flow model developed in MODFLOW. Results demonstrate the effects of heterogeneous actions on outcomes for local cities and basin-level resources. This research explores the mechanisms behind the co-evolution of human-water systems in water management systems that rely on restrictions. The framework provides an approach to develop and evaluate water management strategies that implement mandatory restriction policies for sustainability and resilience metrics.

2. Assessing water restrictions for demand management

A water restriction program prioritizes essential water uses and places restrictions on low-priority end uses such as outdoor irrigation in residential areas. Costs of a restriction program are reflected in the cost of monitoring by municipalities and in fines paid by users for violating restrictions. Mandatory water restrictions can be enforced in reaction to environmental triggers, or they may remain in effect regardless of climate or environmental conditions.

As shown in Fig. 1, by imposing water restrictions on certain water uses, water managers can improve water supply sustainability for a municipality and reduce the depletion of shared regional water resources. At the same time, water restriction programs can enlarge the water deficit, which is the gap between the amount of water that is used and the amount of demand or desired water use. Water restriction programs, therefore, lead to trade-offs between the improvement of regional water resources and local water supply sustainability. When selecting water restriction program designs, such as the frequency and timing of restrictions, water managers can evaluate alternative programs based on their impacts at multiple scales. At the basin-level, groundwater resources are typically evaluated based on depletion of the water table (Konikow and Kendy, 2005; Sophocleous, 2002). Reliability, resilience, vulnerability, maximum deficit, and sustainability are indices for measuring the performance of a local water supply (Loucks, 1997; Sandoval-Solis et al., 2010). These metrics are based on the deficit of water, which is the difference between the demand for water and the actual amount of water delivered. Reliability refers to the probability that there will be no deficit; resilience is the ability of the system to return to a deficit of zero after a non-zero deficit occurs; vulnerability is the volume of the deficit compared to the average demand; maximum deficit is the largest deficit experienced by a community of water users over the time period; and sustainability is an index that synthesizes these metrics in one value between 0.0 and 1.0 (Sandoval-Solis et al., 2010). The definitions of these indices in the context of this study are further described in Section 3.2.

To evaluate mandatory water restriction programs, the system supply performance is measured under alternative levels, timing, and frequencies of restrictions to determine water savings. The water availability for critical end use purposes is evaluated to ensure that required demands are satisfied, and basin-level impacts are evaluated to determine loss of water resources. This research develops a holistic framework to assess the impacts of water restrictions on users, supply, and resources and explore trade-offs among conflicting goals.

3. Materials and methods

Coupled groundwater-ABM (GW-ABM) frameworks have been developed to represent adaptive and dynamic characteristics of complex water resource systems in other studies by tightly coupling ABM and groundwater simulation models to explicitly represent the dynamic decision-making of water managers and water users (Zhou et al., 2015). GW-ABM frameworks have been developed to study the effects of residential land use change (Reeves and Zellner, 2010; Zellner and Reeves, 2012) and agricultural decision-making and land use change (Holtz and Pahl-Wostl, 2012; Mulligan et al., 2014) on groundwater depletion. These studies demonstrate that short-sighted or self-interested behaviors of agents undercut the expected groundwater improvements of policy instruments, as assessed with simplified groundwater modeling. In a methodological study, Castilla-Rho et al. (2015) illustrated an interactive modeling environment for developing GW-ABMs to simulate these complex socio-environmental couplings in groundwater systems and explore emerging groundwater conditions due to agent behaviors and interactions.

The GW-ABM described here is designed to assess water restrictions based on multiple goals: (1) maintenance of the groundwater table at a basin scale, and (2) improvement in city-level water supply sustainability indices. Fig. 2 describes the conceptual framework for the coupled GW-ABM. Municipal water demands are generated based on the dynamic interactions of the population agent and the manager agent in the ABM framework. An explicit climate dependent outdoor demand model is used, which facilitates the opportunity to analyze management alternatives and consider seasonal variations in alternative climate change projections. Aggregated indoor, outdoor, and non-residential demands are used to calculate the water withdrawal from groundwater resources. The water withdrawal affects the groundwater conditions, and the corresponding groundwater level is evaluated using a groundwater simulation model. Manager agents respond to increases in water demand, rather than depletion of water supply, based on data that describes the case study and real system that is explored in the application, and a tightly coupled framework is not needed for this study. The components of the framework are described as follows.

3.1. Process overview and schedule

The schedule of the ABM-groundwater model is summarized here. The agent-based model is run at a monthly time step, representing a typical rate of communication about restrictions between utility managers and customers. Finer time steps, such as daily or weekly, would not be feasible for implementing water restrictions, which involves communication of restrictions and water resources conditions to water users. On the other hand, an annual time step would not allow a utility to react to water resources conditions, and a monthly schedule allows utilities to select different choices depending on the season.

At each time step, indoor and outdoor end uses generate household-

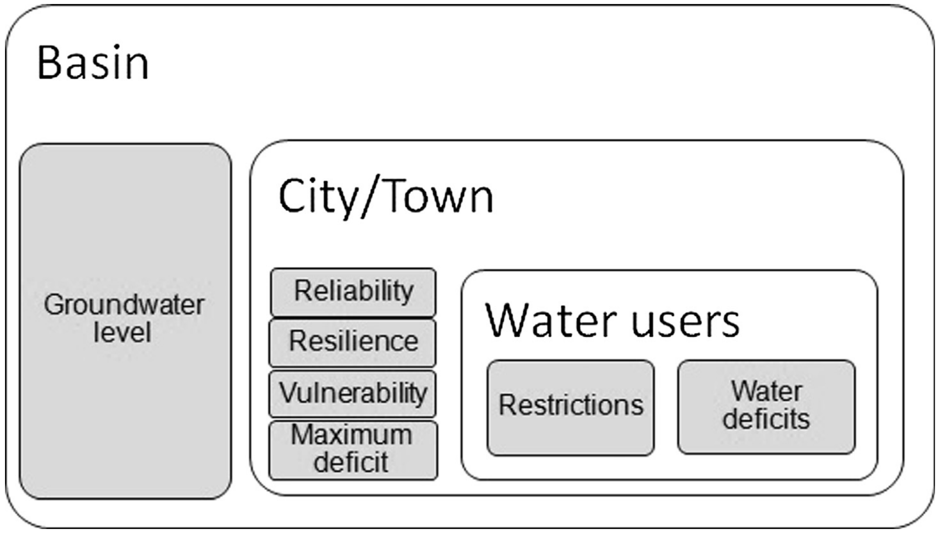

Fig. 1. Interdependence of components in a socio-hydrologic system.

level water demands. The number of households changes according to population growth projections. Household-level water demands are accumulated to generate residential water demands. Non-residential water demands are calculated using a factor based on the assumption that non-residential demands grow linearly with residential demands. Residential and non-residential demands are summed to generate city water demands. Manager agents react to the total demand, based on violation of the safe yield, which is the volume of water that can be safely withdrawn from the aquifer. A proactive manager updates water restrictions corresponding to the month, violation count, and violation magnitude. A reactive manager updates restriction status corresponding to the violation alone. Household end uses are updated for the next time step based on the restrictions that are applied. Groundwater level changes are evaluated corresponding to city water demands through the use of a groundwater model. The sustainability index is calculated based on water savings within each city. In this model formulation, manager agents do not interact directly to communicate about management strategies or performance. Autonomous utilities have individual effects on their local water savings and water supply sustainability, and they exert an aggregated impact on the groundwater table. These three metrics are the emergent features that are studied using this framework. Key design concepts of the coupled groundwater-ABM (GW-ABM) model are summarized in Table 1.

Table 1
Key concepts in the ABM-GW model.

