Key Points:
- We implement a bottom-up model development approach to represent anthropogenic and environmental feedbacks
- Our model allows quantitative simulation of the impact of water user behavior on farmer livelihoods and water security
- We find that changes in behavior may have a greater impact on water resource security in the study region than expected changes to climate

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Including Farmer Irrigation Behavior in a Sociohydrological Modeling Framework With Application in North India

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Abstract Understanding water user behavior and its potential outcomes is important for the development of suitable water resource management options. Computational models are commonly used to assist water resource management decision making; however, while natural processes are increasingly well modeled, the inclusion of human behavior has lagged behind. Improved representation of irrigation water user behavior within models can provide more accurate and relevant information for irrigation management in the agricultural sector. This paper outlines a model that conceptualizes and proceduralizes observed farmer irrigation practices, highlighting impacts and interactions between the environment and behavior. It is developed using a bottom-up approach, informed through field experience and farmer interaction in the state of Uttar Pradesh, northern India. Observed processes and dynamics were translated into parsimonious algorithms, which represent field conditions and provide a tool for policy analysis and water management. The modeling framework is applied to four districts in Uttar Pradesh and used to evaluate the potential impact of changes in climate and irrigation behavior on water resources and farmer livelihood. Results suggest changes in water user behavior could have a greater impact on water resources, crop yields, and farmer income than changes in future climate. In addition, increased abstraction may be sustainable but its viability varies across the study region. By simulating the feedbacks and interactions between the behavior of water users, irrigation officials and agricultural practices, this work highlights the importance of directly including water user behavior in policy making and operational tools to achieve water and livelihood security.

1. Introduction

Globally, water resources face unprecedented challenges due to population growth and changing lifestyles, exacerbated by variations in climate, including more frequent extreme weather events (Famiglietti, 2014; Moors et al., 2011; Schewe et al., 2014). While the impact of these factors on water resources is experienced by many millions of people worldwide, it is typically the vulnerable in society who are most acutely affected (Adger et al., 2003; Amarasinghe et al., 2016a; Conway et al., 2015). Improvements in current water management strategies depend on an in-depth understanding of the drivers behind the water use; among the most important of which are the practices of stakeholders. Human behavior is a significant driver of water resource insecurity (Dalin et al., 2017; Foley et al., 2005; Nazemi & Wheater, 2015). Despite this, inclusion of water end user behavior in planning and management of water resources has to date largely been neglected in research and model development (Nazemi & Wheater, 2015). This leads to an incomplete understanding of the problems and challenges facing communities and may result in poorly conceived water management strategies. Thus, incorporating users' behavior in water resource modeling could improve water resource management and enhanced resilience under changing conditions. This is also the central premise of the Panta Rhei initiative of the International Association of Hydrological Sciences, which aims to reach an improved understanding of the water cycle by focusing on the interactions and feedbacks between hydrology and society (Montanari et al., 2013).

Approaches to water resource management have changed over time, and recognizing the role humans play in water security has become increasingly apparent (see Blair & Buytaert, 2016; Roobavannan et al., 2018). Modeling has played an important role in helping researchers and policy makers to better understand water resource use and resilience. However, while hydrological models are capable of representing complex

physical processes, less progress has been made toward incorporating human behavior (Bierkens, 2015; GEWEX, 2012; Nazemi & Wheater, 2015). Including water user practices within the modeling framework improves our understanding of the complex processes behind water use (Nazemi & Wheater, 2015), helping to identify more suitable coping mechanisms and management strategies.

Addressing this research gap, however, is inhibited by a lack of suitable and relevant *real-world* insights and data to inform, drive, and constrain the models (O'Keeffe et al., 2016). Further complications arise when results derived from regional-scale model applications are inferred to local-scale practices (Macdonald et al., 2016). Sociohydrological models allow for the conceptualization of anthropogenic and physical processes within a hydrological system, providing a framework with which to identify and understand feedbacks and linkages between variables and drivers (Srinivasan et al., 2016). Such models can be of particular use in examining the impacts caused by changes in social and environmental conditions.

