Environmental Modelling & Software 92 (2017) 1–16

Contents lists available at ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

On the role of individuals in models of coupled human and natural systems: Lessons from a case study in the Republican River Basin

Paul H. Noël [a], Ximing Cai [b,*]

[a] Water for Food Institute, University of Nebraska, United States
[b] Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, United States

ARTICLE INFO

Article history:
Received 1 October 2015
Received in revised form
12 September 2016
Accepted 8 February 2017
Available online 20 February 2017

Keywords:
Coupled human and natural systems
Human behavior
Irrigation
Agent-based modeling
High Plains Aquifer

ABSTRACT

In models of coupled human and natural systems (CHANS), the role of individuals and human behavior is often overlooked as data are scarce and assumptions hard to verify. To assess this role, we couple an agent-based model simulating farmers' behavior and a groundwater model and apply the models to the case of groundwater-fed irrigation in a river basin in the High Plains Aquifer region. Results show the crucial role of human behavior in driving the interactions between these coupled systems. Conversely, individuals are impacted by the systems' dynamics in different ways depending on physical, economic and social characteristics. The findings provide implications for local policy making and education and demonstrate that assumptions on human behavior could be treated as an additional source of uncertainty. This work suggests that modeling individuals and human behavior can be an important step to simulate and understand the dynamics of CHANS in a holistic way.

1. Introduction

Climate change, deforestation, disappearing lakes and seas and other large-scale environmental issues, such as the hypoxia zone in the Gulf of Mexico, demonstrate that the Earth has moved into the Anthropocene: an age where humans are the main driver of environmental and ecological changes (Crutzen, 2006; Steffen et al., 2011). This realization has prompted scientists to create a new form of science focusing on coupled human and natural systems (CHANS). This science has been growing steadily over the past 15 years (Liu et al., 2007; Alberti et al., 2011) and advocates for integrated assessment of human and environmental systems. There have also been a number of frameworks and sub-fields that have emerged in this area to study specific CHANS such as socio-hydrology (Sivapalan et al., 2012), social-ecological systems (Schlüter et al., 2012), hydro-economic systems (Cai, 2008; Harou et al., 2009), integrated environmental modeling (Laniak et al., 2013) and others. The science of CHANS calls for interdisciplinary collaboration and systematic modeling of both human and natural systems to reveal the complex dynamics at stake in such coupled systems.

Models of CHANS are designed to integrate both human and environmental dynamics in order to analyze the co-evolution of human and natural systems (Gual and Norgaard, 2010; Laniak et al., 2013). In the past few decades, environmental models have become more and more complex due to improved computing power and improved quality of data, both spatially and temporally. The inclusion of the human component in environmental models is a more recent effort which is still in its infancy. While progress has been made and new tools have been adopted to develop more integrated environmental models (Kelly et al., 2013), much challenging work is still needed to properly represent human behavior and human influence in these models (An, 2012). One of the main challenges is the validation of such models due to the lack of data and understanding of human behavior (An, 2012; Ligtenberg et al., 2010). Moreover, little is known on the effects of human activities to the performance of complex systems such as watersheds or river basins and very few studies have systematically evaluated the impacts of complex human behavior on CHANS (Huang et al., 2013).

It is often not straightforward to decide what model to use for a human system. Various tools have been developed in social sciences (Lave and March 1993), economics (Tesfatsion, 2003), psychology (Gluck and Pew, 2006) and other fields but no model has been universally accepted across all disciplines as the best way to model human behavior. One modeling approach however has

* Corresponding author.
E-mail address: xmcai@illinois.edu (X. Cai).

http://dx.doi.org/10.1016/j.envsoft.2017.02.010
1364-8152/

been regularly cited as being particularly effective for simulating CHANS: agent-based modeling (ABM). An (2012) provides a review of agent-based models (ABMs) used to model human decisions in CHANS, which identifies 121 publications applying ABM to CHANS as of 2011, mainly in the fields of ecology and geography. Kelly et al. (2013) identify ABM as one of the five most common approaches that have been used for integrated environmental assessment and management. In the field of social-ecological systems the use of ABMs is particularly prevalent, as illustrated by Rounsevell et al. (2012), Schlüter et al. (2012) and Filatova et al. (2013). ABMs have also been used to study agricultural and water resources systems by modeling different types of water users such as domestic users (Athanasiadis et al., 2005; Galán et al., 2009), water users in river basins (Schlüter and Pahl-Wostl, 2007; Yang et al., 2009 and Yang et al., 2011), irrigators (Arnold et al., 2014; Berger and Troost, 2014) and farmers (van Oel et al., 2010). These studies show that ABM is a promising, and in some fields well-established, tool to study the interactions between humans and the environment.

Managing water resources systems is usually incredibly difficult not only because of the variability and uncertainty related to climate and hydrology, but also because of the uncertainty and variability related to water demand. The study of individual behavior is particularly important in the field of water demand management. Most water resources systems are dedicated to individuals that need water such as household owners, farmers, fishermen, or users of recreational bodies of water. Understanding these users is therefore a key component of sound management and policy, especially when water is scarce and conservation becomes a major concern. Jorgensen et al. (2009), for example, present an integrated model to better understand household water use behavior. They find that interpersonal and institutional trust are crucial factors of household water consumption behavior, even though such behavioral characteristics of individuals are overlooked in most studies. Russell and Fielding (2010) go even further by studying the psychology of water users in order to understand water conservation behavior. They identify five causes of residential water conservation behaviors: attitudes, beliefs, habits or routines, personal capabilities, and contextual factors. These two examples illustrate the importance of understanding individual behavior to study water demand patterns so as to devise better policies for water conservation. What is true for residential water management holds for irrigation management too. Irrigation varies in space and time and from farmer to farmer. Sauer et al. (2010) show that irrigation development and practices have impacts even at the global scale.

Few studies have shown the role of individuals in CHANS, especially when these studies were designed for water resources systems analysis (An, 2012). Our study is an attempt to understand how individuals matter in modeling CHANS and what can be learned from modeling the human system at the individual level. We address these questions using an integrated ABM and a groundwater model. It should be noted that it is not necessary to use an ABM to simulate a CHANS, as one could focus on the properties of the system, where the microscale interactions may not be important for the study purpose, as seen in many modeling efforts (Laniak et al., 2013). Under some conditions implementing an ABM is not feasible, especially when data required for modeling individuals are hard to obtain because of ethics or other reasons preventing data collection (Filatova et al., 2013). In this paper, we choose to use an ABM because it is a natural framework to model individuals, especially human agents in the human dimension of CHANS. The heterogeneity of the individual behaviors affects the emerging performance of the system. In the ABM, individual farmers are defined as agents who make daily decisions on groundwater use to irrigate cash crops and earn profits. The ABM also includes an agent representing a regulatory agency that monitors water levels and implements water-conservation regulations. The human behavior of an agent is considered as a variable in the ABM. Human behavior heterogeneity is an important characteristic of water users in general although it is difficult to measure and quantify. Two farmers with crop fields in the same physical conditions (i.e., soil type, climate, well yield, etc.) could still make different irrigation decisions following their experience, their perception of risk and other factors. Among the studies of agent-based models on agriculture and agricultural water management issues, Berger (2001) introduced diversified technology adoption behaviors among farms, and using a human behavior parameter on the various thresholds to technology adoption to quantify the human behavior heterogeneity associated with physical heterogeneity of farms. A more recent study by Baggio and Janssen (2013) tested various behavioral theories (i.e. with experimental data of irrigation games). For a review of relevant studies with more detailed discussion on human behavior representation in an ABM, readers should refer to Kremmydas (2012) and Elsawah et al. (2015).

In this framework, farmers and institutions form the human component of the system, rivers and the aquifer form the natural component of the system, and the two coupled systems interact through irrigation, water conservation, and regulations with influence of external factors such as climate and crop market. We show that these two models coupled together and validated for in a watershed of the Republican River Basin (RRB) in Nebraska illustrate the importance of including individuals and human behavior in modeling CHANS. It is important to note that researchers working at the individual level may need to consider ethical integrity when any non-publicly available data are used.

Our work is related to several recent studies, which share a similar context (i.e., connecting agriculture, economics and groundwater) and modeling approach with ours. Castilla-Rho et al. (2015) developed FlowLogo to help researchers develop coupled agent-based groundwater models. It is an interactive modelling environment that allows users to explore how patterns of groundwater movement and social development can emerge from agents' behavior and their interactions. Bulatewicz et al. (2010) use the Open Modeling Interface to integrate models of agriculture, economics and groundwater and applied the methodology to Sheridan County in Kansas located above the High Plains Aquifer. Condon and Maxwell (2014) present an integrated hydrologic model to study the spatial and temporal patterns caused by feedbacks between irrigation and water availability in the Little Washita Basin in Southwestern Oklahoma, USA. Foster et al. (2014) introduce a new modeling approach of irrigation behavior in groundwater systems. Their modeling approach incorporates the impacts of well yield and climate on crop production and water use to determine irrigation demand. Mulligan et al. (2014) present a model which couples an agent-based model of farmers' irrigation behavior with a groundwater model to study a subwatershed of the RRB. We share a similar modeling approach or have a similar study area as these four studies, but what makes our work unique is that we assess the importance of individuals and their behavior in modeling CHANS.

In the rest of this paper, the modeling framework is presented in section 2 and its application to an area located in the RRB is presented in section 3. Results are then described and explained in section 4. Additional discussion on the importance of representing individuals in CHANS and conclusions are provided in section 5.

2. Methodology

2.1. The modeling framework

The structure of the modeling framework is shown in Fig. 1. The ABM and the hydrologic model interact through two variables: farmers' daily pumping decisions for irrigation (from the ABM to the groundwater model) and water table (from the groundwater to the ABM). The ABM is subject to external economic drivers such as fuel and corn prices and both models are subject to external climate drivers such as precipitation and evapotranspiration. Coupled together, the two models are able to simulate irrigation decisions and their impacts on groundwater depletion over a long period of time. Fig. 2 shows the flow chart of the modeling procedures, especially the linkage and information flow between the various components.

The integrated model is structured as follows (Fig. 2). Farmers make daily decisions on the amount of irrigation to apply to their fields based on soil water deficit. These daily pumping decisions are aggregated monthly and used as input for the groundwater model. The groundwater model runs every month and provides updated water-table and baseflow values to the ABM. Every year, the regulatory agent makes decisions on irrigation regulations based on streamflow depletion. Every year, farmers also make decisions on their irrigated surface based on long-term potential and actual evapotranspiration. The ABM is initialized and then runs at a daily time step with actions performed at the daily, monthly and annual time steps. The groundwater model runs at a monthly time step as it is the bottleneck in terms of computation time. This time scale allows the model to reasonably capture the water-table drop during the growing season. Both models are described in more details in the next two sections. Noel (2015) also describes the model and provides a standardized description following the ODD + D protocol (Müller et al., 2013) which is also included in the supplementary material.