Concept	Description
Basic principles	The household agents follow indoor and outdoor water use rules that are heterogeneous, climate-sensitive and reactive to actions of the manager agent. The water utility manager agent uses water restriction policies that are proactive or reactive in response to population and climate
Emergence	Restrictions emerge as a function of frequency and magnitude of safe yield violation. Water consumption depends on the dynamic actions taken by a manager agent and the adaptive response of users. The groundwater depletion emerges as a response to heterogeneous restrictions applied by the cities and the hydrology of the basin
Adaptation	The household agents have alternative sets of end uses and adapt to restrictions applied by the manager agent. The manager agent applies different levels of restrictions based on safe yield violations
Objectives	The manager agents do not have any utility function, but instead follow IF-ELSE conditions to apply restrictions. Restriction policies are mandatory, and household agents fully comply with restrictions
Interaction	The household agents and the manager agent interact directly. The household agents interact with the environment (climate). The manager agents do not interact directly with the environment, but use safe yield as a surrogate for applying restrictions that impact the environment (groundwater)
Observation	The internal dynamics of the model can be viewed as the frequencies of different restriction status levels and water savings by household agents. The system level behavior is captured through sustainability indices and changes in groundwater

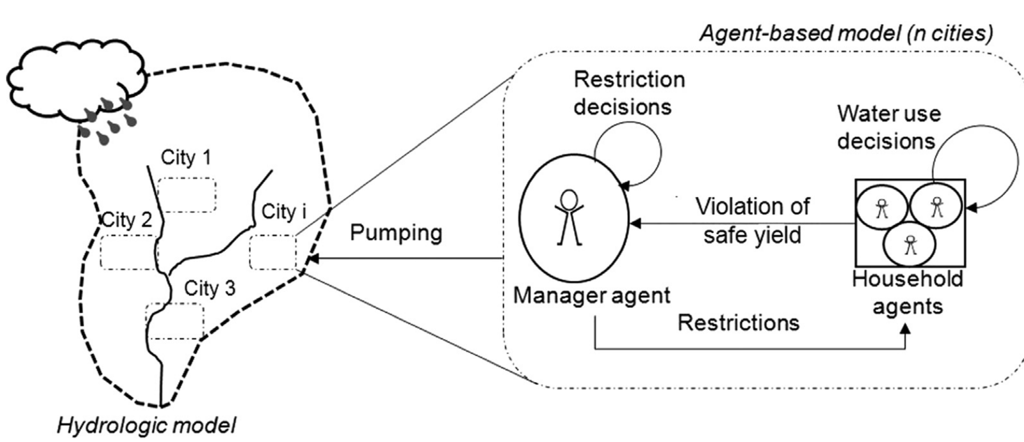

Fig. 2. Process overview of the ABM framework.

3.2. Population agent

Each household is assigned parameters for the household size, indoor end uses, and outdoor lawn watering requirements. These parameters are set based on average values for a city. Households are homogeneous within each city and are combined to act as one agent, the population agent. Total water demands for residential purposes ($D_{R,t}$) at each time step t at the household level are calculated based on indoor ($D_{R-IN,t}$) and outdoor demands ($D_{R-OUT,t}$).

$$D_{R,t} = D_{R-IN,t} + D_{R-OUT,t} \tag{1}$$

$$D_{R-IN,t} = \sum \{MEAN_{END}\}*H_t \tag{2}$$

$$D_{R-OUT,t} = IR_t*\frac{A}{Eff}*K_{CROP}*LWF*L_{ratio} \tag{3}$$

where $MEAN_{END}$ is the average demand volume per capita for a set of designated indoor end uses for one household (i.e., shower, toilet, clothes washer, dishwasher, bathroom, faucet, and leak), and H_t is the household size. A is the lawn area, IR is the irrigation requirement, Eff is the efficiency of irrigation technologies, and K_{CROP} is the crop coefficient. LWF is the lawn watering frequency, which is a behavioral factor to represent how often households water their lawns. LWF is 0 when households never water their lawns; LWF is 0.5 when households water their lawns every alternative day; and LWF is 1 when households water their lawns every day. L_{ratio} is the calibration parameter, which is the ratio of actual outdoor water use to theoretical irrigation requirements. The irrigation requirement is calculated as a function of number of rainy days and evaotranspiration (ET), assuming no irrigation is required on a rainy day. The irrigation requirements are assumed to be constant across a city at each time step.

Non-residential water users are not modeled as interactive agents in this study. Their demands, $D_{NR,t}$, are assumed to increase linearly with residential demand. The non-residential demand in each city is a fixed ratio of the residential demand at each time step.

$$D_{NR,t} = NR_{Ratio}*D_{R,t} \tag{4}$$

$$D_{C,t} = n_t*D_{R,t} + D_{NR,t} \tag{5}$$

where NR_{Ratio} is a ratio of non-residential to residential demands and is based on historical observations. The total water demand ($D_{c,t}$) at each time step is calculated as the sum of water demands for all households (n_t) at time step t and the non-residential demand ($D_{NR,t}$). The set of households and the non-residential sector represents the city, and the city collectively exerts an aggregated demand that is supplied by the municipal agent.

3.3. Water utility manager agent

A water utility manager is represented as a municipal agent. At each time step, the municipal agent observes a parameter representing the status of the stress on water resources and enacts a set of rules for conservation. The water manager agent can enact proactive or reactive management strategies. A proactive approach enacts predefined water restrictions for specific months of the year, such as in the summer when demands are high. The proactive approach may also incorporate some restrictions in response to the increasing demands, when it violates a resource condition (e.g., safe yield) in addition to predefined restrictions. A reactive approach, on the other hand, only applies restrictions when a violation of pre-determined resource conditions occurs. The water manager agent monitors changes in water supply sustainability indices, which are described as follows, with changes to water availability.

3.3.1. Sustainability index

Here the utility manager observes the sustainability index, which was developed by Sandoval-Solis et al. (2010) to quantify the sustainability of water use practices. The sustainability index has been applied for evaluating both Mexican and USA water users, as well as for environmental flows in the Rio Grande basin following the 1944 treaty between United States and Mexico (IBWC, 1944). The index incorporates common indicators of water sustainability performance in a single value, whereas each of the indicators are assumed of equal weight. The water utility manager agent observes the sustainability index (SI), which is calculated for a city as follows:

$$SI = [Rel*Res*(1-MaxDef)*(1-Vul)]^{1/4} \tag{6}$$

where Rel is the reliability of the water supply system. Water demand reliability is the probability that the available water supply meets the water demand during the period of simulation (Sandoval-Solis et al., 2010). For each time period t, where water demand (WD_{it}) in city i is less than the safe yield (SY_{it}), deficit (D_{it}) is zero.

$$D_{it} = \begin{cases} WD_{it}-SY_{it} & if\ (WD_{it} > SY_{it}) \\ 0 & if\ (WD_{it} \leqslant SY_{it}) \end{cases} \tag{7}$$

$$Rel = (\text{no of times} D_{it} = 0)/\text{total no of timestep} \tag{8}$$

Res is the resilience of the water supply system. Resilience is a system's capacity to adapt to changing conditions such as drought (Sandoval-Solis et al., 2010).

$$Res = (\text{no of times } D_{it} = 0 \text{ followed by } D_{it} > 0)/(\text{no of times } D_{it} > 0) \tag{9}$$

Vul is the vulnerability of the system. Vulnerability is the likely value of water deficits, if they occur (Sandoval-Solis et al., 2010). Essentially, vulnerability expresses the severity of water deficit with respect to demands.

$$Vul = (\sum D_{it})/\text{no of times } D_{it} > 0 \text{ occurs} \tag{10}$$

$Maxdef$ is the maximum deficit of the water supply system. The maximum deficit, if deficits occur, is the worst-case annual deficit.

$$Maxdef = Max(D_{it}/WD_{it}) \tag{11}$$

A low value of any of the performance indicator lowers overall the sustainability index commensurately. For example if a city maintains a reliable (0.9) and resilient (0.9) supply with low vulnerability (0.1) but experiences a high maximum deficit (0.9), the SI index will be 0.5, indicating a moderate sustainability. The product of the terms is raised to 1/4 in calculating the SI index to ensure equivalence of the aggregated impacts of four indicators.

4. Illustrative case study: Verde River Basin

The GW-ABM framework is applied for the Verde River Basin (VRB) in Arizona (Fig. 3). The major towns or cities in the VRB include Camp Verde, Payson, Sedona, Cottonwood, and Clarkdale. The Verde River Flows to the south and east and joins the Salt River that plays an important role in the water supply for Phoenix and other downstream localities. The VRB overlays the Big Chino Valley aquifer, and the cities in the VRB rely on groundwater pumping to meet the majority of their demands. Cities including Prescott, Prescott Valley, and Chino Valley belong to the Prescott Active Management Area, which has groundwater rights to export out of the Big Chino and Little Chino aquifer (Wirt et al., 2005), and, as a result, water users in these cities are also hydrologically connected to the VRB. In total, eight population growth centers are included in the simulation of the VRB as a complex system. For simplicity, we refer to them as 'city' in this study.