While sociohydrology specifically refers to the dynamics and coevolution of coupled human and water systems (Sivapalan et al., 2012), the modeling approaches used to represent sociohydrological systems are varied. These include agent-based modeling, system dynamics, pattern-orientated modeling, Bayesian networks, coupled component modeling, scenario-based modeling, and heuristic-based modeling (for an overview see Blair & Buytaert, 2016). Top-down approaches, which may include system dynamics, aim to determine overall system functioning and are useful in situations where local-scale understanding is lacking (Blair & Buytaert, 2016). A disadvantage of this approach is that it can miss some underlying processes, producing a result that may be too simple for certain applications. On the other hand, bottom-up approaches such as agent-based modeling focus on the behavior and decision making of individuals (Bousquet & Page, 2004). Agents operate under rules, which determine the interactions and feedbacks between agents and their environment, and the approach has also been used to investigate water resource management problems (Madani & Dinar, 2012; Ng et al., 2011). The approach can also examine societal impacts on the environment and the reactions of humans to environmental or policy change. Sociohydrology is an evolving field, and among the recommendations for its advance is public participation (Lane, 2014; Srinivasan et al., 2016). Involving stakeholders has many advantages, including improved data collection and promoting a buy in to model results (Mostert, 2018). In addition, direct inclusion of stakeholders' insights and experience in model development increases model realism and real-world relevance.

In order to fully represent water use, it is necessary to directly include human behavior. This is an important step in developing tools to better manage water resources and the feedbacks to water users. Attempting to do so through modeling physical processes alone is less likely to produce realistic results or lead to the right results for the wrong reasons. A variety of models have been developed to represent the interactions between human behavior and the environment. These include farm level decision making based on economic and resource availability (Foster et al., 2014; Inam et al., 2017), water resource competition between humans and ecosystems (van Emmerik et al., 2014), the system dynamics of small holder farmers (Pande & Savenije, 2016), and the feedbacks between climate change and societal adaptation (Kuil et al., 2016). Complete behavioral representation is difficult to achieve through a top-down approach as data and regulations rarely reflect what takes place on the ground, particularly in developing countries where data are scarce and governance is often inadequate or poorly enforced.

This is the case in India where water resource resilience has become one of the country's most important challenges (Amarasinghe et al., 2009; Briscoe & Malik, 2006; Shah, 2016). India's vulnerability to environmental and socioeconomic changes highlights the necessity of good resource management practices. The introduction of improved irrigation technology, high yielding drought-resistant seed varieties, and artificial fertilizers allowed Indian agriculture to expand rapidly and go from what was a famine prone country, to one that is now food self-sufficient (Jewitt & Baker, 2007; Singh, 2000). Despite the manifest benefits, however, the green revolution has led to increased strain on the regions water resources (Amarasinghe et al., 2009; Briscoe & Malik, 2006; Macdonald et al., 2016; Shah, 2016). Consequently, an understanding of the drivers and outcomes of change in water use is vital to develop sustainable and realistic management options to help safeguard water resources.

This paper outlines the development of a water resource and farmer livelihood modeling framework developed from the bottom up, which incorporates the behavior of water users. The framework provides a unique tool for identifying and testing potential water management options by incorporating real-world insights from observed farmer behavior informed by field collected information (O'Keeffe et al., 2016), improving

Table 1
Mean Observed Annual Precipitation and Temperature Values Between 1971 and 2005, and the Range of Mean Predicted Values Across GCM's Used Under RCP 4.5 and RCP 8.5 Between 2006 and 2040 Calculated Using the Delta Change Method

District	Observed	RCP 4.5	RCP 8.5
Sitapur	885 mm | 25.3 °C	840–947 mm | 25.4–26.2 °C	846–896 mm | 25.9–26.2 °C
Sultanpur	1,082 mm | 25.6 °C	967–1,097 mm | 26.0–26.7 °C	956–1,099 mm | 26.2–26.7 °C
Jalaun	720 mm | 25.7 °C	678–789 mm | 26.0–26.9 °C	678–789 mm | 26.4–26.6 °C
Hamirpur	884 mm | 25.7 °C	835–957 mm | 26.0–26.8 °C	835–957 mm | 26.4–26.5 °C

Note. GCM = general circulation model; RCP = Representative Concentration Pathway.

the representation of feedbacks, and tipping points between water use and the environment. The model is applied to a number of districts in northern India; however, when local knowledge is collected, it is envisaged that the framework can be applied to a wide variety of locations, realistically representing the actions of water users under changes in anthropogenic and environmental conditions. The following sections outline the data (section 2, model conceptualization and development (section 3), followed by model application (section 4), a description of the results (section 5), and a discussion of the outcomes, including limitations of the model (sections 6 to 7).