2.2. The agent-based model

There are two types of agents defined in the ABM: a number of farmers and one regulatory agency (a Natural Resources District (NRD) in this study). The NRD agent sets up regulations when the flux of water from the aquifer to the streams – used as a proxy for

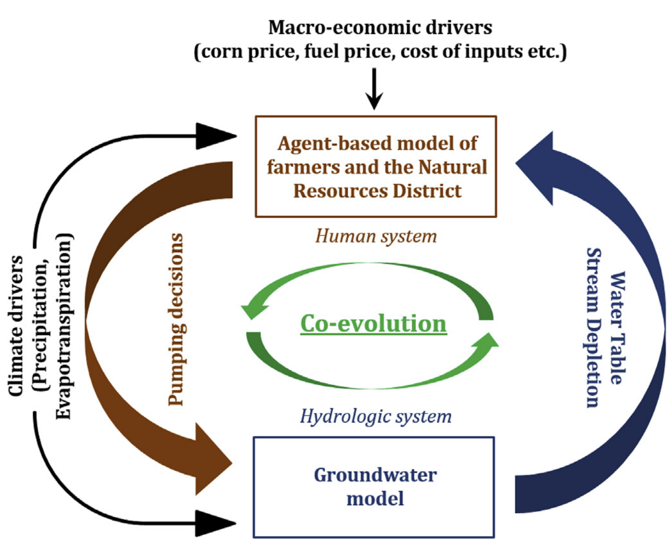

Fig. 1. Structure of the modeling framework.

baseflow – drops under some thresholds. While this model does not simulate streamflow directly, baseflow is a portion of streamflow that comes from groundwater seeping into the streams. Regulatory agencies often implement regulations based on streamflow (Republican River Compact Administration). These thresholds were calibrated to ensure that the regulation decisions made by the NRD agent in a historical simulation approximately match in time the actual regulation implementations in Nebraska (also see the presentation of the case study in section 3.1). Each regulation is a cap on the annual amount of irrigation withdrawal that is imposed on all farmers. For example, if baseflow drops under the threshold of 200 ft^3/day in 1978, the NRD agent sets a first irrigation cap of 22 inches per year.

In the model, farmers make decisions on daily irrigation and annual crop land with irrigation. The framework used for farmers to decide on daily irrigation is based on soil water deficit. This approach was developed by the Food and Agriculture Organization (FAO) using crop evapotranspiration (Allen et al., 1998). Farmers may own several wells and each well is associated with a separate field. Many irrigation scheduling and water management approaches provided to farmers rely on the soil water deficit method (Rhoads and Yonts, 1991; Lamm et al.; Andales et al., 2011). In practice, farmers can also visually assess soil moisture or use soil moisture sensors to determine soil water deficit and make a decision on irrigation timing and amount (Hanson et al., 2000). Foster et al. (2014) recommends using such intra-annual methodology to model farmers' behavior on irrigation as opposed to simulating farmers' behavior at an annual time scale. All variables are summarized in Table 1 in alphabetical order.

Each day, it is assumed that farmers know soil water deficit at each of their fields (via soil moisture sensors or validated model simulation) and use this information to decide if and how much to irrigate as described by equations (1) and (2):

$$ID = SWD - d_{MAD} \tag{1}$$

$$SWD = SWD_p + ET - P - IS \tag{2}$$

where ID is the irrigation demand, SWD is the soil water deficit and d_{MAD} is the managed allowed deficit (all in inches). If SWD is smaller than d_{MAD}, irrigation requirement is then set to 0. SWD_p is the soil water deficit from the previous day, ET is the corn evapotranspiration, P is the precipitation and IS is the irrigation supply (all in inches). ET is calculated using the equation below:

$$ET = k_c \times k_s \times ET_0 \tag{3}$$

where ET_0 is the reference evapotranspiration, k_c is the crop coefficient for corn which varies with crop development stages and k_s is a water stress coefficient varying between 0 and 1 (both coefficients are dimensionless). k_s is estimated based on a simple equation using SWD, the total available water TAW (in inches), and the managed allowed deficit (in %) MAD:

$$k_s = \frac{TAW - SWD}{(1 - MAD)^{*}TAW} \tag{4}$$

The total available water is simply the product of the available water capacity of the root zone AWC (inch of water/inch of soil) with the total depth of the root zone D_{rz} (inches). AWC is a characteristic of the soil. D_{rz} varies during the crop growth season.

$$TAW = AWC \times D_{rz} \tag{5}$$

Equations (1)–(5) are adapted from Allen et al. (1998) and Andales et al. (2011). After daily irrigation demand is calculated,

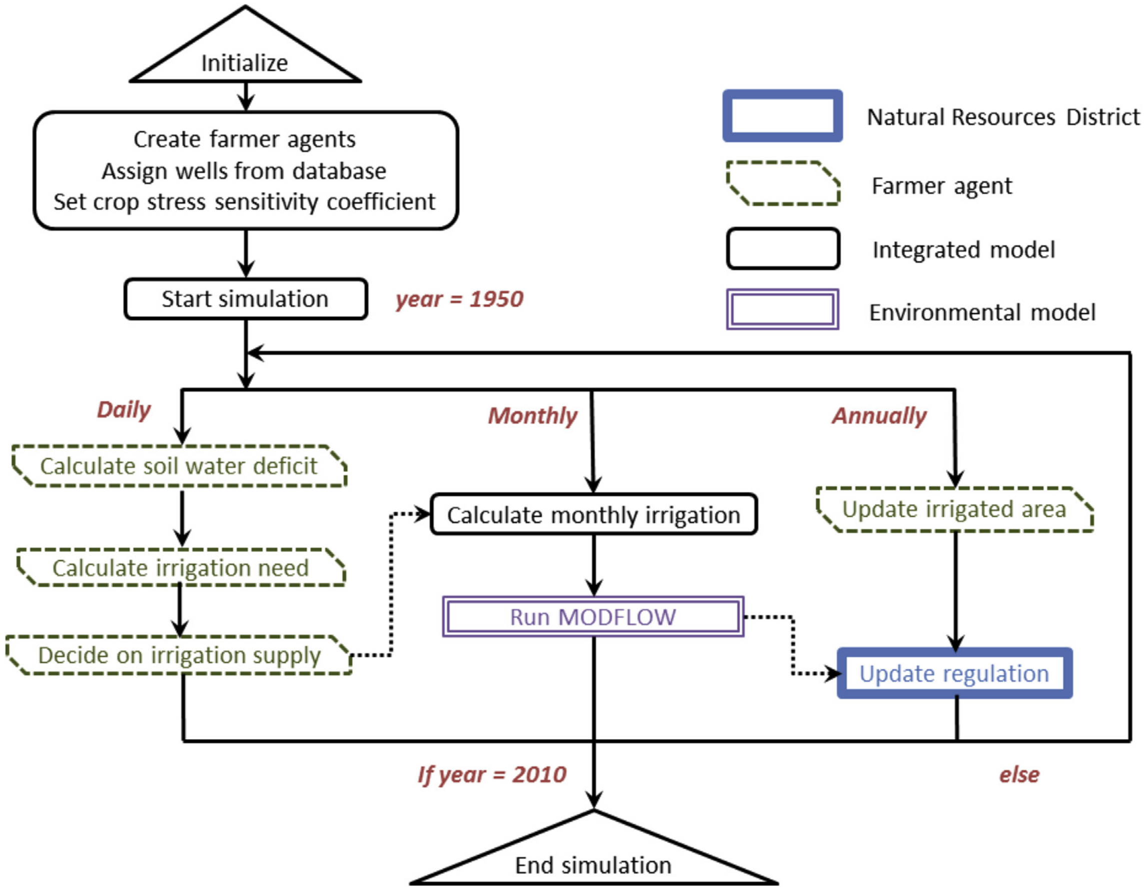

Fig. 2. Flow Chart of the integrated models.

farmers calculate daily irrigation supply for each active well. Irrigation Supply (*IS*) is restricted by well yield and the annual irrigation water use permit. It is assumed that a well can only be pumped for a time of operation (*TO*) of 20 h per day (Merkley and Allen, 2004). Knowing the acreage *A* of each field and the irrigation efficiency (*IE*) assumed to be 90% in the model – a typical value for center-pivot, it is possible to calculate the necessary pumping rate (*PR*) (in gallons per minute) and then obtain *IS* depending on whether *PR* is above or below the well yield (*WY*) in gallons per minute which is taken from the well database used in the case study:

$$IS = \begin{cases} ID & \text{if } PR < WY \\ 0.0022 \times TO \times \dfrac{WY}{A} & \text{if } PR \geq WY \end{cases} \tag{6}$$

$$PR = \frac{ID \times A}{0.0022 \times TO \times IE} \tag{7}$$

in which 0.0022 is a unit conversion factor. *IS* is then updated based on the annual amount of irrigation (*AI*) on the current day of the simulation, which is the cumulative amount of water used for irrigation until this day during this growing season, and the regulation *R* currently followed by the farmer (both in inch) as described in Equation (8) below. This means that the farmer stops irrigating once the cumulative annual irrigation reaches the annual irrigation cap. Farmers in the model do not do long-term planning ahead of the season. While real farmers attempt to conduct long-term planning, it is still a challenge for them to know ahead of a growing season if it will be a dry or wet year (Shafiee-Jood et al., 2014).

$$IS = \begin{cases} IS & \text{if } AI + IS \leq R \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

In our study, farmers' behavior is differentiated through the introduction of a coefficient characterizing their sensitivity to crop water stress (*SC*), following the work of Miro (2012). This coefficient is used to modify farmers' management allowed deficit (*MAD*). Recommended values of *MAD* are usually provided for each stage of a crop growth season. Equation (9) redefines managed water deficit (Allen et al., 1998; Andales et al., 2011) in inch (d_{MAD}) by considering the impact of *SC*.

$$d_{MAD} = \frac{MAD}{100} \times TAW * SC \tag{9}$$

If *SC* is set to 1, it means that the farmer will follow the recommended values of *MAD*; otherwise it means that the farmer will be less (when $SC > 1$) or more ($SC < 1$) sensitive to crop water stress. If *SC* is close to zero for example, d_{MAD} will be very low which means that the farmer will irrigate very often. At the end of the growing season the crop yield (*CY*) is estimated by

$$CY = CY_{\max} \times YR \tag{10}$$

where CY_{max} is calculated with an empirical equation (11), which is calibrated against corn yield data from the United Stated Department of Agriculture (USDA) and accounts for the increase of maximum corn yield with time due to improving agricultural

Table 1
Variables and Parameters in model.

Variables and Parameters	Name	Units
A	Acreage of field	acre
AI	Annual irrigation depth	inch
A_w	Acreage of field irrigated by well w	acre
AWC	Available Water Capacity of the root zone	inch of water/inch of soil
CP	Corn price	$/bushel
CY	Crop yield	bushel/acre
CY_{max}	Maximum or potential crop yield (increases over the years)	bushel/acre
CY_w	Crop yield at well w	bushel/acre
DC	Diesel cost	$/gallon
ΔA	Reduction of irrigated area	acre
d_{MAD}	Managed allowed deficit	inch
D_{rz}	Depth of the root zone (varies during growing season)	inch
E^*	Threshold relative ET	–
ET	Corn evapotranspiration	inch
ET_0	Reference or potential evapotranspiration	inch
FC	Fixed costs	$/acre
HDC	Harvesting and drying cost	$/bushel
ID	Irrigation demand	inch
IE	Irrigation efficiency	%
IS	Irrigation supply	inch
k_c	Crop coefficient for corn (varies by crop growth stage)	–
k_s	Crop water stress coefficient	–
k_y	Crop yield coefficient for corn (varies by crop growth stage)	–
MAD	Managed allowed deficit	%
P	Precipitation	inch
PC_w	Pumping cost at well w	$
PE	Pump performance	horsepower.hour/gallon
PP	Pumping pressure	psi
PR	Pumping rate	gallon/minute
R	Irrigation cap or regulation	inch
SC	Coefficient of sensitivity to crop water stress	–
SWD	Soil water deficit	inch
SWD_p	Soil water deficit on previous day	inch
TAW	Total available water	inch
TO	Time of operation	hour/day
WD	Water depth in the well	feet
WY	Well yield	gallon/minute
YR	Yield ratio	–

practices (United States Department of Agriculture, 2013):

$$CY_{max} = \begin{cases} 4 \times n + 76.937 & \text{if } n \leq 38 \\ 200 \times \log((n-1) \times 2) - 150 & \text{otherwise}. \end{cases} \quad (11)$$

The yield ratio (*YR*) is calculated with the following equation (Jensen, 1968):

$$YR = \prod_{i=1}^{6} \left(1 - k_y \left(\frac{ET^i}{ET_0^i}\right)\right) \quad (12)$$

where *i* denotes the crop growth stage (accounting for 6 stages in this study). Equation (12) shows that the crop yield is reduced when the actual crop evapotranspiration (*ET*) is inferior to the potential evapotranspiration (ET_0) which happens if precipitation plus irrigation do not provide enough water to the crop. The coefficient k_y is a crop coefficient for corn yield that varies per crop growth stage. Finally, the net profit is calculated as:

$$P = \sum_{w \in W} [(CP - HDC) \times CY_w \times A_w - A_w \times FC - PC_w] \quad (13)$$

where *W* is the ensemble of wells owned by a farmer, *CP* is the corn price, *HDC* the harvesting and drying cost, *FC* is the fixed costs, and PC_w is the pumping cost at well w. *PC* is calculated by:

$$PC = DC \times PR \times \frac{(WD + 2.308 \times PP)}{3960} \times TO \times PE \quad (14)$$

where *DC* is the diesel cost, *PR* the pumping rate, *WD* the water depth in the well, *PP* the pumping pressure – assumed to be 60 psi, *TO* the time of operation – assumed to be 20 h – and *PE* the performance (i.e., the amount of work that can be obtained from a unit of energy) assumed to be 8.75 hp.hr/gal for a center-pivot pump. Equation (14) and the values for *PP* and *PE* are adapted from Martin et al. (2011).