The 1980 Arizona Groundwater Management Act defines safe yield as a groundwater management goal. Safe yield attempts to achieve and maintain a long-term balance between the amount of groundwater withdrawn and the annual amount of natural and artificial recharge in designated active management Areas. The safe yield is evaluated through hydrologic modeling, and unique yield limits are assigned to

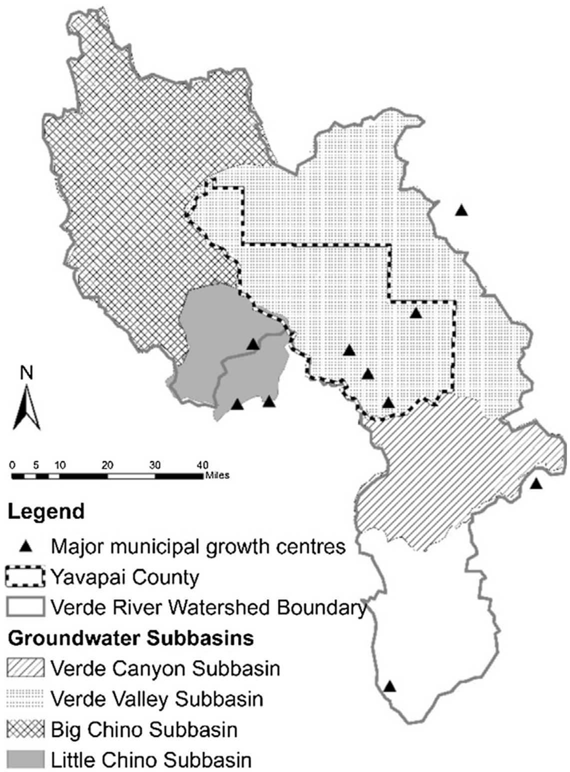

Fig. 3. Groundwater Subbasins in the VRB.

different cities, determined by the Arizona Department of Water Resources (ADWR). Cities within the VRB use different management approaches to restrict demands. For example, the Town of Payson uses the number of consecutive days that safe yield is violated as a trigger for application of different levels of mandatory conservation measures. While the Town of Payson responds reactively to groundwater safe-yield violations, other cities act in a proactive or static manner. The City of Cottonwood, for example, uses static mandatory high-level restrictions from May to September.

The ABM-GW framework was developed for application to the VRB using MASON, a discrete-event multiagent simulation library core in Java (Luke, 2011), which was loosely coupled with the groundwater model MODFLOW (Harbaugh, 2005). Further details are provided as follows.

4.1. Population agent

Each city is represented as one water user. Residential water use is modeled based on the water use data for calendar years 1990 through 1997, collected from surveys conducted by the ADWR (Pearson et al., 2000). The ratio of indoor end use to the per capita water use is available through an end-use survey conducted in Phoenix, AZ, and indoor end uses in each municipality are assumed to have the same percentage that is reported for Phoenix (30.5%) (Nelson et al., 1999). The lawn area is estimated using land-use maps and corresponding housing data in each city (City of Sedona Community Development Department, 2014; Town of Camp Verde, 2016; Town of Payson, 2014; Cottonwood, 2014). Based on the acreage and relative contribution of residential land use types, the average lot size for a household is estimated for each city. The lawn area is assumed to be 50% of each lot. The ratio of actual outdoor water use to theoretical irrigation requirements (L_{ratio}) for each population agent was adjusted to match residential water demand to survey results from 1990 to 1997 (Pearson et al., 2000) (Fig. 4). The baseline water demands show an increasing trend in all major cities, which indicates population growth is a major driving factor in demand dynamics in the basin. Population and population growth rates for each city are shown in Table 2.

Non-residential water users are not modeled as interactive agents in this study. Non-residential water demands show an increasing trend in the study area for the period 1990–1997 (Pearson et al., 2000), and the ratio of non-residential water use to residential water use (NR_{Ratio}) is calculated from corresponding data.

4.2. Water utility manager agent

The water managers monitor water demands to determine if they exceed the safe yield. The safe yield for each city (Table 2) is based on city water reports (Payson, 2013; Cottonwood, 2006; Centre, 2015), or assumed equal to the groundwater recharge in 2005 (Pool et al., 2011) for cases in which a safe yield value is not available. Although safe yield is subject to change with decisions to transfer water from other basins and water right acquisition, we assume safe yield for each city remains constant, and future expansion of supply capacity is not considered. The demand reduction strategy that is used by each city is shown in Table 2. The proactive and reactive manager agents are coded following the water restriction programs as described for the Town of Payson and City of Cottonwood, respectively. The rules for the interactions of household agents and manager agents are described in detail in Table 3.

4.3. Groundwater model

The Northern Arizona Regional Groundwater Flow Model (NARGFM) is a numerical flow model (MODFLOW) of the groundwater flow system in the primary aquifers in northern Arizona, developed by the US Geological Survey (USGS) to simulate interactions among the aquifers, perennial streams, and springs for predevelopment and transient conditions during the period 1910–2005 (Pool et al., 2011). The Verde River Basin Groundwater Model (VRBGM) has been derived from the NARGFM model with appropriate boundary condition considerations. The model simulates groundwater flow across the entire basin. The model boundaries were set along the boundary of the Verde River Basin and no flow conditions were assumed across boundary perimeters.

Cell sizes of 1000 m by 1000 m are used in the VRBGM, following the original USGS model. A grid of 285 rows, 187 columns, and three layers are used to represent the VRBGM. The three layers in the model represent the aquifer structures (Fig. 5). Layer 1 is the uppermost layer. It represents the thick silt and clay and adjacent inter-bedded alluvial deposits in the Big Chino Valley and the fine-grained part of the Verde Formation in the Verde Valley. Layer 2 represents the sand and gravel in the Verde and Big Chino Valleys, and the lower volcanic unit in the Little Chino Valley. Layer 3 is the lowest of the layers and it extends across the entire model domain, and represents the Redwall-Muav aquifer and crystalline rocks that are exposed at the land surface in the southern and eastern parts of the model domain (Pool et al., 2011).

The model simulates groundwater condition from 1910 through 2065. Steady-state conditions are assumed in 1910 and transient conditions are assumed from 1910 through 2065. The simulation period is divided into eleven multi-year stress periods in the historical period from 1910 to 2015 and another ten multi-year stress periods for future scenarios. The model does not simulate any seasonal or annual varioations. Each stress period consists of five time steps where each subsequent time step increases in length by a factor of 1.2, compared to the previous time step.

MODFLOW recharge package (RCH) is used to simulate the natural recharge. Groundwater recharge is calculated as the total difference of inflows and outflows and is applied to the topmost model cell in the spatial extent of the model. MODFLOW stream (STR) and drainage (DRN) packages simulate intermittent streams and springs. Stream-aquifer interactions of the Verde River drainage system are also simulated using the STR package. Surface water entities in the area include

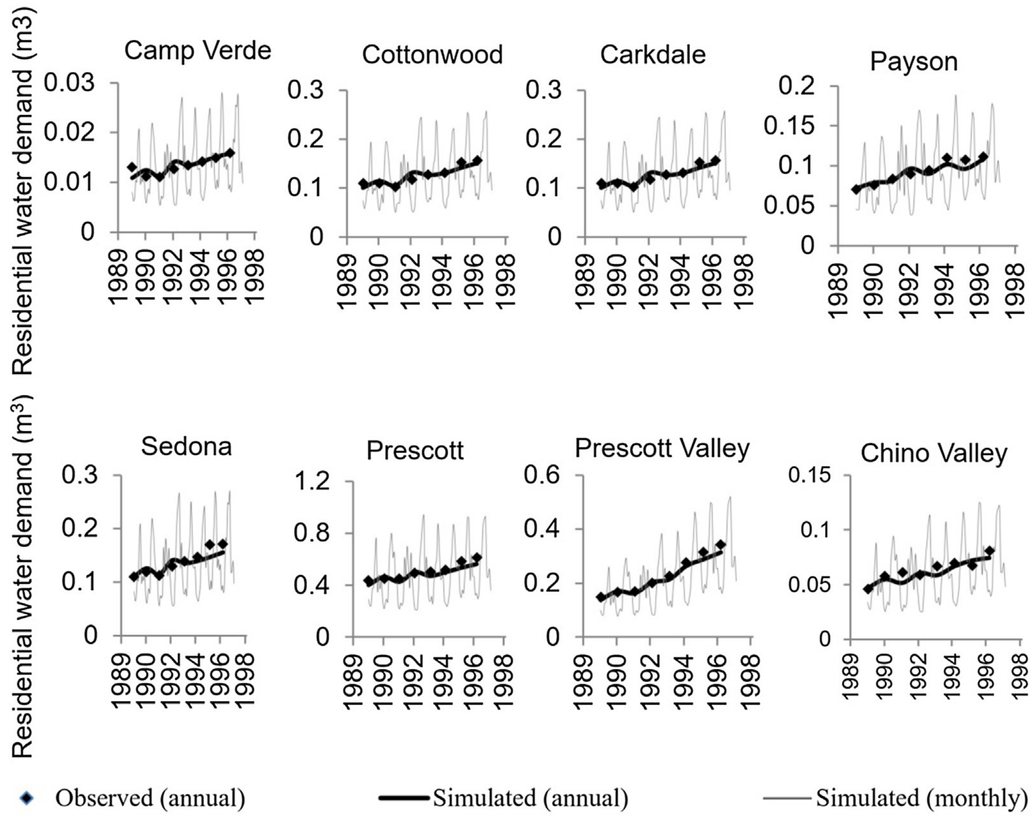

Fig. 4. Calibrated residential water demand projections for eight VRB cities.