2. Data and Fieldwork

2.1. Fieldwork and Socioeconomic Data

More than 200 semistructured farmer interviews were carried out by the first author in Uttar Pradesh, a large and diverse state within the Gangetic plains of North India. The interviews were conducted across four districts (Sitapur, Sultanpur, Jalaun, and Hamirpur), which are representative of agricultural and water use practices in the region (ICRISAT-ICAR-IRRI Collaborative Research Project, 2012). The interviews sought to obtain information on water use and constraints as well as socioeconomic and environmental factors, which influence rural livelihoods. A complete description of the methodology and results of the field campaign is provided in O'Keeffe et al. (2016). Collected data include water application rates, irrigation scheduling, and water source along with information describing cropping practices, particularly during the dry Rabi season, approximately November to March, and the monsoonal Kharif season from June to October. Additional socioeconomic information such as crop yields and fertilizer costs were obtained from secondary data sources, including the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT-ICAR-IRRI Collaborative Research Project, 2012) and the Indian Government of India, Department of Fertilizers, Ministry of chemicals and fertilizers (2015). Fertilizer application rates were taken from Yadav (2003).

2.2. Climate Data

Observed rainfall and temperature data were obtained from the Indian Meteorological Department and Tropical Rainfall Measuring Mission multiprecipitation analysis products, 3B42 version 7 from the National Aeronautics and Space Administration archive (Huffman et al., 2007). To examine periods beyond 2005, projections from three different general circulation models; NOAA GDFL: GDFL-CM3, NOAA GDFL: GDFL-ESM2G and MIROC: MIROC5 were obtained from the CMIP5 (Coupled Model Intercomparison Project: Phase 5) website (World Climate Research Program, 2013).

While the general circulation models were selected according to their ability to accurately model monsoon conditions in the region, the large spatial heterogeneity in convective rainfall patterns make projections highly uncertain. To date, there has been little research on the possible effects of changes in climate on groundwater resources (Holman et al., 2012). In order to represent future climate uncertainty, emission scenarios Representative Concentration Pathway (RCP) 4.5 and RCP 8.5, derived from CMIP5 projections were chosen (Wayne, 2013). Time series representative for future climate conditions were obtained by perturbing the observed data using the delta change method (see Prudhomme et al., 2010). Relative change (for precipitation) and absolute change (for temperature) were calculated between the periods 1971–2005 and 2006–2040. The latter period was chosen as being most relevant for policy. Historical and perturbed values can be seen in Table 1. While considerable uncertainty surrounds Indian rainfall projections, research points toward more frequent extreme events (see Barik et al., 2017; Jena et al., 2015; Johnson et al., 2016; Menon et al., 2013; Moors et al., 2011; Roxy et al., 2015; Sinha et al., 2006).

2.3. Groundwater Data

Data describing groundwater levels between 2002 and 2013 in the districts were obtained from the Central Groundwater Board of India (Central Ground Water Board, 2014). No groundwater level information was available prior to 2002 for the study region. While each district has numerous monitoring wells, many were excluded due to poor consistency in data recording. As a result, 14 monitoring wells were used in Sitapur, 44 in Sultanpur, 21 in Hamirpur, and 26 in Jalaun. Despite the poor spatial distribution (1 monitoring well/410 km^2 in Sitapur, 1 monitoring well/100 km^2 in Sultanpur, 1 monitoring well/150 km^2 in Jalaun, and 1 monitoring well/200 km^2 in Hamirpur), this information represents the best available observation data for the study area. The regional geology, alluvial aquifers comprising silts, sands, clays, and gravels, suggests less groundwater level spatial variability than would be found in hard rock aquifers, increasing confidence in applying these groundwater levels to the study region.

3. Model Development

3.1. Conceptual and Perceptual Model Development

3.1.1. Perceptual Model

The field observations were analyzed in detail in a previous study (O'Keeffe et al., 2016). Here we synthesize them in a set of dominant observed processes, which together constitute our perceptual model (Beven, 2012):