Farmers' annual decisions on irrigated area are modeled using the framework described by Rosegrant et al. (2002) based on the ratio between actual and potential crop ET averaged over the three previous years. That is to say, each year farmers decide if they should reduce their irrigated acreage or use all the available land depending on the long term water-deficit in their fields. Equation (15) adapted from Rosegrant et al. (2002) estimates the reduction of irrigated area ΔA in current year (n) assuming a threshold relative ET (E^*) of 0.6:

$$\Delta A = A \left[1 - \left(\frac{1}{3} \sum_{k=n-3}^{n-1} \frac{ET^k}{ET_0^k} / E^*\right)\right] \quad (15)$$

2.3. The groundwater model

The groundwater model was developed with MODFLOW (Harbaugh, 2005). MODFLOW uses the finite-difference method to solve the three-dimensional groundwater flow equation for a porous medium and calculate hydraulic head in each rectangular grid cell for each time step. It is a fully distributed numerical program designed for high modularity. The governing equations account for hydraulic parameters such as hydraulic conductivity, transmissivity, and specific yield, spatially varying boundary conditions, and other volumetric fluxes such as pumping wells, recharge, and evapotranspiration. In this study, the groundwater model was established to simulate groundwater flow in an area within the RRB (see section 3.1. for the description of the case study). All the data used to develop the model were extracted from the Republican River Compact Administration (RRCA) model (McKusick, 2003). The RRCA model was calibrated to historical water table observations at the various locations throughout the basin. The RRCA model represents both groundwater levels and baseflow in the stream network. The groundwater model developed as part of this integrated model runs with a monthly stress period and water head is calculated 10 times per stress period. It consists of 1 layer and 2500 grid cells with a size of one square mile per cell. Data from the RRCA model used to develop this model include the top and bottom layers of the aquifer, aquifer properties such as hydraulic conductivity and storativity, stream location and monthly ET. All these data vary spatially and ET also varies temporally. Other time-varying inputs to the model include recharge and pumping rates at wells, both of which are monthly outputs from the ABM. Boundary conditions were created based on water-levels in the pre-development period calculated in the RRCA model.

3. Application to the Republican River Basin

3.1. Case study area

The RRB is shared between the States of Colorado, Kansas and Nebraska. The basin's area is 24,900 square miles, located above the High Plains Aquifer, one of the largest aquifers in the world. The economy of the basin is dominated by agriculture and corn is the predominant crop grown in the area. Most of the 8.5 million acres dedicated to agriculture in the region are irrigated by nearly 100,000 wells within the basin (Nebraska Department of Agriculture, 2013). Complex interactions between farmers who irrigate and the environment have shaped both the economics and the hydrology of the region. Decades of extensive groundwater irrigation for cash crop agriculture have depleted both groundwater and surface water in many areas of the aquifer, causing conflicts and concerns on the sustainability of agriculture in the region (Scanlon et al., 2012; Steward et al., 2013; Zeng and Cai, 2014). In 1942, the three States signed the Republican River Compact to divide surface water in a fair way. However, over-pumping of the aquifer eventually led to streamflow depletion, a more visible issue that triggered a conflict between Kansas and its two neighbors (Republican River Compact Administration). In Nebraska, Natural Resources Districts are responsible for the integrated management of ground water and surface water. Providing local governance, they implement groundwater regulations for irrigation wells. Two Natural Resources Districts are present in the case study region: the Middle Republican Natural Resources District and the Upper Republican Natural Resources District (Nebraska Association of Resources Districts, 2014). For simplicity and data availability, only the Upper Republican Natural Resources District was considered in the ABM.

The region chosen for the case study has an area of 2500 square-mile (6475 square-kilometer), which roughly covers the counties of Chase, Hayes, Dundy and Hitchcock in southeastern Nebraska sharing the border with Colorado and Kansas. The region receives an average of 20 inches (508 mm) of precipitation annually. Fig. 3 shows the location of the area of study, along with the streams, wells and climate stations used in the model. There are about 2200 registered irrigation wells in the area. The colors indicate how many acres can be irrigated by each well. The well database from the Nebraska Department of Natural Resources also includes data such as well yield, year of activation of the well, irrigated acres, etc. The sources for all the different datasets used in the case study are presented in Table 2.

The scale of the region was chosen so to be small enough to model every individual farmer, yet large enough to model the feedbacks occurring between the human system and the natural system. Fig. 4 shows the increase in irrigated area in the region along with the decrease of annual streamflow a few miles downstream of the outlet of the region. The causal relationship between the two variables illustrates the challenges faced by stakeholders in the region in terms of human development and the impact on the environment. Furthermore, Fig. 4 partially demonstrates how humans and the environment have been co-evolving over the past hundred years. The human activities include not only active irrigation development but also response to environmental change. For example, in the Upper Republican Natural Resources District, annual irrigation allocations decreased from 20 inches in 1978 to 13.5 inches in 2005 (Nebraska Association of Resources Districts, 2014). Other policies have also been implemented such as well spacing regulations, incentives provided to farmers to reduce water consumption, purchasing of formerly irrigated land, and moratoriums on drilling new wells.

In the ABM, agents are created by dividing the 2500-square mile study area into grids of 1 square-mile and assigning an agent to each square containing one or more pumping wells. The average farm size in Nebraska is 972 acres (Nebraska Department of Agriculture, 2013), which is 1.5 times of the size of an agent in the model − 640 acres. However, the model uses certified irrigated acres from the data on pumping wells to delineate the agents. Thus the crop acreage with one agent (i.e., in each grid) can be different from that of others. With this assumption, 1040 agents are delineated in the ABM. Rainfed farming is not considered in this study. For simplicity, this study only considers corn, which represents the predominant crop grown in Nebraska accounting for 82% of the total cropland in Chase County, 70% in Dundy County, 51% in Hayes County and 45% in Hitchcock County (United States Department of Agriculture, 2013). Corn is also the main irrigated crop representing around 95% of total irrigated cropland in Hitchcock County for example (United States Department of Agriculture, 2013).

3.2. Validation of the model

Although this model is used in an exploratory way to study the importance of individuals in CHANS, it is important to demonstrate that the results obtained with this model are reasonable. In this case, the ideal would be to validate the model against irrigation data. However, irrigation data are usually hard to obtain, especially in the RRB because of on-going law-suits and conflicts (Popelka, 2004) and because farmers are not required to document their water-use (Szilagyi, 1999). Thus, this study only validates a historical or baseline simulation running from 1950 to 2009 using available data. In this historical simulation, all farmers are assumed to have the same behavior and follow the recommended values for *MAD* (in other words, *SC* is set to 1 for all farmers). As a first validation, the long-term average irrigation predicted by our model

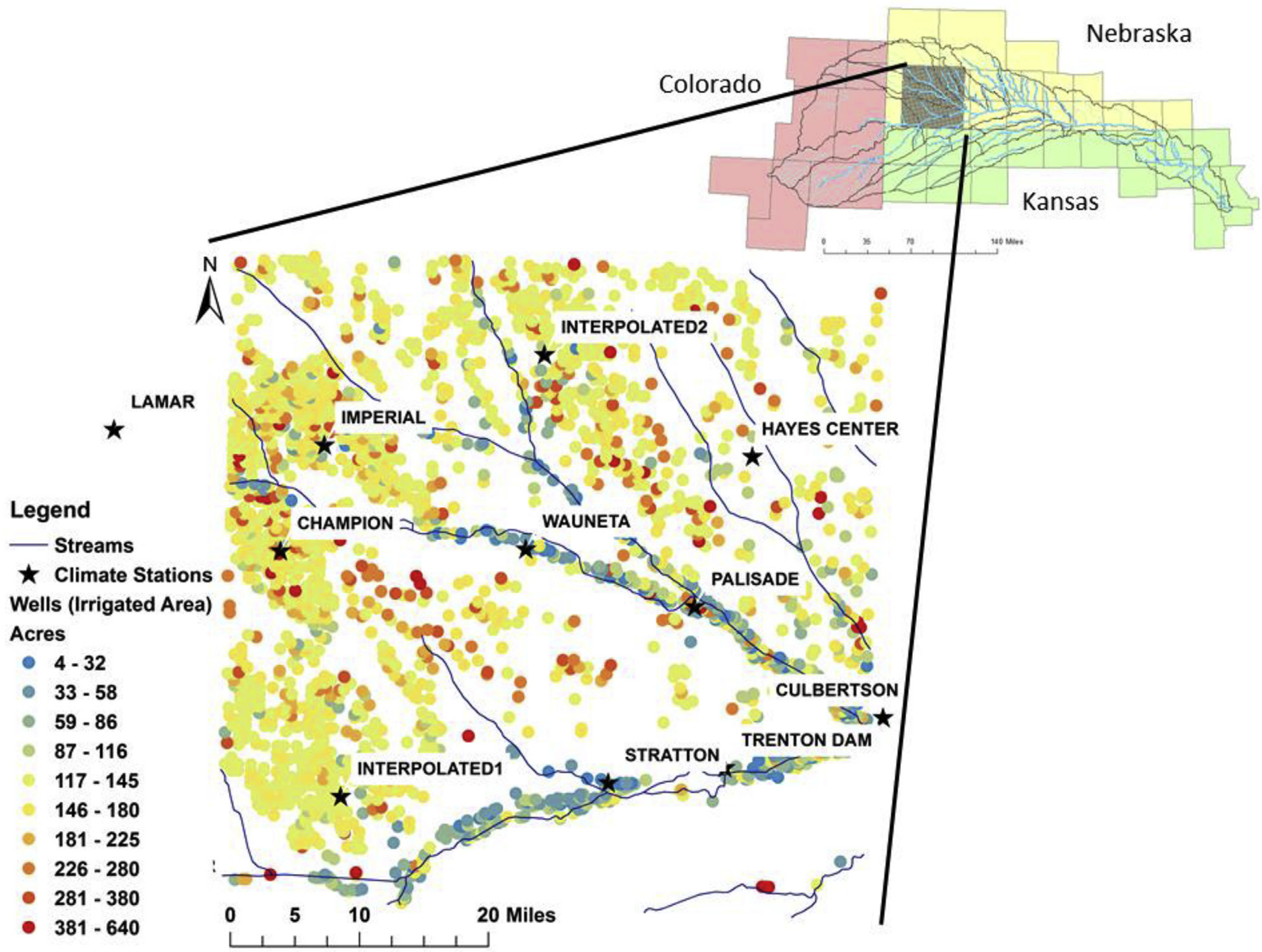

Fig. 3. Area of study in the Republican River Basin with pumping wells of various sizes (supporting irrigated field ranging from 4 to 640 acres).

Table 2
Datasets used in the model and their sources.