Table 2
Population estimation in 2016, average growth rate for 2016–2065, water rates, safe yield and water strategies in the VRB.

City	Population (growth rate)	Safe yield (Mgal/year)	Demand reduction strategy
Cottonwood	11649 (0.97)	1955.1	Proactive [1]
Clarkdale	4337 (1.03)	871.65	Proactive
Camp Verde	11191 (0.84)	58.21	Other[2]
Payson	15881 (0.63)	595	Reactive
Sedona	7520 (0.88)	145.88	Other
Prescott	40731 (0.5)	934.42	Other
Prescott Valley	41699 (1.48)	528.88	Other
Chino Valley	11718 (1.3)	195.95	Other

[1] Refers to rules described in Table 2.
[2] Other refers to Per capita and non per capita requirements for large municipal providers, conservation requirements for individual users, distribution system requirements in the Prescott AMA, education and outreach, incentive programs in Sedona and Camp Verde.

the Verde River and several Creeks. These are Sycamore Creek, Oak Creek, Wet Beaver Creek, West Clear Creek, and several major springs. The Verde River stream network also includes intermittent stream reaches of Williamson Valley Wash and Little Chino Wash (Pool et al., 2011).

The MODFLOW well package (WEL) is used to simulate groundwater withdrawal. Pool et al. (2011) provide historical water withdrawal data, well locations, withdrawal rates, and model layer from which withdrawals are taken. For wells that lacked depth information, wells were assigned to the uppermost layer or to the primary layer used by other nearby wells following the original model. A constant decadal withdrawal rate is used for each well from 1940 to 2065.

4.4. Assessing the groundwater model

MODFLOW results are compared with the observed groundwater levels to ensure that the model accurately simulates the Verde River Basin groundwater conditions, after changes were made to the original NARGFM model. Observed data series from 44 locations were used to assess the model performance. The data series includes 407 observations at nine locations in layer one, 1141 observations at 26 locations in layer two, and 292 observations at nine locations in layer three (Fig. 6). The observations are all between the historical period of 1920–2015. The model performance is evaluated using the Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970) and root-mean-square error (RMSE). The NSE measures the goodness of model fit. NSE value of unity (1.0) indicates that simulations perfectly represent the observations. A negative NSE indicates that model predictions are worse than a prediction performed using the average of all observations as an alternative model, and in general, a value of greater than 0.6 is accepted as a good model. The RMSE measures model accuracy in terms of deviations between predictions and observations. The VRBGM performed well compared to the original NARGFM (Table 4) and the observed data (Fig. 6). The NSE values were better in layer two (0.93) and layer three (0.89) compared to layer one (0.69), though the model overall (0.94) performed better than the NARGFM (0.74). The NSE values for all the layers and that of the overall VRBGM model are greater than 0.6 which indicates the acceptance of the model as a good one. The RMSE values were lowest in layer three, and the VRBGM performed better than the NARGFM in terms of RMSE.

4.5. Modeling scenarios

Four management scenarios are simulated using the GW-ABM framework:

- No management: Groundwater level changes are projected for

Table 3
Rules for interactions for municipal and household agents.

Current status	Resource condition	New status	Restrictions
Proactive Management			
1, 2	**IF** safe production capacity > city water demand **AND** month = October to April	1	None
1, 2	**IF** 1.2 * safe production capacity ⩾ city water demand **AND** month = May to September		
1	**IF** safe production capacity < city water demand ⩽1.2 * safe production capacity **AND** month = October to April	2	**SET** lawn watering frequency = 0.5
3	**IF** city water demand ⩽1.2 * safe production capacity		
1, 2	**IF** 1.33 * safe production capacity ⩾ city water demand > 1.2 * safe production capacity		**SET** lawn watering frequency = 0.5 and non-residential demand reduction = 0.1
4	**IF** 1.33 * safe production capacity ⩾ city water demand	3	
1, 2, 3	**IF** 1.33 * safe production capacity ⩽ city water demand	4	**SET** lawn watering frequency = 0.0 and non-residential demand reduction = 0.1
Reactive Management			
1, 2	**IF** safe production capacity > city water demand	1	None
1	**IF** safe production capacity ⩽ city water demand in 1 time step	2	**SET** lawn watering frequency = 0.5 and non-residential demand reduction = 0.1
3	**IF** safe production capacity > city water demand		
1	**IF** safe production capacity ⩽ city water demand in 2–11 time step	3	**SET** lawn watering frequency = 0.0 and non-residential demand reduction = 0.25
4	**IF** safe production capacity > city water demand		
3	**IF** safe production capacity ⩽ city water demand in 12 time step	4	**SET** lawn watering frequency = 0.0 and non-residential demand reduction = 0.25

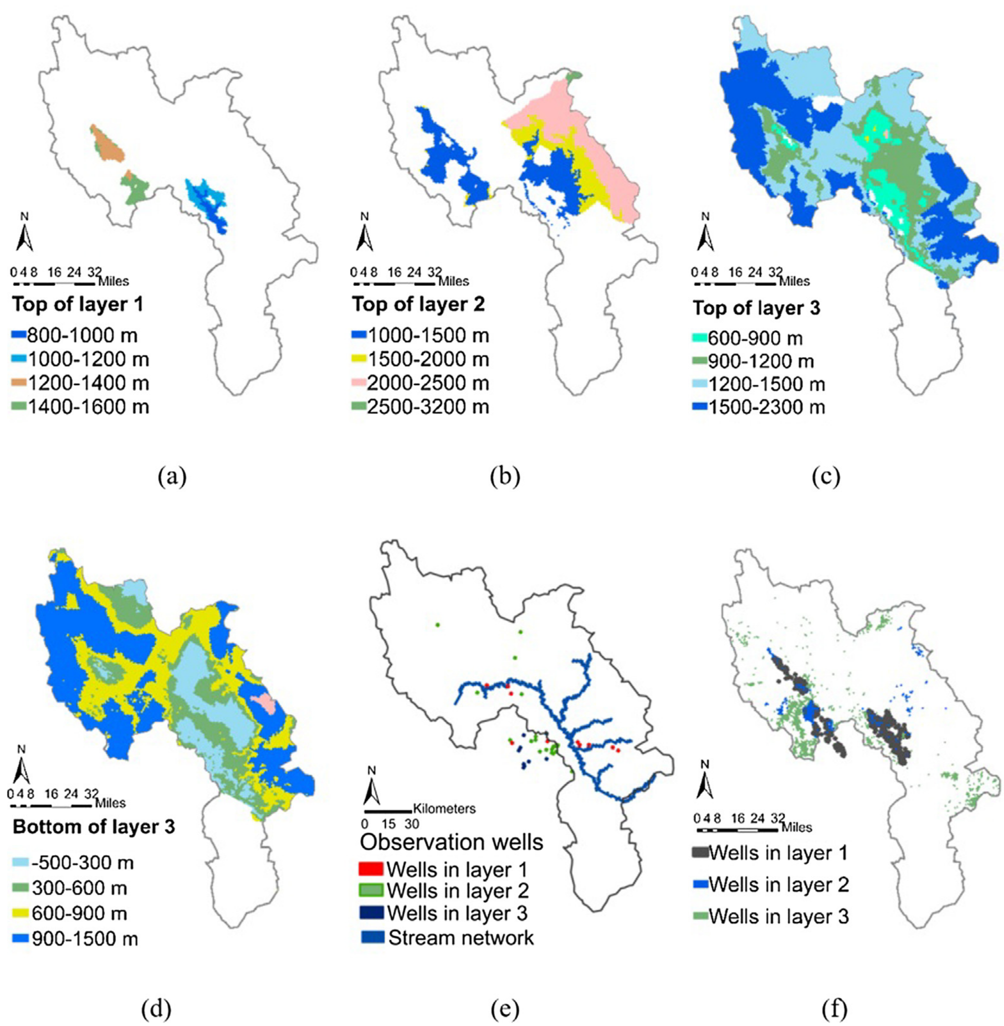

Fig. 5. Verde River Basin Groundwater Model layers (a) Top of layer 1, (b) Top of layer 2 (c) Top of layer 3, (d) Bottom of layer 3 (e) observation wells and stream network, (f) production wells.