1. *Irrigation scheduling depends on water availability, seed developer guidelines, and local knowledge.* Farmers typically follow a set irrigation schedule. However, since access to or availability of water can be an issue, farmers may not always irrigate at the optimum time.
2. *Conjunctive use of water sources is widespread.* Irrigation canals provide an irregular but important source of water to some farmers and because their low cost are used in preference to groundwater when possible. Proximity to a canal is not always an indication of access.
3. *Farmers will continue to irrigate despite increasing prices.* While the price of irrigation was found to be a major concern for farmers, it did not have a significant influence on irrigation practices. Farmers' first priority was to provide food for their own families, and they were willing to spend more to achieve this.
4. *Canal recharge benefits all.* Farmers with land located close to a working canal may benefit from the contribution of canal leakage to aquifer recharge, leading to more stable groundwater levels and lower pumping costs.
5. *Water application is not measured.* Farmers do not record the volume of water they apply to crops; instead, observing the approximate depth water reaches within their bunded fields.
6. *Irrigation return flow is an important hydrological process.* The majority of farmers use flood irrigation, much of which is lost through evaporation or returned to the underlying aquifer.
7. *Irrigation time increases with decreasing water tables.* Farmers described increasing irrigation costs with decreasing groundwater levels, particularly during the dry, premonsoon season, as lower water levels mean that pumps are required to run for longer in order to abstract the same quantity of water.
8. *Farmers' solution to lack of water: drill deeper wells.* The most common solution to declining water tables reported by farmers was to drill deeper wells.

This information was used to develop a conceptual model, which is described in detail in the remainder of section 3 and in Figure 2. The most important feedbacks between the physical and behavioral elements of the framework can be seen in Figure 1.

3.1.2. Conceptual Model

In a next step, we conceptualized our perceptual model as three coupled submodels representing hydrology, crop yield, and farmer livelihood, which are described in detail in the following sections. Throughout, we use indices t and T to index days and years respectively. Thus, $\Delta t = 1$ day and $\Delta T = 1$ year.

3.2. Hydrology

A single cell model is employed to simulate the response of water resources to changing socioeconomic and environmental conditions. This class of hydrological model is commonly used in the field of water resources economics and there is an extensive body of literature describing their application (see de Frutos Cachorro et al., 2014; Gisser & Mercado, 1973; Koundouri, 2004). The soil column is represented in terms of the *total available water*, TAW (M/L^2), which describes the maximum amount of water that is available to plants at field capacity:

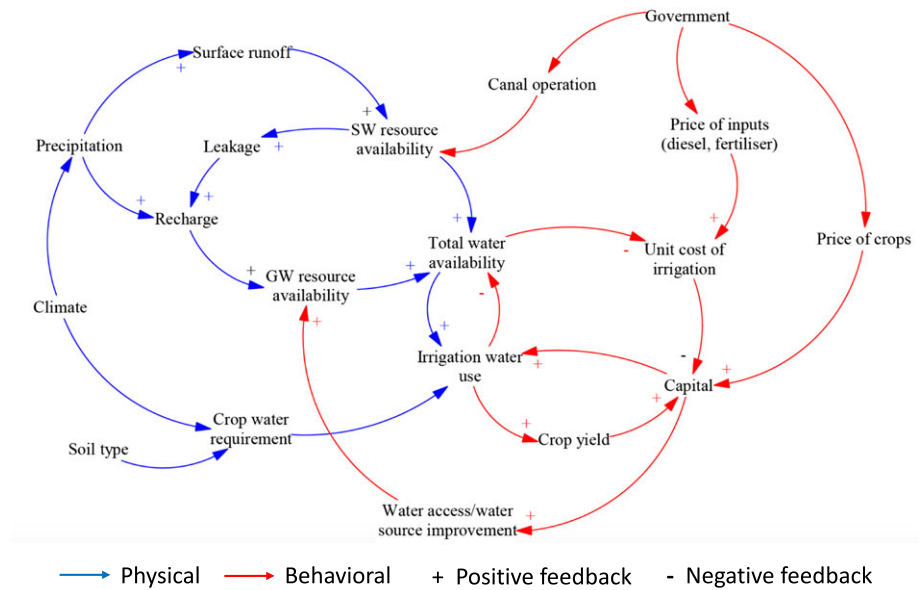$$\text{TAW} = \left(\theta_{\text{FC}} - \theta_{\text{WP}} \right) Z_r, \tag{1}$$

Figure 1. A causal loop diagram showing the feedbacks between the anthropogenic and environmental variables and fluxes which are represented within the model.