Dataset	Model parameters and variables	Source	Link
Soil type	Available water capacity	STATSGO, Nebraska	http://water.usgs.gov/GIS/metadata/usgswrd/XML/ussoils.xml
Well inventory	Well location, Maximum well yield, Irrigated acres, Well activation date	Nebraska Department of Natural Resources	http://dnr.nebraska.gov/gwr/registered-groundwater-wells-data-retrieval
Crop growth	Depth or rooting zone, Crop coefficient, Management allowed deficit	Andales et al., 2011	
Climate	Daily Precipitation, Daily Potential Evapotranspiration	High Plains Regional Climate Center	http://www.hprcc.unl.edu/index.php
Costs	Corn prices	Farmdoc, University of Illinois Extension	http://www.farmdoc.illinois.edu/manage/uspricehistory/us_price_history.html
	Diesel prices	U.S. Energy Information Administration	www.eia.gov/ae
	Other costs (fertilizers, pesticides, labor etc.)	Texas AgriLife Extension Service	http://agrilifeextension.tamu.edu
Groundwater	Top and bottom elevation, Hydraulic conductivity, storativity, Monthly ET, Stream network, Initial head	Republican River Compact Administration (RRCA)	http://www.republicanrivercompact.org/index.html
Regulations	Regulations	Nebraska's Natural Resources Districts	http://nrdnet.org/water.php

over the region was calculated. The value was 14.1 inches, which is close to the value of 14 inches estimated by University of Nebraska Crop Watch page on Irrigation and Water Management for Corn as the average irrigation need for corn in western Nebraska (Irrigation and Water Management for Corn). The most reliable data that we found for the validation are USDA county-level historical corn yields, which are available for the entire simulation period (from 1950 to 2009) for the four counties in the area (United States Department of Agriculture, 2013). The average reported corn yield for the region during the simulation period is 119.7 bushels per

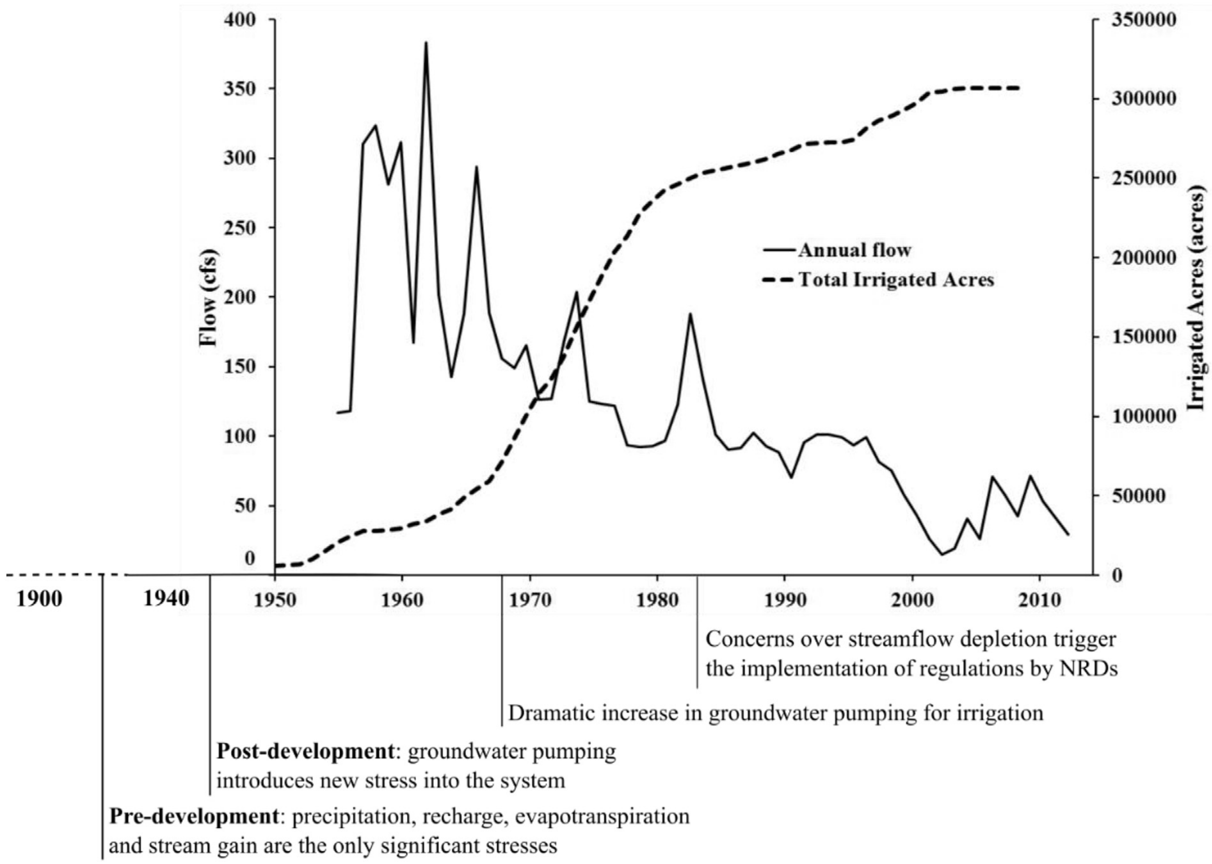

Fig. 4. History of irrigation and streamflow depletion in the region.

acre. The average simulated corn yield of 120.9 bushels per acre is close to the reported value and the root-mean-square deviation is 23.5 bushels per acre over the 60 years of the simulation with a coefficient of variation is 0.2, showing that the model performs well in terms of determining the regionally-averaged corn yield. It is worthy of noting that most of the deviation between historical and predicted corn yield derives from the processes that are not captured by the model such as crop damages from flooding. For example, the model predicts a high average corn yield of 206 bushels per acre in 1993 whereas yields were actually really low in the region on that year (average of 108.5 bushels per acre) due to the Great Flood of 1993 and related crop damages (Perry and Combs, 1998).

The groundwater model developed for this study was not calibrated, which constitutes a limitation in terms of representing accurately historical groundwater and baseflow levels, although the model is based on the RRCA model which is itself calibrated. The accuracy of the model is sufficient to allow the spatial simulation of distributed impacts of pumping on water head and baseflow for an exploratory analysis. However, reproducing accurately water head in the aquifer is beyond the scope of this paper as the integrated model is developed for an exploratory analysis of the role of individuals and human behavior on CHANS.

4. Results

To assess the role of individuals in CHANS models, we focus on the coefficient of sensitivity to crop stress *SC* introduced in equation (9). We run a set of experiments from simple to complex cases by changing *SC* in different ways to investigate how farmers' responses to water stress and the various levels of heterogeneity with individuals' responses affect and are affected by the system. *SC* is a key parameter that accounts for a farmer's behavior with regards to personal preferences and irrigation decisions in face of crop water stress, one of the most important factors of irrigation management especially in arid and semi-arid environments (Clarke, 1997; Colaizzi et al., 2003; Ghulam et al., 2008). However, it is difficult to measure this parameter that captures human characteristics. Understanding more thoroughly the role of the human characteristics can help determine the data need for the human dimension in CHANS models. We assess the role of individuals in the system in section 4.1 and their impacts on system dynamics in section 4.2. To further understand the feedbacks between individual behaviors and system dynamics, we discuss the role of human behavior heterogeneity in section 4.3 and in section 4.4, where we analyze behavior adaptation through an additional model experiment.

4.1. Assessing the role of individuals in the system

In the first experiment, we assess the impacts of individuals on the system-level performance using the historical simulation described in the validation section. In this simulation, the sensitivity coefficient *SC* is set to 1 for all farmers, which assumes all farmers respond to crop water stress homogenously by adopting the "most accepted" knowledge of water deficits. Fig. 5 displays a map of corn yield in bushels per acre at the end of each decade and shows how spatial and temporal corn yield patterns emerge as a result of heterogeneous physical parameters but homogenous behavior parameters (*SC*). The first visible pattern is the exogenous increase in well density due to the adoption of center-pivot

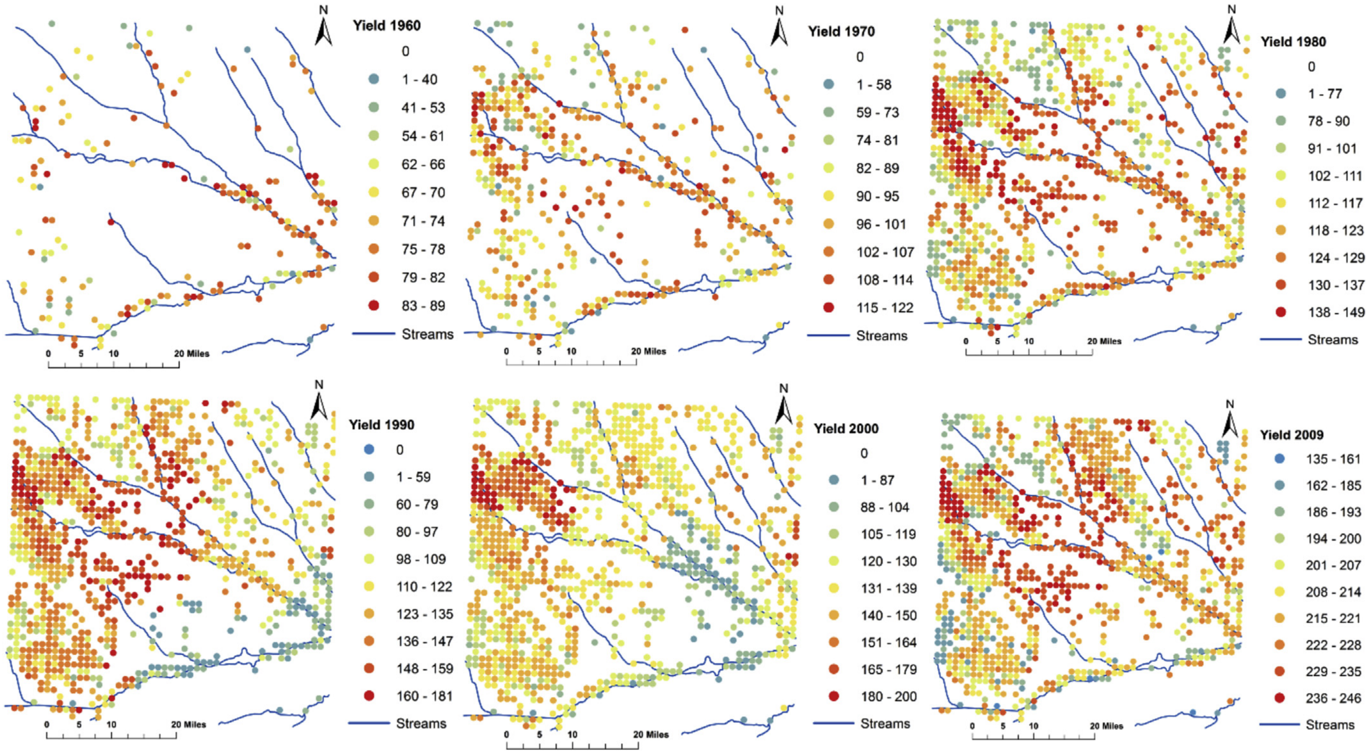

Fig. 5. Evolution of corn yield during the 60 years of simulation.

irrigation in the basin from 1950 to 2009. This pattern appears due to historical data used to determine when farmers will start using irrigation. The second pattern is the exogenous increase of maximum yield from a high of 90 bushels per acre in 1960 to a high of 250 bushels per acre in 2009 due to the improving technology and agricultural practices captured by equation (11). The third pattern is the spatial variability of corn yield caused by heterogeneous well characteristics, soil types and climatic conditions across the area and how this variability also changes with time. The spatial patterns change over time and the zones of high yield and low yield move around over the 60 years of the simulation. However, one area located in the North-West section of the region has consistently the highest corn yield from 1950 to 2009. Even though their behavior is homogeneous, the farmers make their decisions on irrigation based on heterogeneous physical parameters such as soil type, climate or well yield. Similar results were obtained by Condon and Maxwell (2014), who observed spatial and temporal patterns caused by physical heterogeneity of factors affecting farmers' decisions.