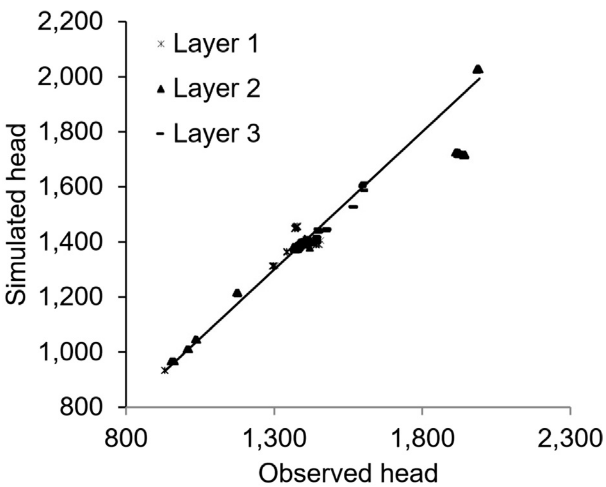

Fig. 6. Comparison of simulated heads and observed heads in layers 1, 2, and 3.

Table 4
Summary of model performance compared to NARGFM model.

Model	Root Mean Square Difference (RMSD)	Nash-Sutcliffe Efficiency (NSE)	Total observations
VRBGM	44.51	0.94	1840
Layer 1	81.18	0.69	407
Layer 2	51.8	0.93	1141
Layer 3	22.5	0.89	292
NARGFM	121.19	0.74	6960

future demands without management over the period 2016–2065.

- Business as usual: Cities apply proactive, reactive or no management practices based on their current management preference (Table 2). Groundwater level changes are assessed for projected future demands.
- Proactive water restrictions: Groundwater depletion is assessed for future population and climate changes from 2015 to 2065, following the mandatory conservation program in Cottonwood. In this approach, some restrictions are implemented based on the season, without regard for the state of the demands. Restrictions are also implemented in reaction to the total water demand in the city, as compared to the safe yield.
- Reactive water restrictions: Groundwater depletion is assessed for future population and climate changes from 2015 to 2065, following the mandatory conservation program in Payson, AZ. The trigger for enacting different levels of restrictions is total water demands in the city relative to the safe production capacity. The water manager updates its rules based on demands alone.

Three climate scenarios are tested for each of the four cases described above. Three different Bias Corrected Spatially Downscaled CMIP5 (Climate Model Intercomparison Project) projections were used in this study. The dataset was taken from Geophysical Fluid Dynamics Laboratory, USA, NASA Goddard Institute for Space Studies, USA and National Center for Atmospheric Research, USA (Maurer, 2012). An emission path of RCP 6.0 was assumed in all cases. The variation in climate components impact both water withdrawals and groundwater recharge. The variation in groundwater withdrawal is caused due the variation of outdoor lawn watering, which is dictated by evapotranspiration and number of rainy days and captured using Eq. (3). The higher the evapotranspiration and the lower the number of rainy days are, the higher the irrigation requirements are. These values vary across spatial (cities) and temporal scale and produce different outdoor water usage across climate projections and are ported to groundwater model in the form of groundwater withdrawals at cities (well package). The climate components also affect the groundwater recharge calculated as the total difference of inflows and outflows (Stonestrom, 1984), where the inflows are calculated as the sum of precipitation, snow-melt and soil storage from last time step, and the outflows are calculated as the sum of runoff, evapotranspiration and snow accumulation. The recharges are calculated for each cell in the grid of 285 rows and 187 columns for each stress period and are incorporated into the groundwater model using the recharge package.

5. Results

5.1. Occurrence of restrictions for management strategies

Under the three different climate projections, municipal water demands are projected for the future period of 2016–2065. Based on the projected demands, the cities are grouped into three different types: low stress, moderate stress, and high stress cities. Low-stress cities are those where safe yield is not violated by city demands for the projected 20–45 years. Moderate-stress cities have growing demands that are projected to surpass the safe yield over the next 20–45 years. For high-stress cities, the safe yield is violated under current demands or projected as violated within the next 20 years.

Fig. 7 shows the average occurrence of each status as the number of

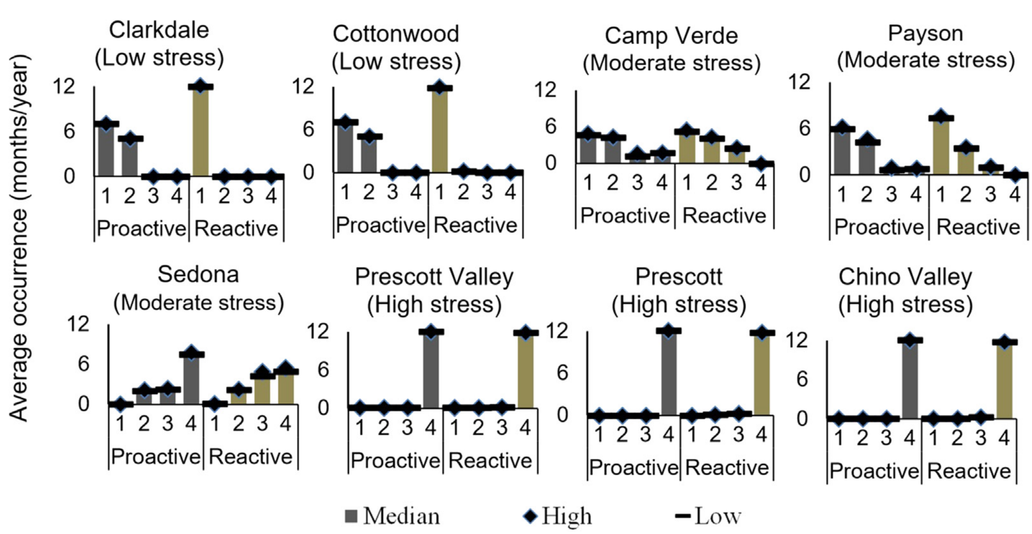

Fig. 7. Average occurrence of each status level under proactive and reactive management for eight cities in the VRB.

months per year that a system spends in each status level. Results are shown for both proactive and reactive management approaches for each of the eight cities. For high stress systems, systems remain in high water restriction status levels. High water restriction status levels indicate that more restrictions are enforced to curb water consumption. Restrictions that are imposed vary between proactive and reactive approaches. For Cottonwood and Clarkdale (low-stress cities) under reactive management, the water systems remain in status 1 (no restrictions) for the majority of the simulated period. Higher status restrictions are seldom applied. For these cities, proactive managers remain in status 2 from May to September and in status 1 from October to April. Moderate-stress cities include Camp Verde, Payson, and Sedona. These cities have a higher occurrence of status levels 2, 3, and 4, compared to low-stress cities. Payson and Camp Verde remain in status level 1 for approximately 50% of the simulated months. Sedona remains in status level 1 less than 1% of the simulated months, but it is in moderate status levels (2 and 3) for most of the simulated period. High-stress cities include Prescott, Prescott Valley and Chino Valley. These cities are almost continuously in status level 4.

5.2. Household water savings

Results as described above for Fig. 7 focus on system-level restrictions. Fig. 8, on the other hand, demonstrates household-level water savings that emerge due to water restrictions. Water savings are simulated as they vary in response to restrictions that are applied due to the magnitude and frequency of safe yield violations. Results are reported for cities representing low-stress (Cottonwood), medium-stress (Payson), and high-stress (Prescott Valley) systems. The three cities are stressed at different levels initially and the water stress changes over the time; as a result, the safe yield violation also changes over the time. In the City of Cottonwood, safe yield violations are not observed until 2050–2065 (Fig. 8b), and, as a result, reactive restrictions are not applied until this time. Waters savings are not observed until 2035. For proactive restrictions, however, mandatory water restrictions are in place from May to September for the entire simulated period. Three climate projections are simulated and show differences in projected water savings, due to variations in evapotranspiration among the three projections. In Cottonwood, water saving varies by 6.8 m^3/year under proactive management and 3.4 m^3/year under reactive management across the three climate projections for the projected time period. For proactive management, this represents 7% of the average annual savings. For reactive management, this is 1.06 times the average annual savings, which are relatively low as shown in Fig. 8.