where θ_{FC} and θ_{WP} (M/L^3) are, respectively, field capacity and wilting point and Z_r (L) is the maximum root depth in meters. The proportion of TAW that can easily be extracted from the root zone before the soil moisture deficit impedes plant growth is termed the *readily available water*,

$$RAW = (1 - p)TAW, \tag{2}$$

where p is the crop-specific depletion factor and the dimensions of RAW are the same as those for TAW. The daily water balance equation expressed in terms of root zone depletion, D_r (M/L^2), is written

$$\frac{dD_r}{dt}(t, T) = ET_c(t, T) + R(t, T) - (P(t, T) - RO(t, T)) - I(t, T), \tag{3}$$

where ET_c is actual crop evapotranspiration, R is recharge, P is precipitation, RO is surface runoff, and I is irrigation ($M \cdot L^{-2} \cdot T^{-1}$). Crop evapotranspiration is determined as

$$ET_c(t, T) = K_s(t, T)K_c(t, T)ET_0(t, T), \tag{4}$$

where K_c is a crop coefficient, which varies according to the crop growth, K_s is a water stress coefficient, and ET_0 is reference evapotranspiration. We use the Hargreaves-Samani equation to estimate ET_0, but other approaches can be used (see Itenfisu et al., 2003; McKenney & Rosenberg, 1993). Crop coefficients are obtained from Allen et al. (1998) and from field work conducted in North India by Choudhury et al. (2013). The water stress coefficient is calculated as follows:

$$K_s(t, T) = \frac{TAW - D_r(t, T)}{(1 - p)\,TAW}. \tag{5}$$

Spatial and temporal rainfall variability is taken into account by adding a noise component drawn from a normal distribution. A runoff coefficient is used to partition rainfall into runoff and infiltration. Farmers in the surveyed districts typically use flood irrigation and apply water to their crops at set intervals during the growing season. Thus, farmers are assigned an irrigation volume drawn from a normal distribution with mean and standard deviation derived from field data. To account for spatial and temporal heterogeneity in irrigation, timing the model is programmed to randomly select the day irrigation takes place from a normal distribution where the parameters are again based on observations. Recharge from the root zone to the underlying aquifer is assumed to occur when the water content of the root zone exceeds field capacity:

$$R(t, T) = \begin{cases} -D_r(t, T)/\Delta t, & \text{if } D_r(t, T) < 0 \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$
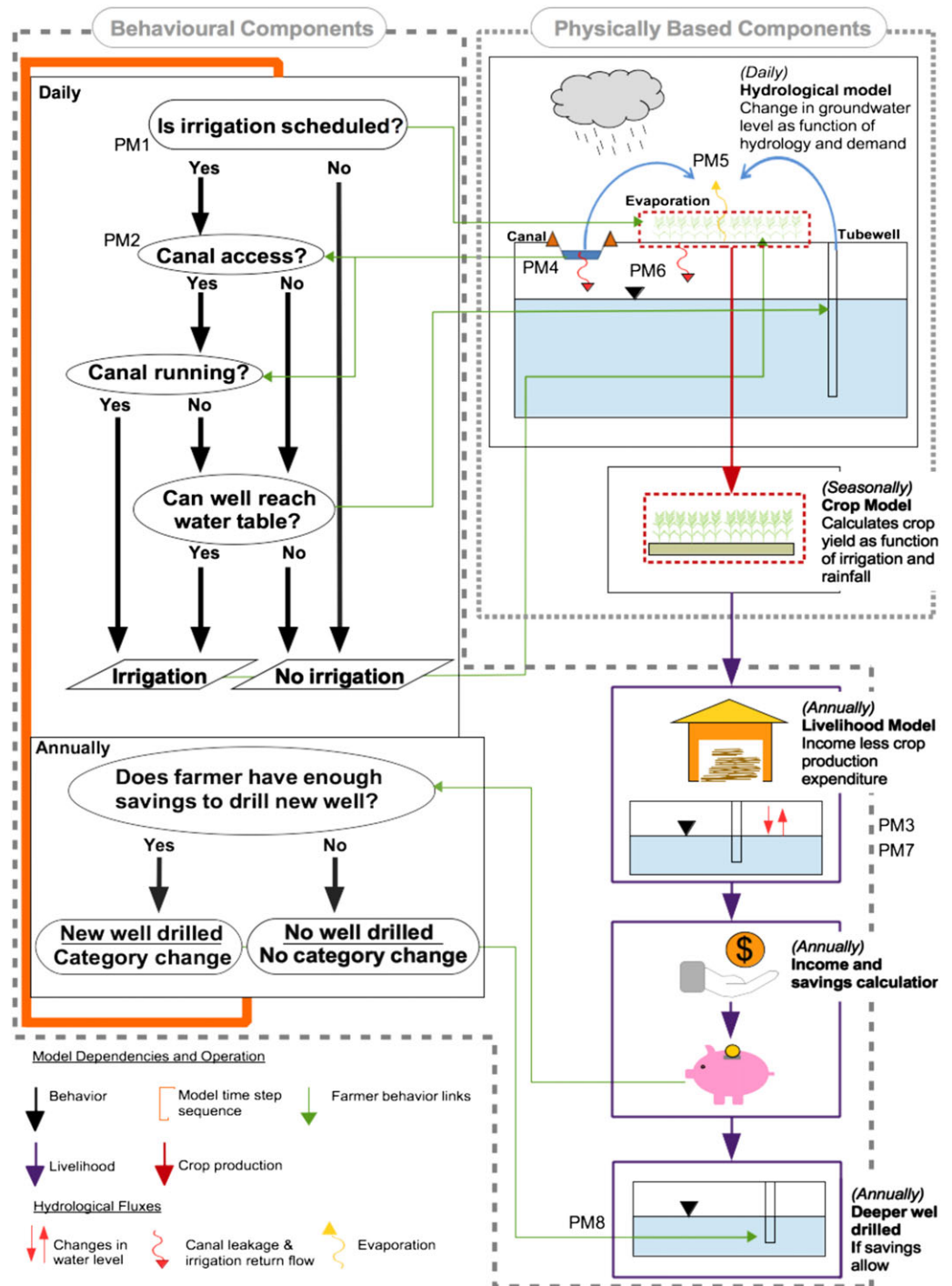
Figure 2. Schematic overview of the conceptual model, highlighting behavioral and physically based elements and how farmer behavior links to the models hydrological, crop, and livelihood components. Perceptual model observations (PM1–PM8) are also highlighted within the diagram. Arrows show model dependencies and feedbacks.