In a second experiment, two additional simulations are performed to analyze more specifically the role of "human" behavior: farmers' personal sensitivity to crop water stress. In these two simulations, all farmers were assigned the same value of 0.8 in one case and 1.2 in the other for the sensitivity coefficient *SC*. These two simulations show how the dynamics of the coupled systems would be affected if all the farmers were much more or much less sensitive to crop water stress. Fig. 6 shows the results for irrigation, regulation and the flux of water from the aquifer to the streams for the two simulations. As can be expected, when the value of *SC* is low and farmers are more sensitive to crop stress, annual irrigation is higher than that from the historical simulation where $SC = 1$. As a result, streamflow decreases more quickly due to declining baseflow, and NRD implements regulations earlier. In the case of a high *SC* value where farmers are less sensitive to crop water stress, irrigation rates are significantly lower, causing lower streamflow decline and triggering regulations later. Regulations play a stronger role in the case with high sensitivity to crop water stress as farmers pump up to the limit enforced by the regulations, while the role of regulations is not obvious in the case where farmers are less sensitive to crop water stress and use less water to irrigate their fields. These two simulations show how different human behaviors will affect the environment (in this case streamflow) in different ways. Indeed, if farmers' behavior regarding crop water stress could be improved, significant reductions of streamflow depletion could be achieved as shown on Fig. 6, keeping in mind that profits would be affected too as shown in the next section.

Next, we turn to an experiment that illustrates the importance of individual behavior as presented on Fig. 7. This figure shows how irrigation varies from year to year and between farmers in a simulation where farmers' preference over crop stress is heterogeneous. The only difference between this simulation and the historical simulation is that the sensitivity to crop stress coefficient is assigned to farmers using one realization of a normal distribution with a mean of 1 and a standard deviation of 0.01. Nine other realizations were used but are not shown here for conciseness and because results were similar to the one shown on Fig. 7. The figure shows a box plot of irrigation and blue dots representing the average annual precipitation over the region (both in inches). This figure shows how water demand for irrigation changes with time, not only because of precipitation variability, but also the behavior heterogeneity among farmers. Dry years show high irrigation variability between farmers as not all farmers irrigate the same amounts, and wet years show much lower variability since most farmers do not need to irrigate much. It is important to note that the number of active farmers in the simulation increases with time which also has impacts on the variability. In the 1980s, for example, a farmer with very low annual irrigation rates due to very low well yield becomes active,

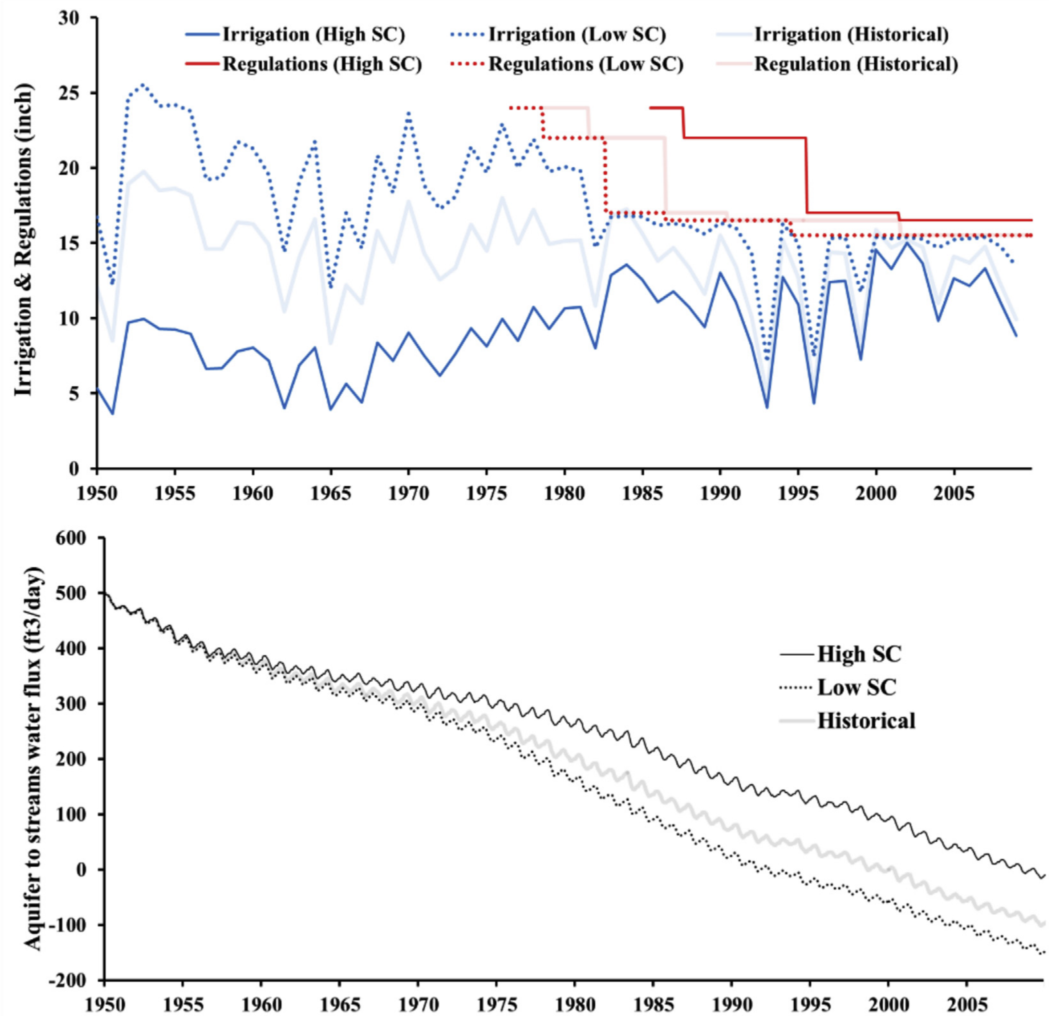

Fig. 6. Irrigation, regulations and flux of water from the aquifer to the streams for two simulations with high and low values for the sensitivity coefficient and the historical simulation.

keeping the minimum irrigation low for the rest of the simulation period. Other patterns can be found like the decrease of maximum irrigation due to stricter regulations. Long term climate trends also seem to cause a general decrease of irrigation in the first 15 years of the simulation followed by a general increase of irrigation in the following 15 years of simulation until regulations come into play. Fig. 7 also highlights the role of individual behavior in causing variability in water demand and how this variability interacts with regulations. In the period of 1980–2009, the impacts of regulations are visible through the reduction of the upper whisker for most of the years. In others words, regulations impacted mainly farmers with the highest annual irrigation rates while the average or median annual irrigation remained high. This might not be the most efficient way to tackle the issue of streamflow depletion as other factors such as the location of the wells and the local physical characteristics of the aquifer are just as important as irrigation rate in affecting streamflow. Location-based policies and educational programs could be more effective in changing farmers' behaviors and could potentially have larger impacts in mitigating streamflow depletion than those by lowering the upper whisker only. In particular, some incentive programs and education programs can encourage all farmers to voluntarily reduce their irrigation rates and target water use efficiency in sensitive areas of the aquifer or areas close to streams.

4.2. Assessing the impacts of system dynamics on individuals

Understanding how individual behavior impacts the system is only one side of the picture; the other side lies with the impacts of system dynamics on individuals. New policies and regulations, environmental change such as decreasing water table in the aquifer, and/or climate extremes such as droughts affect the farmers in an area differently due to complex factors, including the location and size of farms, physical characteristics of the aquifer underneath a farm, annual income of the farmer, etc. Modeling at the level of the individual (i.e, a farm in this study) makes it possible to keep track of individuals and thus to understand how they interact with each other and with the environment (i.e., the aquifer and stream in this study). We explore this statement by going back to the historical simulation described in the first experiment and in the validation section of this paper. Fig. 8 presents the evolution of farmers' average profit in the period of 1980–2009 compared to the average profit in the period of 1960–1980 along with the profit distribution during 1960–1980. The x axis shows each profit category or range, i.e. farmers making less than $40/acre, between $41/acre and $50/acre etc. As can be seen, most farmers earn between $70 and $100 per acre from selling corn during this period and a few farmers earn less than $40 per acre. Profit change varies monotonically with the average profit in the period. Farmers

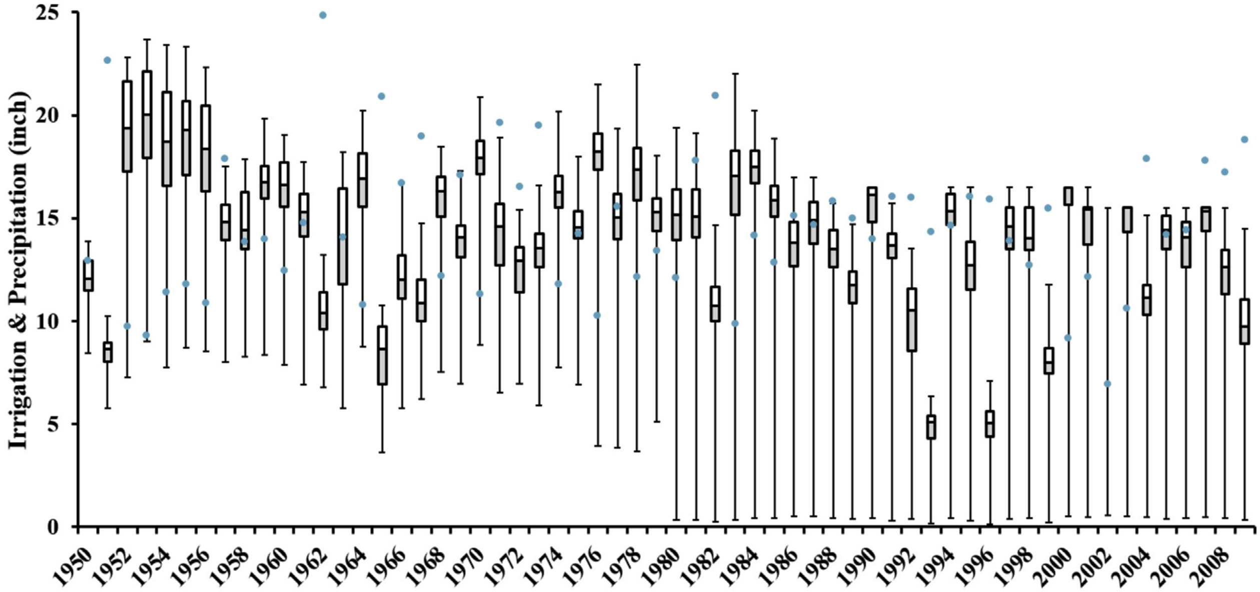

Fig. 7. Box plot of annual irrigation for baseline simulation. The blue dots represent average annual precipitation in the region. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

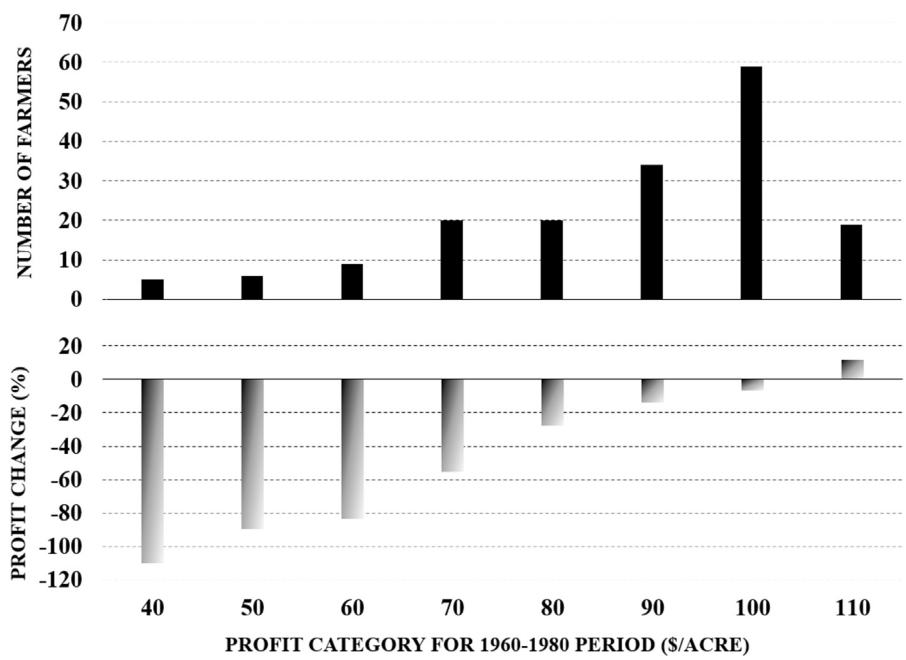

Fig. 8. Number of farmers in each category of average profit between 1960 and 1980 (black bars) and change of average profit after 1980 for each category (grey bars).

making less than $40 per acre before 1980 see their profit decrease by over 100% after 1980 and are now making a loss. On the contrary, farmers making $110 per acre before 1980 see their profits increase by 10% after 1980. The overall decrease of profits resulting from the model is due to several factors. Over the 60-year simulation, profits on wet years increase but losses on dry years increase even more. This is because the model does not account for other income sources of farmers such as crops other than corn and insurances, and it does not capture farming practices used to mitigate losses either, while it captures profit losses in dry years after 1980 with irrigation regulations and increased pumping cost due to lower water table in the aquifer. Despite the limitations, the model shows how farmers are impacted differently by regulatory change and pumping cost variability.