For medium stress cities (such as Payson in Fig. 8), water savings increase over the simulated period for both proactive and reactive water management. The amount of water savings varies over a wide range during the years 2015–2035 for reactive management, compared to proactive management, due to the differences among the climate projection scenarios and the occurrence of safe yield violations. Households use more water for outdoor purposes in hotter, drier climate projections, and, as a result, safe yield violations occur more frequently. Over the entire simulated period, water savings projections vary by 10.9 m^3/year (18% of average annual savings) and 12.5 m^3/year (23.7% of average annual savings) for proactive and reactive approaches, respectively. Reactive and proactive management approaches save similar amounts of water in high-stress cities, such as Prescott Valley, where status 4 is applied through the projected period. The range of variation in water savings across the three climate projections is 31.3 m^3/year for both management approaches, representing 7.4% of average annual savings.

5.3. Municipal water savings

Fig. 9 shows changes in water demands under no management scenarios- compared to proactive and reactive management scenarios for the 50-year simulation period. The corresponding water restriction status levels are shown for low-stress (Cottonwood), medium-stress (Payson), and high-stress (Prescott Valley) systems. City water demand generally grows over the time due to population growth. Proactive and

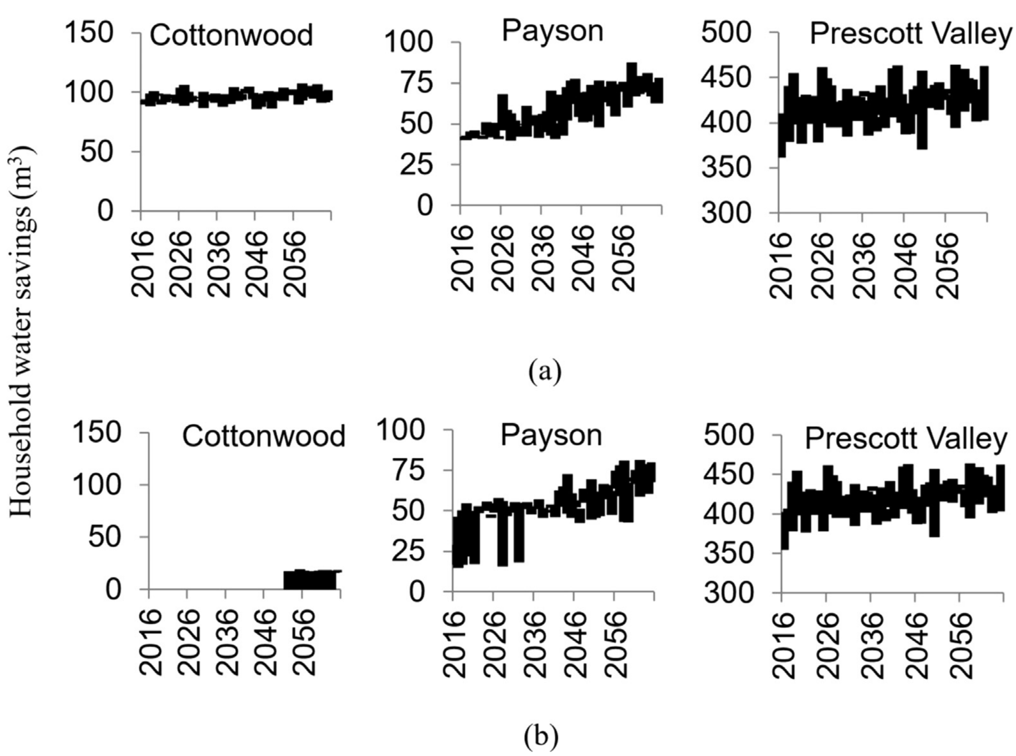

Fig. 8. Range of household level water savings for (a) proactive and (b) reactive approaches in low (Cottonwood), medium (Payson) and high (Prescott Valley) stress cities for 2016–2065. Ranges are shown to represent variation in results due to three climate scenarios.

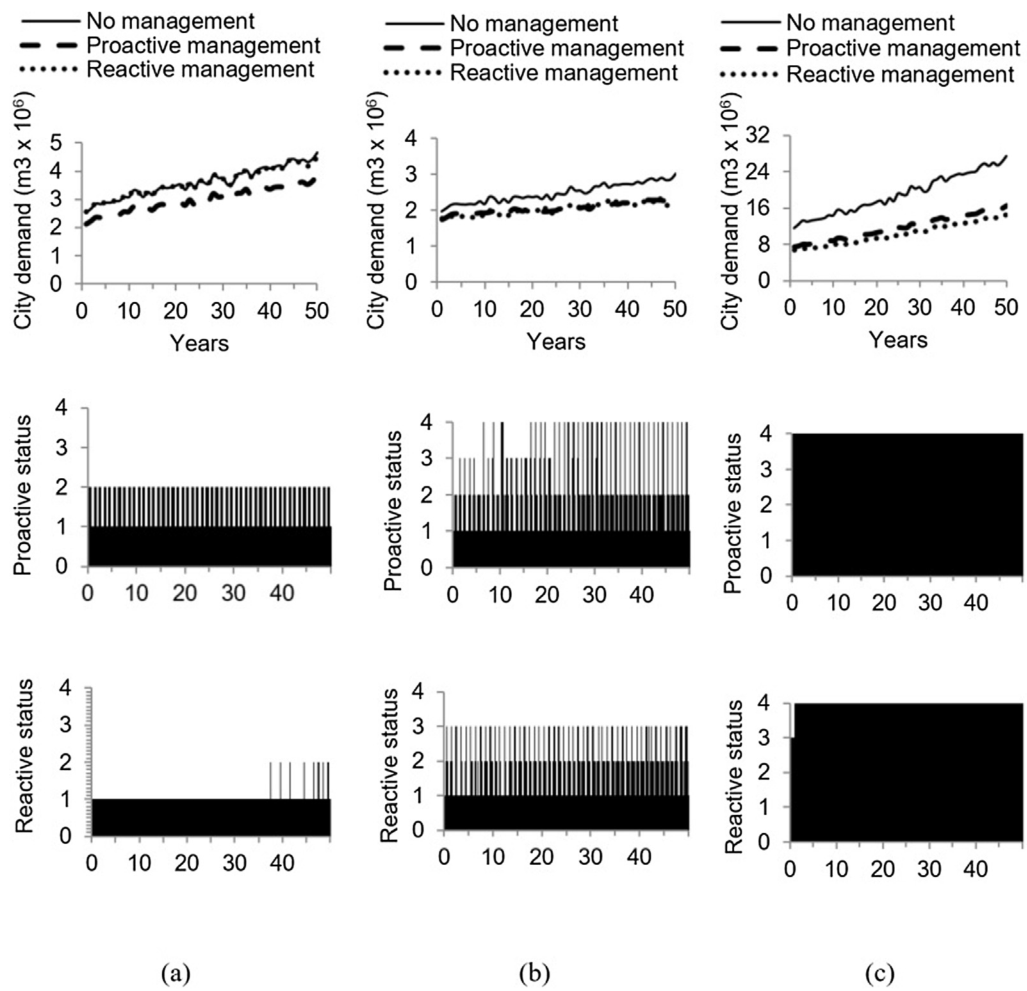

Fig. 9. City level water demands and corresponding management status in proactive and reactive approach in (a) low (Cottonwood), (b) medium (Payson) and (c) high (Prescott Valley) stress cities for 2016–2065 under climate projection 1.

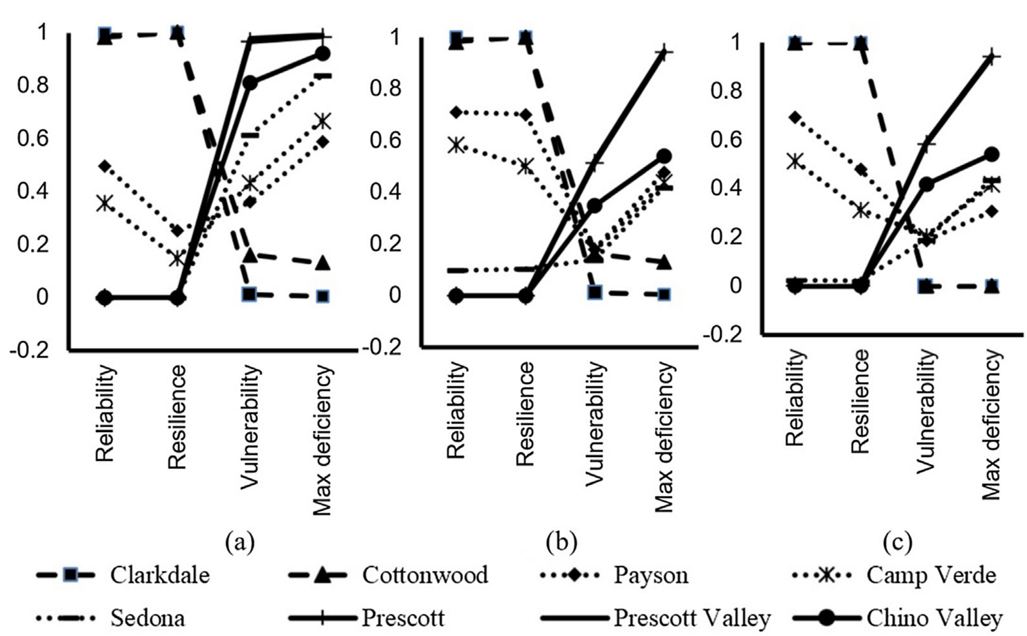

Fig. 10. Sustainability index metrics under (a) no management, (b) proactive management, and (c) reactive management.