Canals in India are typically operated by the Irrigation Department, and while water supply is often unreliable, it is typically free or very cheap (O'Keeffe et al., 2016). Within the model, farmers' access to canals is predetermined and does not change during the simulation. On the other hand, groundwater abstraction through private tube wells, which considerably outnumber all other types of well, is more expensive to the farmer because of the upfront cost of installing the well in addition to the cost of buying and operating the pump. Outside northwest India, where many farmers have access to heavily subsidized electricity, we found

that farmers typically rely on diesel pumps with comparatively expensive running costs. Thus, we assume that farmers with access to a canal preferentially use this water source when it is available, otherwise relying on groundwater if they have access to a borehole of sufficient depth. We assume that farmers outside the canal command area only irrigate if they have access to an operational borehole. Lastly, we assume a leaky canal system, which contributes recharge to the aquifer (Macdonald et al., 2016). Consistent with the single cell paradigm, the aquifer is represented as a *bathtub* with spatially homogeneous hydrogeological characteristics such as groundwater level, aquifer thickness, and specific yield. Drawing together these assumptions, we can express the change in aquifer storage, H (M/L^2), as

$$\frac{dH}{dt}(t, T) = \begin{cases} R(t, T) + (I \times V(t, T)), & \text{if canal irrigation} \\ R(t, T) - I(t, T), & \text{if groundwater irrigation} \\ R(t, T), & \text{otherwise,} \end{cases} \tag{7}$$

where V (M) is the amount of water held in the canal and I (L^{-2}/T) is a leakage coefficient.

3.3. Crop Yield

Within the model, crop yield is the principal link between farmer livelihood and agricultural water use. It is calculated using the relationship between crop production and evapotranspiration developed by Doorenbos and Kassam (1979), which can be expressed as

$$\left(1 - \frac{Y_a(T)}{Y_x(T)}\right) = K_y \left(1 - \frac{\sum_{t=d_s}^{d_h} ET_c(t)}{\sum_{t=d_s}^{d_h} ET_x(t)}\right), \tag{8}$$

where Y_x is maximum yield, Y_a is actual yield (both with dimensions M/L^2), K_y is the yield response factor, ET_x is maximum evapotranspiration, ET_c is actual crop evapotranspiration, d_s is sowing day, and d_h is harvesting day. Y_x is taken from annual field reported information, which implicitly incorporates the biophysical impacts of fertilizer, improvements in seed variety, or crop disease. While other factors limit crop production, such as labor and nutrient availability, farmers in the surveyed districts stated that water availability, in terms of timely access and volume, was the largest constraint on production.