Fig. 9 shows the relationship between average annual irrigation and farm-level simulated drawdown. The x axis shows average irrigation category or range, i.e. farmers irrigating less than 9.2inch, between 9.3inch and 9.9inch etc. Most farmers irrigate on average between 14.1 and 15.5 inches annually but a small number of farmers have rates as low as 9.2 inches per year. Interestingly, there is no clear relation between the amount pumped by farmers for irrigation and the drawdown in the aquifer. In other words, farmers who pump more do not necessarily cause larger drawdown. Drawdown for farmers irrigating on average less than 9.2 inches per year is 41.3 feet, compared to 44.3 feet with farmers irrigating more than 15.5 inches per year. However, farmers pumping between 9.2 and 9.9 inches and between 12 and 12.7 inches per year are associated with drawdown of 15.2 feet and 20.8 feet,

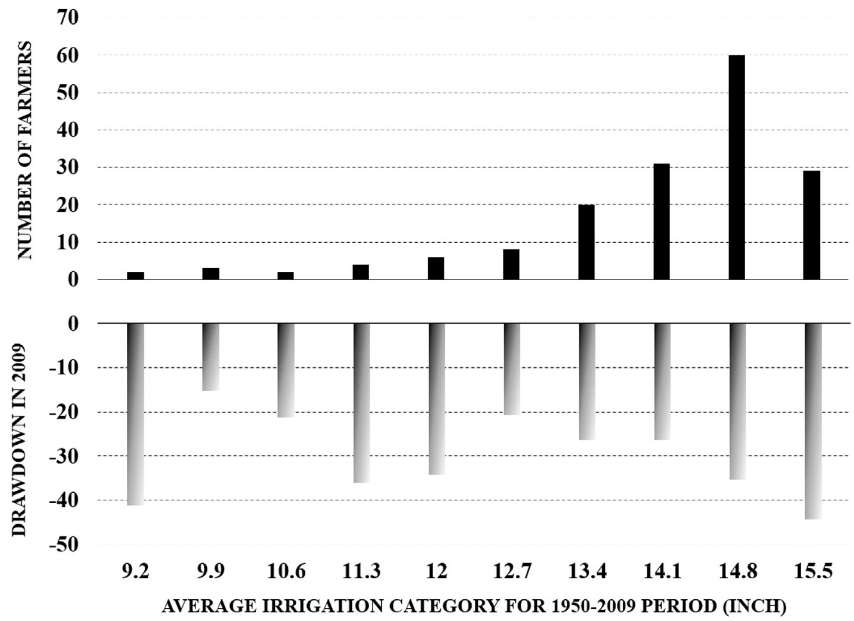

Fig. 9. Number of farmers in each category of average annual irrigation over the entire simulation (black bars) and average drawdown in 2009 in each category (grey bars). The black bars show the distribution of average annual irrigation over the 60 years of simulation for all the farmers active during the entire period.

respectively. As irrigation increases, the average drawdown in each category does not exhibit a change in a specific direction, implying that there does not seem to be any relationship between irrigation and drawdown. The reason for this behavior is that physical characteristics of the aquifer such as conductivity and thickness of the aquifer are heterogeneous and play a crucial role in controlling water level. Depending on these characteristics, similar pumping rates can lead to either similar or different drawdowns. Another important reason is that the density of pumping wells in an area can play a more important role than the pumping rate of individual farmers in affecting water table. Results shown in Fig. 9 have implications from a policy making perspective as they show that water table drawdown might not be directly related to individual pumping rates but rather to the density of wells within an area. Indeed, Fig. 9 shows that farmers with the lowest irrigation depth are associated with almost the highest drawdown at their sites. These farmers are negatively impacted by other farmers' pumping rates, as well as the physical properties of the aquifer.

4.3. The role of human behavior heterogeneity

To better understand the impact of human behavior heterogeneity on the system-level performance, we analyze another experiment where a set of simulations was performed with heterogeneity from low to high levels, assuming a normal distribution of *SC* with a mean value of 1.00. The average profits of all farmers in the study area are plotted with increasing standard deviation of *SC* in Fig. 10.

As can be seen, the average profit of farmers decreases as the behavior heterogeneity increases. When $SC = 1.0$ for all farmers, they start to irrigate their crops when soil water deficit is exactly equal to the management allowed deficit (*MAD*). However, as heterogeneity increases, more and more farmers over- or under-respond to the *MAD* when the *SC* value is lower or higher than 1.0. Farmers with $SC > 1.0$ start to irrigate when the soil water deficit is higher than *MAD*. As a result, they tend to pump less and their crop yield and profit decline in response. On the contrary, farmers with $SC < 1.0$ start to irrigate when the soil water deficit is lower than *MAD*. Consequently, they tend to pump more and their crop yield and profit may increase. However, the marginal increase of crop yield is usually less than the marginal decrease given that crop yield is usually a concave function of water with diminishing marginal value from increasing water use (Klocke et al., 2011). Moreover, for farmers who tend to pump more water for irrigation, their actual amount of pumping may also be constrained by water use regulation (i.e., pumping permit). On the other hand, nothing prevents farmers to pump less if they want to in the model. Thus, with less over-than under-response to crop water stress, overall, the total profit in the study area (i.e., the system-level profit) declines. Fig. 10 shows that individual behavior heterogeneity generates a systematic pattern at the system level (i.e., declining profit with increasing heterogeneity). Moreover, the results here show the value of scientific knowledge if it is used to change human behavior. In particular, for the case study presented here, if the knowledge on optimal *MAD* can be delivered to farmers in a form that they can understand and then use in their decision making, then more farmers will tend to respond to crop water stress in an appropriate way, which will reduce *SC* deviation among farmers toward a mean value of 1.0 and thus increase crop profit at the system level (i.e., moving from right to left on the curve in Fig. 10). Farmers might have various reasons for under- or over-irrigating; however, helping them to change their behavior through incentive-based policies, educational programs and innovative technologies could significantly improve both individual-level and system-level profits. For example, for the case study in this paper, the change can be achieved by assisting farmers to acquire soil moisture probes and advanced irrigation systems with variable irrigation rates.

4.4. Behavior change through adaptations

Human behavior changes over time. Thus to implement an ABM, one would need to specify not only the rules to represent an agent's current behavior but also the rules on how behavior rules change over time. Berry et al. (2002) and a set of associated papers from a workshop on ABM discussed some key concepts on adaptive

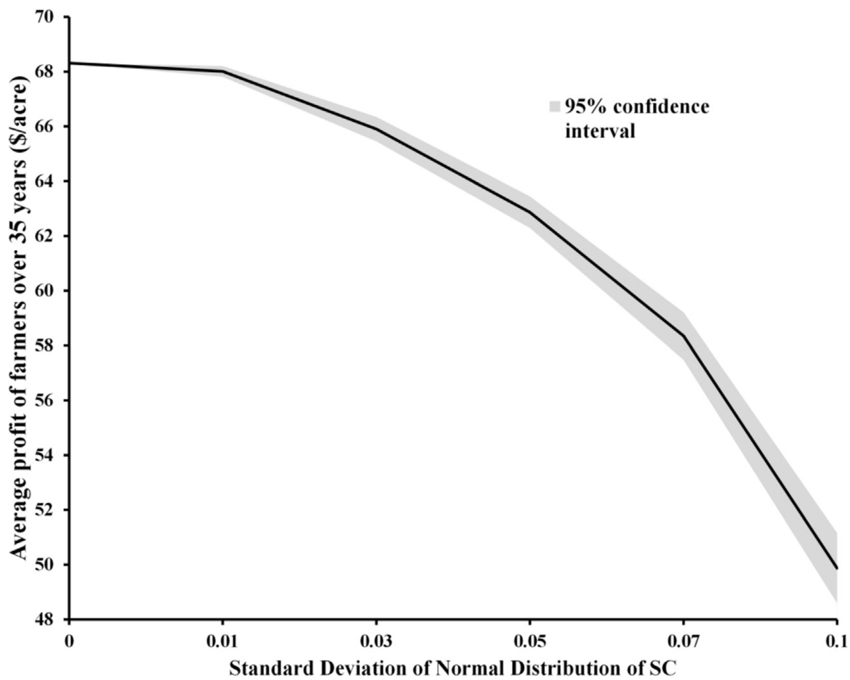

Fig. 10. Average profit of all farmers in the study area as a function of behavior heterogeneity.

agents, intelligence, and emergent human organization involved in agent-based modeling of a complex system. Machine learning methods have been tested to simulate agents' adaptation based on both prior knowledge and new observation, for example, Bayesian inference (e.g., Navarro et al., 2006; Ng et al., 2011). The psychological component of individual behavior was accounted for in a simple way in our model by assuming a normally distributed random variability in individuals' behaviors (as shown above from this study) or simply no variability as adopted in many previous studies that assume homogenous human behavior. However, human behavior is more complex and includes interactions between individuals and behavior change with time (i.e. learning or human intelligence (Ng et al., 2011)).