reactive management affect the volume of city level water savings (Figs. 9 and 10). For low-stress cities, proactive management saves more water than reactive management (see Cottonwood in Fig. 9). Because safe yield violation acts as a trigger for enacting a higher status for the reactive management approach, the reactive manager does not save much water for low-stress cities, as shown in the case of Cottonwood. The water restriction status is limited to status 1, with occasional changes to status 2 toward the end of the projected period. The city water savings, which largely depend on residential water consumption, followed similar trends, and reactive management saves more water through the use of mandatory level 2 status restrictions from May to September. The reactive management approach applies status 2, 3, and 4 restrictions more frequently in moderate- and high- stress cities (Payson and Prescott Valley in Fig. 9).

The proactive management approach saves more water both at the household and city-level for moderate-stress cities (Payson in Fig. 9). In high-stress cities, proactive and reactive management save similar amounts of water at both household and city levels (Prescott Valley in Fig. 9). Lawn watering restrictions are similar when status 4 is applied for both proactive and reactive approaches (Table 3).

5.4. Water supply sustainability

Low-stress cities are characterized by high reliability and resilience and low vulnerability and maximum deficiency (Fig. 10). For both Cottonwood and Clarkdale, reliability and resilience are higher than 0.98 in no management, and these values increase to 1.0 under both proactive and reactive management. For these cities, vulnerabilities and maximum deficits are less than 0.2, and these values reduce to 0.0 under reactive management.

For medium-stress cities, Camp Verde and Payson, the reliability ranges between 0.3–0.5 and the resilience between 0.1 and 0.3 under no management. The reliability and resilience is 0.0 for Sedona, which is also a medium-stress city. The indices increase to the range of 0.5–0.6 for Camp Verde and Payson and to 0.1 for Sedona under proactive management. Proactive management improves the resilience more than the reactive management because of the proactive restrictions in place between May-September. The improvement in resilience is close to 0.2 for Camp Verde and Payson and 0.02 for Sedona. High-stress cities are characterized by zero reliability and resilience, and vulnerability and maximum deficit are above 0.8. Proactive and reactive management approaches cannot improve reliability and resilience; however, they do decrease the vulnerability within the range of 0.3–0.6. The improvement in maximum deficit is small (less than 0.05) for Prescott valley and Prescott, though larger (greater than 0.4) for Chino Valley.

5.5. Groundwater level changes under management scenarios

The safe yield based water restriction programs are mandated to safeguard water resources from long term water withdrawals for municipal and other water uses. Here, we explore the change in depletion that restrictions can generate. A Water level depletion of around 20–25 m in the southern part (Big Chino and Verde Valley Subbasin) is expected without any management and can be attributed in part to preexisting and constant withdrawals (Fig. 11). The eight cities are located in the Little Chino Subbasin (Prescott AMA) and Verde Valley Subbasin. An average groundwater depletion of 0–10 m is observed at these cities. The depletion varies among projections due to a variable recharge as calculated using projected rainfall, evapotranspiration, runoff, snowmelt, and storage.

Compared to business as usual cases (Fig. 11), the proactive (Fig. 11) and reactive management (Fig. 11d) both improve the water level by as much as 3 m in the central area of Verde Valley Subbasin and as much as 3–6 m in the Little Chino Subbasin. The cities in the Little Chino Subbasin include Prescott Valley, Town of Prescott, and Chino Valley. These cities have municipal demands that lead to water withdrawals beyond safe yield. The proactive and reactive management approaches, therefore, both apply high levels of restrictions in these cities for the projected future. Water level improvements are thus higher in the Little Chino Subbasin. The cities in the Verde Valley Subbasin have low or moderate stress, and water savings and the corresponding groundwater improvements are comparatively lower in this zone. The groundwater in the upper Big Chino (north), Verde Valley (central) and Verde Canyon (south) Subbasin are hydrologically connected. The water table improvements in the Verde Valley Subbasin, therefore, improves water level in these zones as well.

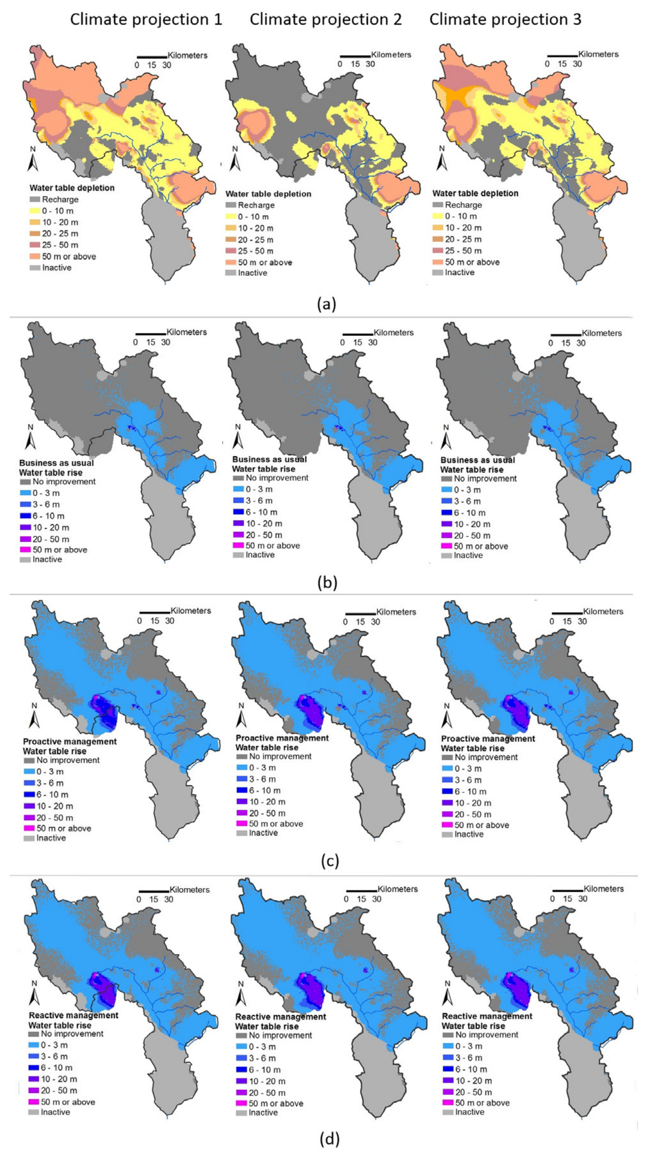

Fig. 11. Groundwater conditions in the Verde River Basin: (a) projected water table depletion under no management; (b) water table improvement compared to no management for business as usual management; (c) water table improvement compared to no management for proactive management at all cities; and (d) water table improvement compared to no management for reactive management at all cities.