3.4. Livelihood

The conceptualization of the feedbacks between farmer livelihood and irrigation behavior is fundamental to the model. Farmer livelihood, L, is considered in terms of the difference between farm income, m, and farm expenditure, z, as follows:

$$L(T) = m(T) - z(T). \tag{9}$$

Farm income is limited to the amount of money that farmers' receive at the market for their crop, expressed as follows:

$$m(T) = \sum_{c=1}^{n_c} Y_a(T)q(T)A(T), \tag{10}$$

where n_c is the number of crops grown in an agricultural year and q and A (L^{-2}) are the price and area of crop c, respectively.

The model explicitly includes expenditure on irrigation and fertilizer. Other items, such as living expenses, education, and loan repayments, are represented by a single a parameter, γ, which represents the fraction of income that is saved on an annual basis. We assume that canal irrigation is free, while the cost of groundwater irrigation is a function of the cost of diesel, pump efficiency, and depth to groundwater. The consumption of diesel, V_d (L^3/T), required to abstract groundwater from depth h (L) is estimated from empirical data collected by the University of Nebraska (Martin, 2003) as follows:

$$V_d(t, T) = I(t, T) \left(\frac{(0.1133 \times h(t, T)) + 0.7949}{102.87}\right) \eta \tag{11}$$

where η is the pump efficiency. The total cost of groundwater abstraction, m_a, can then be calculated as follows:

$$m_a(T) = \sum_{t=1}^{365} V_d(t, T) \times q_d(T) \qquad (12)$$

where q_d is the unit cost of diesel.

At the end of each year, if net farm income (i.e., livelihood) is positive, the farmer saves a proportion, γ_s, of the difference between income and expenditure, as follows:

$$S(T) = \begin{cases} S(T-1) + L(T) \times \gamma_s, & \text{if } L(T) > 0 \\ 0, & \text{otherwise.} \end{cases} \qquad (13)$$

During periods of low income farmers use their savings as a buffer to sustain production. During this time irrigation may still take place until a lower groundwater limit is reached. In reality, the shortfall in revenue may be compensated by off-farm activities, loans, and/or scaling back other outgoings, which the model does not explicitly consider. Once the lower limit is reached, irrigation no longer takes place and rainfall becomes the only source of water sustaining crop growth.

The water use options available to each farmer vary in time and space. As highlighted in the perceptual model, farmers who rely on groundwater for some or all of their water supply will often drill deeper wells in order to safeguard their water supply. We conceptualize this behavior by dividing farmers into categories according to the depth of their well. This approach follows Srinivasan et al. (2010), who categorized households in Chennai, India, according to their level of access to municipal water supply. The number of categories and actors within each category is set by the modeler. At model initialization all farmers are randomly assigned a category, C_w and at the end of the year farmers with sufficient savings change categories by paying for a deeper well, as follows:

$$C_w(T) = \begin{cases} C_w(T-1), & \text{if } S(T) < m_w(T) \text{ or } C_w(T-1) = C_w^{\max} \\ C_w(T-1) + 1, & \text{otherwise,} \end{cases} \qquad (14)$$

where m_w is the cost of installing a new well, assumed to be the same regardless of the depth of the new well and $C_w^{\max}$ is the category corresponding with the maximum well depth. The cost of installing a new well is subtracted from the farmer's savings.

3.5. Behavior
Human behavior forms the backbone of the modeling framework, acting as the control structure, which coordinates the operation of the hydrological, crop production, and livelihood components. This is shown graphically in Figure 2 where the behavioral elements driving the modeling framework are identified. Observed farmer behavior is represented in the hydrology model in equation (7) and in the livelihood model in equations (9), (11), (13), and (14).

4. Model Application
4.1. Behavioral and Climate Change Scenarios
While many plausible future socioeconomic scenarios may exist, including changes in dominant crop types, or changes in the cost of energy sources, the scenarios outlined in Table 2 were chosen as plausible present and future versions of the water use environment in North India. These were informed through relevant literature, as well as field work in the study region (Amarasinghe et al., 2016b; Barik et al., 2017; O'Keeffe et al., 2016). An initial baseline, *business as usual* run was completed and compared with the limited observed data available for the study region. Given the strain India's growing population is likely to place on food demand, an increase in irrigation intensity encouraged by government is likely. This is modeled in scenario 2 as an additional irrigation event, which takes place during the dry season. For scenarios 2 and 3, this same change in farmer behavior is modeled under predicted changes in climate. No changes were made to farming practices except inclusion of an additional irrigation event.