In our final experiment, we integrate the change of farmers' behaviors with time in our model and perform a new simulation. It is assumed that 1) farmers assess their crop yield compared to the average yield in the region every year, and they also assess their annual pumping cost subject to the average value in the region; 2) farmers with lower yield in the current year will be more sensitive to crop stress and therefore irrigate more in the following years. Equation (16) was designed to fulfill these two assumptions and shows how SC is updated year by year in the model as explained above:

$$SC^{n+1} = SC^n + \min\left(\frac{CY - 0.75 \times ACY}{ACY}, 0\right) + \max\left(\frac{PC - 1.5 \times APC}{APC}, 0\right) \quad (16)$$

Where *CY* is the corn yield in bushels per acre, *ACY* is the average corn yield over all farmers in that year in bushels per acre, and *APC* is the average pumping cost over all farmers in dollars per acre. *SC* is subject to a range of reasonable values between 0.8 and 1.2 and all farmers are assigned an initial value of 1, meaning that they neither under- nor over-irrigate their crops. This equation is used to decrease *SC* when a farmer's corn yield is lower than 75% of the average corn yield over all farmers, and to increase *SC* when a farmer's pumping cost is higher than 150% of the average pumping cost over all farmers. Figs. 11 and 12 illustrate the impacts of including such adaptation in the model. Fig. 11 presents the distribution of profit change averaged over the 60 years. Farmers' profits change when their behavior changes through adaptation. Profits do not necessarily increase in the case with adaptation. This is due to the fact that some farmers reduce their irrigation because of high pumping cost even though the marginal value of increased yield is higher than the marginal value of decreased pumping cost. Likewise, some farmers increase their irrigation because of low yield but their pumping cost might increase more than their profit gain from the increased yield. Profit change appears to be highly variable with some farmers losing up to $180 per acre on average by adapting their behavior while others gaining up to $80 per acre. This high variability is caused by the relationship between profit and irrigation. Fig. 12 shows that there is a significant drawdown difference across the region between the historical simulation and the simulation with behavior adaptation, which implies that the changes in individual behaviors over time can have system-level impacts. Again, heterogeneity is present with spatial patterns of drawdown difference. Four areas seem to particularly benefit from farmers' adaptive behavior. In these regions up to 16 feet of water are saved in the aquifer in the simulation with adaptive behavior. These results show how additional behavior heterogeneity with agents' adaptations to changes affects the environmental system, as well as individual variables such as profit. These results also show that farmers' behavior change toward better practices can be effective to tackle issues of streamflow and aquifer depletion. One main implication of these results is that human behavior plays a crucial role in CHANS modeling and should therefore be at least considered as a source of uncertainty if necessary data are available instead of being the elephant in the room.

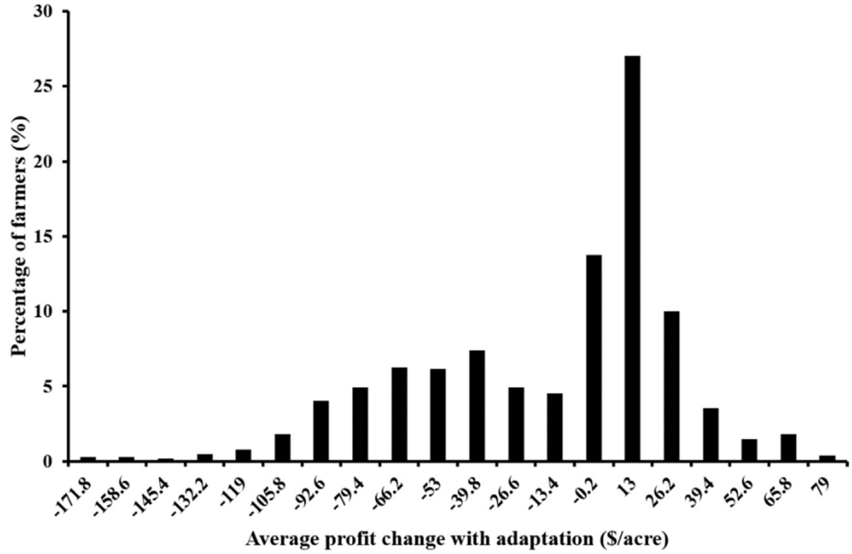

Fig. 11. Profit change with behavior adaptation.

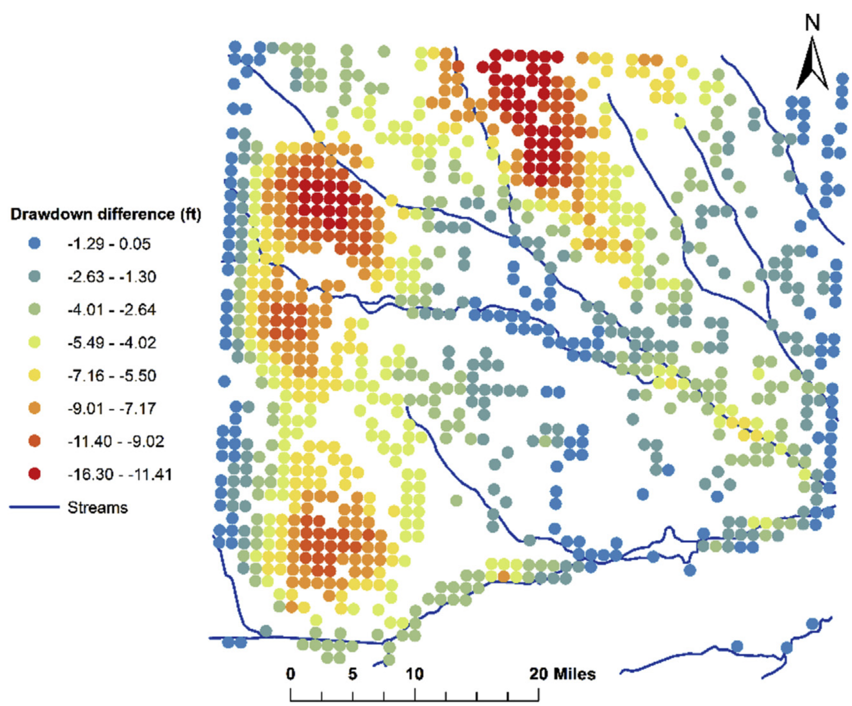

Fig. 12. Drawdown difference with behavior adaptation.

5. Discussion and conclusion

The results presented in section 4 illustrate the role of individuals and their behavior in large-scale groundwater-fed irrigated agriculture in the High Plains region. It appears that modeling individuals in this context is important because of their influence on the system and because of the knowledge that can be gained on how differently they are impacted by the systems' dynamics. While physical attributes characterizing farmers' decisions on irrigation such as soil type or irrigated area can be measured and easily incorporated in models, it is more difficult to incorporate the psychological or social attributes of farmers' behavior in models as these attributes are hard to characterize and to quantify. However, farmers' human behavior, here accounted for with the sensitivity to crop stress, seems to play an important role in this system as shown on Figs. 10–12. Figs. 6 and 7 show how education and information can have significant impacts in reducing streamflow and aquifer depletion. In other words, institutions and regulatory agencies can use information access and educational programs to improve farmers' behavior as a way to mitigate environmental impacts of groundwater pumping for irrigation. These findings support current efforts at the national and international levels to improve irrigation practices and conserve decreasing water resources (English et al., 2002; Pereira et al., 2002; Schaible and Aillery, 2012). With dropping water levels in aquifers and the looming threat of climate change, education and information diffusion can help farmers reduce their water consumption, adopt new technologies and switch to more adequate practices resulting in reduced water depletion with potential positive or negative financial impacts to keep in mind.

Using a single parameter can be seen as a limitation of the paper, especially since real values of *SC* are not known, but we believe that using this straightforward method can provide very valuable insights and lay the work for more complex analyses in the future, as the results above illustrates. Our model for example could be improved to account for behavior heterogeneity through a more realistic distribution than the normal distribution that we used to modify farmers' preferences over crop water stress or to better account for behavior adaptation and other characteristics of human behavior.

To conclude, this paper illustrates the role of individuals, human behavior and heterogeneity in modeling CHANS in the context of this case study. Results from our integrated models shed light on the significant role of individuals and human behavior in creating spatial and temporal patterns within a coupled human and natural system. Crop yield, profit, irrigation and groundwater depletion vary considerably in time and space, even in a small region, because of physical and behavioral heterogeneity. Model results also illustrate that modeling individuals allows the quantification of the heterogeneous impacts of systems' dynamics on individuals. For example, farmers with lower profits might be more affected by irrigation regulations or increased pumping cost than farmers with high profits; farmers with low pumping rates can be negatively affected by the physical characteristics of the underlying aquifer and by neighboring farmers as pumping well density is a major factor of groundwater depletion. Overall, these results show the breadth of information that can be gained from considering individuals in modeling CHANS. Thus averaging over all agents may provide a misleading basis for modeling unless the population at stake is well studied, understood and can be segmented accurately into representative groups. The importance of modeling individual differences has been addressed in psychology (e.g., Ashby et al., 1994; Navarro et al., 2006) in terms of human behaviors and in ecology (e.g., DeAngelis and Mooij, 2005) in terms of the heterogeneity of ecological agents.

In the case of the Republican River Basin, our model suggests that scientific knowledge dissemination and education programs to promote behavior change could be effective in tackling environmental issues such as groundwater and streamflow depletion while providing economic benefits, which emphasizes the complementary role of non-market methods in water demand management. Based on our results, we recommend that human behavior is at least considered as an additional source of uncertainty in modeling CHANS as it can have such a significant role in the dynamics of the coupled systems. There is much to learn from economists, social scientists and psychologists to better quantify and represent human behavior.

Acknowledgments

This work was funded by the U.S. National Science Foundation (NSF) (U.S. NSF grant EFRI-083598). The authors thank three anonymous reviewers for their very helpful suggestions in revising the primary manuscript.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.envsoft.2017.02.010.

References

Alberti, M., Asbjornsen, H., Baker, L., Brozovic, N., Drinkwater, L., Drzyzga, S., et al., 2011. Research on coupled human and natural systems (CHANS): approach, challenges, and strategies. Bull. Ecol. Soc. Am. 92 (2), 218–228.
Allen, R., Pereira, L., Raes, D., Smith, M., 1998. Crop Evapotranspiration. FAO Irrigation & Drainage Paper No. 56. FAO, Rome, Italy.
An, L., 2012. Modeling human decisions in coupled human and natural systems: review of agent-based models. Ecol. Model. 229, 25–36.
Andales, A., Chávez, J., Bauder, T., 2011. Irrigation Scheduling: the Water Balance Approach. Colorado State University Extension.
Arnold, R., Troost, C., Berger, T., 2014. Quantifying the economic importance of irrigation water reuse in a Chilean watershed using an integrated agent-based model. Water Resour. Res. 51, 648–668.
Ashby, F.G., Maddox, W.T., Lee, W.W., 1994. On the dangers of averaging across subjects when using multidimensional scaling or the similarity-choice model. Psychol. Sci. 5 (3), 144–151.
Athanasiadis, I., Mentes, A., Mitkas, P., Mylopoulos, Y., 2005. A hybrid agent-based model for estimating residential water demand. Simulation 81 (3), 175–187.
Baggio, J.A., Janssen, M.A., 2013, December. Comparing agent-based models on experimental data of irrigation games. In: Simulation Conference (WSC), 2013. IEEE, Winter, pp. 1742–1753.
Berger, T., 2001. Agent-based spatial models applied to agriculture: a simulation tool for technology diffusion, resource use changes and policy analysis. Agric. Econ. 25 (2–3), 245–260.
Berger, T., Troost, C., 2014. Agent-based modelling of climate adaptation and mitigation options in agriculture. J. Agric. Econ. 65 (2), 323–348.
Berry, B.J., Kiel, L.D., Elliott, E., 2002. Adaptive agents, intelligence, and emergent human organization: capturing complexity through agent-based modeling. Proc. Natl. Acad. Sci. 99 (Suppl. 3), 7187–7188.
Bulatewicz, T., Yang, X., Peterson, J., Staggenborg, S., Welch, S., Steward, D., 2010. Accessible integration of agriculture, groundwater, and economic models using the Open Modeling Interface (OpenMI): methodology and initial results. Hydrology Earth Syst. Sci. 14 (3), 521–534.
Cai, X., 2008. Implementation of holistic water resources-economic optimization models for river basin management–reflective experiences. Environ. Model. Softw. 23 (1), 2–18.
Castilla-Rho, J.C., Mariethoz, G., Rojas, R., Andersen, M.S., Kelly, B.F.J., 2015. An agent-based platform for simulating complex human–aquifer interactions in managed groundwater systems. Environ. Model. Softw. 73, 305–323.
Clarke, T.R., 1997. An empirical approach for detecting crop water stress using multispectral airborne sensors. Hort. Technol. 7 (1), 9–16.
Colaizzi, P.D., Barnes, E.M., Clarke, T.R., Choi, C.Y., Waller, P.M., Haberland, J., Kostrzewski, M., 2003. Water stress detection under high frequency sprinkler irrigation with water deficit index. J. Irrigation Drainage Eng. 129 (1), 36–43.
Condon, L., Maxwell, R., 2014. Feedbacks between managed irrigation and water availability: diagnosing temporal and spatial patterns using an integrated hydrologic model. Water Resour. Res. 50 (3), 2600–2616.
Crutzen, P.J., 2006. The "anthropocene". In: Ehlers, E., Krafft, T. (Eds.), Earth System Science in the Anthropocene. Springer, Berlin Heidelberg, pp. 13–18.
DeAngelis, D.L., Mooij, W.M., 2005. Individual-based modeling of ecological and evolutionary processes. Annu. Rev. Ecol. Evol. Syst. 147–168.
Elsawah, S., Guillaume, J.H., Filatova, T., Rook, J., Jakeman, A.J., 2015. A methodology for eliciting, representing, and analysing stakeholder knowledge for decision making on complex socio-ecological systems: from cognitive maps to agent-based models. J. Environ. Manag. 151, 500–516.
English, M.J., Solomon, K.H., Hoffman, G.J., 2002. A paradigm shift in irrigation management. J. irrigation drainage Eng. 128 (5), 267–277.
Filatova, T., Verburg, P., Parker, D., Stannard, C., 2013. Spatial agent-based models for socio-ecological systems: challenges and prospects. Environ. Model. Softw. 45, 1–7.
Foster, T., Brozović, N., Butler, A., 2014. Modeling irrigation behavior in groundwater systems. Water Resour. Res. 50 (8), 6370–6389.
Galán, J., López-Paredes, A., Del Olmo, R., 2009. An agent-based model for domestic water management in Valladolid metropolitan area. Water Resour. Res. 45 (5).
Ghulam, A., Li, Z.L., Qin, Q., Yimit, H., Wang, J., 2008. Estimating crop water stress with ETM+ NIR and SWIR data. Agric. For. meteorology 148 (11), 1679–1695.
Gluck, K., Pew, R., 2006. Modeling Human Behavior with Integrated Cognitive Architectures: Comparison, Evaluation, and Validation. Psychology Press, Mahwah.
Gual, M.A., Norgaard, R.B., 2010. Bridging ecological and social systems coevolution: a review and proposal. Ecol. Econ. 69 (4), 707–717.
Hanson, B., Orloff, S., Peters, D., 2000. Monitoring soil moisture helps refine irrigation management. Calif. Agric. 54 (3).
Harbaugh, A.W., 2005. MODFLOW-2005, the US Geological Survey Modular Ground-water Model: the Ground-water Flow Process (pp. 6-A16). US Department of the Interior, US Geological Survey, Reston, VA, USA.
Harou, J., Pulido-Velazquez, M., Rosenberg, D., Medellín-Azuara, J., Lund, J., Howitt, R., 2009. Hydro-economic models: concepts, design, applications, and future prospects. J. Hydrology 375 (3).
Huang, Q., Parker, D., Sun, S., Filatova, T., 2013. Effects of agent heterogeneity in the presence of a land-market: a systematic test in an agent-based laboratory. Comput. Environ. urban Syst. 41, 188–203.
Irrigation and Water Management for Corn. (n.d.). Retrieved 04 20, 2015, from