5.6. Trade-offs among water supply sustainability, water savings and groundwater improvements

Two-tailed student's t-tests assuming unequal variance indicates that the business as usual, proactive and reactive management can improve the groundwater conditions significantly ($p < 0.01$ at 95% CI

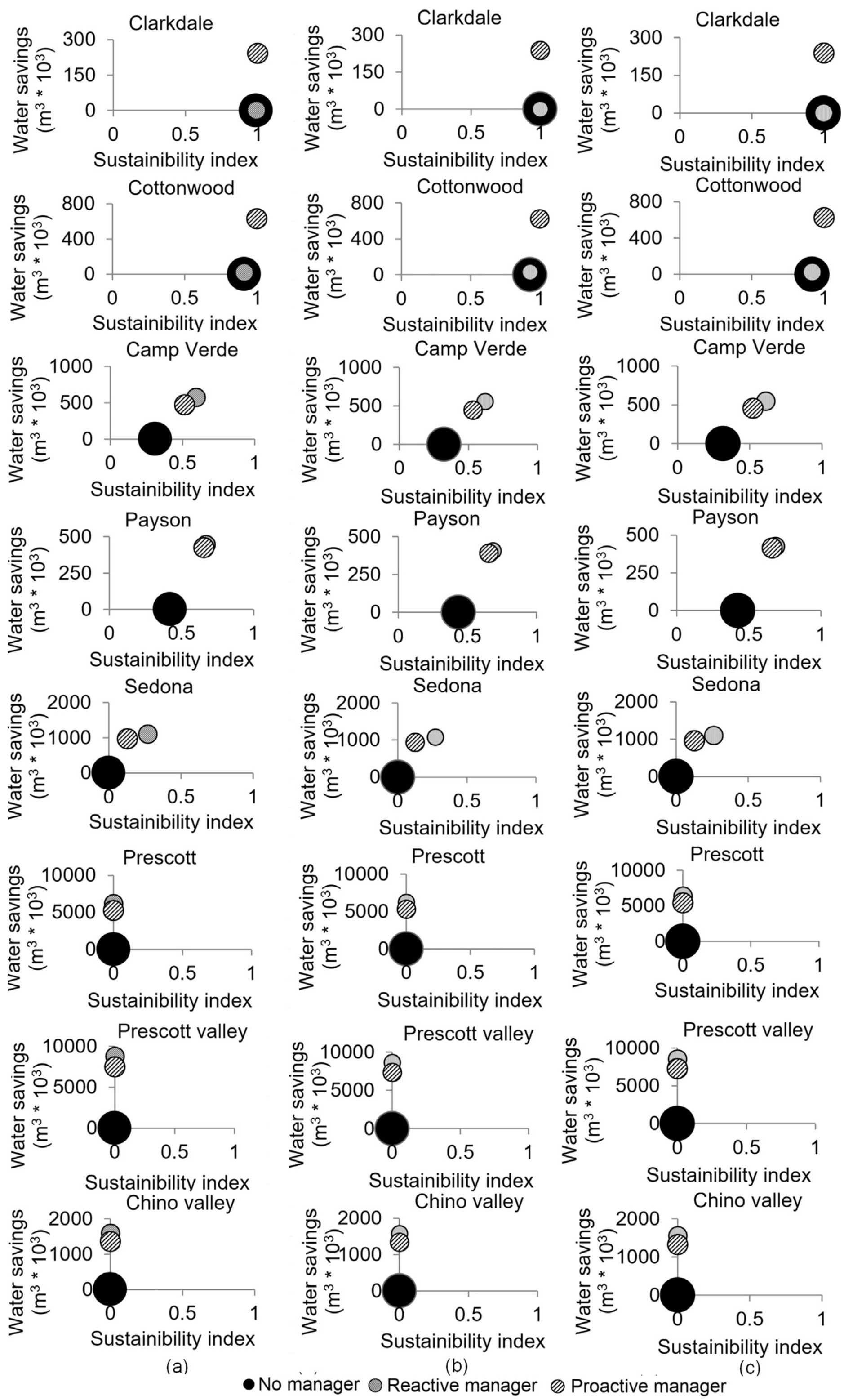

Fig. 12. Trade-offs among the sustainability index, welfare loss and groundwater depletion under climate (a) projection 1, (b) projection 2 and (c) projection 3. The size of the markers are proportional to groundwater depletion.

in all cases) compared to no management scenarios across all climate projections. However the improvements vary across climate projections. The variation is caused due to the variation in climate components that impact both water withdrawals and groundwater recharge. Fig. 12 shows the average water level drop in depleted areas (cells in which the water depletion is greater than 0 m) in eight cities between 2016 and 2065 under different management alternatives and three climate projections. The no management water level depletion is projected to be 16.2 m, 17.0 m and 17.5 m under climate projection 1, 2 and 3. Under the proactive management, the depletion is projected to be 9.9 m, 9.0 m and 9.9 m, respectively for climate change scenarios. The reactive management projections are 8.7 m, 7.6 m and 8.6 m, respectively. The proactive and reactive management significantly improves the groundwater levels at the location of withdrawal. Average improvements at the basin level, however, are much lower (< 0.3 m).

Management that improves water supply sustainability is also associated with water savings in the city, calculated as water demand difference under no management and a certain management approach. The water savings is thus an indicator of the difference between unrestricted expected demands and the restricted actual water consumption. The difference may have economic and welfare consequences based on the actual total demand, water prices and price elasticities (Wan et al., 2013). The sustainability index is calculated based on four water supply indices, as described above. For low-stress cities, the sustainability index is at a high value for the base case, close to the maximum (1.0). The two management approaches could not improve the metric in this case. Within a limited scope, proactive management improves the sustainability index more but with higher stress on water users causing higher water savings, compared to reactive management (Fig. 12). Improvements in maximum deficit and vulnerability are better for reactive management, and the reliability and resilience improve more under proactive management. The total sustainability index is higher for proactive management. For moderate- and high-stress cities, the reactive management approach improves the sustainability index more than the proactive management approach and increases water savings, compared to a proactive manager. For extreme cases, such as Prescott Valley, where safe yield was violated throughout the projected period, neither proactive nor reactive management could improve the sustainability index.

Proactive management can save more water in low- to moderate-stress cities, which are identified based on the time it is expected for cities to violate safe yield limits on withdrawals, while reactive management can save the same or higher volumes of water in high-stress cities in our study. While comparing the two management policies, it is important to underline the triggers for both the management alternatives that was coded based on local setups. As shown in Table 3, for the reactive management, restrictions are only applied reactively to frequency and magnitude of safe-yield violation. For proactive management, similar restrictions are applied due to safe-yield violations in addition to proactive restrictions that are applied regardless of safe yield violations. If an area is subject to repetitive safe-yield violation, it may save more water using a reactive management policy because for high stress cities both the management approaches yield higher status (status 4 mostly) for most part of the simulation period. In the reactive management approach, however, restrictions for non residential demand reductions are higher compared to proactive management (refer to Table 3) at status level 4. Local context, in terms of restrictions under different status, affects the performance of proactive and reactive management alternatives in this case. The water stress, which is the magnitude and frequency of safe-yield violation and the complexity of the rules affect the comparison between strategies.

6. Conclusions

This research develops a holistic approach to evaluate alternative management approaches for water restriction programs. As water stress continues to increase, cities across the globe are expected to improve their water use efficiency in terms of both consumption and management. The framework developed here assesses water management plans based on indices that have been developed to evaluate management decisions for sustainability, social welfare, and groundwater depletion. The Verde River Basin is explored as an illustrative case study to incorporate context-specific variables, including projected population growth and climate change. The model includes several simplifying assumptions and aggregated representation of each cities that may not reflect the actual long-term portfolios and policies of the cities. We rather present an analysis of inter dependence of the cities in meeting water demands locally and preserving water tables in groundwater for future uses. Two water conservation programs were studied, a reactive and proactive approach to limit outdoor lawn watering. A significant difference in water savings was observed for proactive and reactive management strategies.

Contextual information is needed to compare proactive and reactive management strategies. Proactive management can save more water in low- to moderate-stress cities, while reactive management can save the same or higher volumes of water in high-stress cities. If an area is subject to repetitive safe yield violation, it may save more water using a reactive management policy. For high stress cities in this study, higher restrictions are applied under reactive management, compared to proactive management in similar safe-yield violation conditions. The amount of water saved through different management approaches can significantly affect sustainability by changing the vulnerability and maximum deficit of the system. The reliability and resilience also depend on how these restrictions are applied and the condition of the resources. A restriction program with higher water savings does not necessarily generate sustainability index improvements. The water savings, which represents the difference between unrestricted water demand and actual water consumption, increases with higher restrictions and water savings.

The scope of this study was limited by the availability of data for end uses. The indoor and outdoor end uses in this study were assumed to remain constant throughout the future projections. An end use survey can improve the understanding of the complex interactions in human-nature environment and can improve the application of this framework. The safe yields in this study were maintained at conservative levels, based on the literature of baseline conditions in 2010 or according to the average historical recharge in cities where values were not available. More realistically, safe yields may be dynamically updated through management decisions to import water and utilize other surface or reclaimed water sources. Many of these cities may plan to increase their safe yield within the projected time frame, and changing safe yield values were not considered in this study.

One extension of this work can be to incorporate adaptation and learning for both the users and the water managers with increasing stress on resource and corresponding restrictions. The ABM framework may be transformed into a cooperative or competitive framework where users can interact at household levels and water managers at city or basin level. Responses of managers in setting the safe yield may be simulated dynamically with climate change and population growth. The impact of climate variability and management decisions on groundwater and other resources should be explored to evaluate the magnitude of uncertainty in long term planning.

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