University of Nebraska - Lincoln, Crop Watch: http://cropwatch.unl.edu/corn/water.
Jensen, M., 1968. Water Consumption by Agricultural Plants. Academic Press Inc, New York.
Jorgensen, B., Graymore, M., O'Toole, K., 2009. Household water use behavior: an integrated model. J. Environ. Manag. 91 (1), 227–236.
Kelly, R., Jakeman, A., Barreteau, O., Borsuk, M., ElSawah, S., Hamilton, S., et al., 2013. Selecting among five common modelling approaches for integrated environmental assessment and management. Environ. Model. Softw. 47, 159–181.
Klocke, N.L., Currie, R.S., Tomsicek, D.J., Koehn, J., 2011. Corn yield response to deficit irrigation. Transaction ASABE 54 (3), 931–940.
Kremmydas, D., 2012. Agent Based Modeling for Agricultural Policy Evaluation: a Review. AUA Working Paper Series No.2012-3 December 2012.
Lamm, F., Rogers, D., & Clark, G. (n.d.). Irrigation Scheduling for Corn: Macromanagement. K-State Research & Extension.
Laniak, G., Olchin, G., Goodall, J., Voinov, A., Hill, M., Glynn, P., et al., 2013. Integrated environmental modeling: a vision and roadmap for the future. Environ. Model. Softw. 39, 3–23.
Lave, C., March, J., 1993. An Introduction to Models in the Social Sciences. University Press of America, Lanham.
Ligtenberg, A., van Lammeren, R., Bregt, A., Beulens, A., 2010. Validation of an agent-based model for spatial planning: a role-playing approach. Comput. Environ. Urban Syst. 34 (5), 424–434.
Liu, J., Dietz, T., Carpenter, S., Alberti, M., Folke, C., Moran, E., et al., 2007. Complexity of coupled human and natural systems. Science 317 (5844), 1513–1516.
Martin, D., Dorn, T., Melvin, S., Corr, A., Kranz, W., 2011, February. Evaluating energy use for pumping irrigation water. In: Proceedings of the 23rd Annual Central Plains Irrigation Conference, pp. 22–23.
McKusick, V., 2003. Final report for the special master with certificate of adoption of RRCA groundwater model. State of Kansas v. State Neb. State Colo. Supreme Court U. S. 3605.
Merkley, G.P., Allen, R.G., 2004. Sprinkle & Trickle Irrigation: Lecture Notes. Biological and Irrigation Engineering Department, Utah State University.
Miro, M., 2012. Integrating Institutional and Local Decision-making with Emergent Environmental Phenomena: the Case of the Republican River Basin (Master's Thesis). University of Illinois at Urbana-Champaign.
Müller, B., Bohn, F., Dreßler, G., Groeneveld, J., Klassert, C., Martin, R., Schlüter, M., Schulze, J., Weise, H., Schwarz, N., 2013. Describing human decisions in agent-based models—ODD+ D, an extension of the ODD protocol. Environ. Model. Softw. 48, 37–48.
Mulligan, K., Brown, C., Yang, Y., Ahlfeld, D., 2014. Assessing groundwater policy with coupled economic-groundwater hydrologic modeling. Water Resour. Res. 50 (3), 2257–2275.
Navarro, D.J., Griffiths, T.L., Steyvers, M., Lee, M.D., 2006. Modeling individual differences using Dirichlet processes. J. Math. Psychol. 50 (2), 101–122.
Nebraska Association of Resources Districts, 2014. Nebraska's Natural Resources Districts. Retrieved December 10, 2014, from. http://www.nrdnet.org/.
Nebraska Department of Agriculture, 2013, February. Nebraska Agriculture. Retrieved December 4, 2014, from. http://www.nda.nebraska.gov/. http://www.nda.nebraska.gov/publications/ne_ag_facts_brochure.pdf.
Ng, T., Eheart, J., Cai, X., Braden, J., 2011. An agent-based model of farmer decision-making and water quality impacts at the watershed scale under markets for carbon allowances and a second-generation biofuel crop. Water Resour. Res. 47 (9).
Noel, P., 2015. Studying Coupled Human and Natural Systems from a Decentralized Perspective: the Case of Agent-based and Decentralized Modeling (Master's thesis). University of Illinois at Urbana-Champaign.
Pereira, L.S., Oweis, T., Zairi, A., 2002. Irrigation management under water scarcity. Agric. water Manag. 57 (3), 175–206.
Perry, C., Combs, L., 1998. Summary of Floods in the United States, January 1992 through September 1993. Geological Survey, Denver, Colorado: U.S.
Popelka, A., 2004. Republican River dispute: an analysis of the parties' compact interpretation and final settlement stipulation. Neb. Law Rev. 83, 596.
Rhoads, F., Yonts, C., 1991. Irrigation Scheduling for Corn - Why and How. National Corn Handbook.
Rosegrant, M., Cai, X., Cline, S., 2002. World Water and Food to 2025. International Food Policy Research Institute, Washington, D.C.
Rounsevell, M., Robinson, D., Murray-Rust, D., 2012. From actors to agents in socio-ecological systems models. Philosophical Trans. R. Soc. B Biol. Sci. 367 (1586), 259–269.
Russell, S., Fielding, K., 2010. Water demand management research: a psychological perspective. Water Resour. Res. 46 (5).
Sauer, T., Havlík, P., Schneider, U., Schmid, E., Kindermann, G., Obersteiner, M., 2010. Agriculture and resource availability in a changing world: the role of irrigation. Water Resour. Res. 46 (6).
Scanlon, B., Faunt, C., Longuevergne, L., Reedy, R., Alley, W., McGuire, V., et al., 2012. Groundwater depletion and sustainability of irrigation in the US high Plains and central valley. Proc. Natl. Acad. Sci. 109 (24), 9320–9325.
Schaible, G., Aillery, M., 2012. Water conservation in irrigated agriculture: trends and challenges in the face of emerging demands. USDA-ERS Econ. Inf. Bull. 99.
Schlüter, M., Pahl-Wostl, C., 2007. Mechanisms of resilience in common-pool resource management systems: an agent-based model of water use in a river basin. Ecol. Soc. 12 (2), 4.
Schlüter, M., McAllister, R., Arlinghaus, R., Bunnefeld, N., Eisenack, K., Hoelker, F., et al., 2012. New horizons for managing the environment: a review of coupled social-ecological systems modeling. Nat. Resour. Model. 25 (1), 219–272.
Shafiee-Jood, M., Cai, X., Chen, X., Liang, X., Kumar, P., 2014. Assessing the value of seasonal climate forecast information through an end-to-end forecasting framework: application to U.S. 2012 drought in central Illinois. Wat. Resour. Res. 50 (8), 6592–6609. http://dx.doi.org/10.1002/2014WR015822.
Sivapalan, M., Savenije, H., Blöschl, G., 2012. Socio-hydrology: a new science of people and water. Hydrol. Process. 26 (8), 1270–1276.
Steffen, W., Persson, Å., Deutsch, L., Zalasiewicz, J., Williams, M., Richardson, K., Crumley, C., Crutzen, P., Folke, C., Gordon, L., Molina, M., 2011. The anthropocene: from global change to planetary stewardship. Ambio 40 (7), 739–761.
Steward, D., Bruss, P., Yang, X., Staggenborg, S., Welch, S., Apley, M., 2013. Tapping unsustainable groundwater stores for agricultural production in the high plains Aquifer of Kansas, projections to 2110. Proc. Natl. Acad. Sci. 110 (37), E3477–E3486.
Szilagyi, J., 1999. Streamflow depletion investigations in the Republican River basin: Colorado, Nebraska, and Kansas. J. Environ. Syst. 27 (3), 251–263.
Tesfatsion, L., 2003. Agent-based computational economics: modeling economies as complex adaptive systems. Inf. Sci. 149 (4), 262–268.
United States Department of Agriculture, 2013. United States Department of Agriculture, National Agricultural Statistics Service. Retrieved 12 4, 2014, from. http://www.nass.usda.gov/Quick_Stats/index.php.
van Oel, P., Krol, M., Hoekstra, A., Taddei, R., 2010. Feedback mechanisms between water availability and water use in a semi-arid river basin: a spatially explicit multi-agent simulation approach. Environ. Model. Softw. 25 (4), 433–443.
Yang, Y., Cai, X., Stipanović, D., 2009. A decentralized optimization algorithm for multiagent system—based watershed management. Water Resour. Res. 45 (8).
Yang, Y., Zhao, J., Cai, X., 2011. Decentralized optimization method for water allocation management in the Yellow River basin. J. Water Resour. Plan. Manag. 138 (4), 313–325.
Zeng, R., Cai, X., 2014. Analyzing streamflow changes: irrigation-enhanced interaction between aquifer and streamflow in the Republican River Basin. Hydrology Earth Syst. Sci. 18 (2), 493–502.