4.2. Calibration
4.2.1. Model Initialization and Calibration
Model calibration and output verification requires observations, which is a major challenge in data scarce environments. Relevant socioeconomic data for comparison with model outputs are particularly difficult to

Table 2
List of Climate and Agricultural Practice Scenarios Investigated in This Study

Scenario ID	Scenario rationale
Establishment of baseline conditions	Investigation of business as usual agricultural practices and historical environmental conditions
Increased groundwater abstraction	Investigate the impacts of increased groundwater abstraction for irrigation
Increased abstraction under RCP 4.5	Investigate the impacts of increased groundwater abstraction under predicted future climate
Increased abstraction under RCP 8.5	Investigate the impacts of increased groundwater abstraction under predicted future climate

Note. RCP = Representative Concentration Pathway.

obtain as details of incomes, savings, and expenditure are limited. Model applications in each of the four study districts were manually calibrated using groundwater levels and crop yields which represented the best available observed data. The conceptual model, which was developed using observations of local conditions, was considered throughout the procedure to ensure that all parameters were realistic. Calibration was performed manually by visually comparing simulated groundwater levels and crop yield against available ground water level observations. Two parameters were adjusted: the runoff coefficient and the evaporation coefficient. Calibration took place during initial model runs, establishing a base case (Harou et al., 2009). Subsequent model outputs are compared to observed groundwater levels and reported crop yields to evaluate the outcomes of changes in scenarios with the baseline conditions. Initialization values and parameters used during model operation are shown in Table 3.

5. Results

The following sections describe the model results from each of the scenarios. Output variables include changes to groundwater, crop yield and farmer income.

5.1. Groundwater

To evaluate model operation, modeled groundwater outputs (1971 to 2013) are compared to the best available observed groundwater data (Figure 3). Observed data lie within the range of modeled outputs in all four study districts and largely mirrors the trends of reported groundwater levels. The median modeled outputs are used as a baseline for comparison across all other modeled scenarios. Modeled changes in groundwater levels due to predicted climate change are shown in Figure 4. In the northern districts of Sitapur and Sultanpur, groundwater levels are predicted to remain largely unchanged. In the southern district of Jalaun, modeled groundwater levels increase by approximately 5 m over baseline conditions by 2005. Water levels in Hamirpur under RCP 8.5 are expected to fall approximately 5 m while remaining to baseline conditions under RCP 4.5.

As expected, under additional irrigation practices, ground water levels deplete at an increased rate when compared to the baseline scenario. This is more pronounced in the southern districts of Jalaun and Hamirpur (Figure 5). In Sitapur, median water levels vary between 2 and 9 mBGL throughout the model run reaching approximately 5 mBGL by 2005. Median water levels under increased abstraction are 5 to 6 m lower than under current business as usual conditions by 2005. Overall, however, water levels appear sustainable, showing an increasing trend post 2002. There is little variation between increased groundwater abstraction under baseline conditions and the same behavior when predicted future climate is taken into account (Figure 5).

Sultanpur maintains an extensive canal system and groundwater levels in the district are predicted to remain largely stable under an increased irrigation scenario. Between 1971 and 2005 the aquifer depletes at approximately 0.14 m/year ranging from 5 to 10 mBGL. Under increased irrigation and predicted future climate, median modeled groundwater levels are by 2005 expected to fall by approximately 10 m when compared to groundwater levels under current irrigation practices.

Water is also supplied through canals in Jalaun. Despite this, the model suggests declining water levels, falling to approximately 30 mBGL by 2005. Overall groundwater levels are expected to reduce by up to 25 m by end of the model run, suggesting that additional premonsoon irrigation from groundwater sources is unsustainable in the district. When predicted future climate is accounted for, groundwater levels are expected to be broadly similar under increased abstraction (see Figure 5)

Table 3
Overview of Initialization Values and Parameters Used in Model Operation (at t=0)

Model Parameters	Sitapur	Sultanpur	Jalaun	Hamirpur
Initial GW head (mASL)[a]	132	98	134	124
Specific yield	30%	30%	15%	12%
Evaporation Loss	0.85	0.59	0.45	0.64
N application (kg/ha)	120	120	120	120
P application (kg/ha)	26	26	26	26
K application (kg/ha)	48	48	48	48
Wheat irrigation depth (m)	0.05–0.1	0.1–0.2	0.07–0.3	0.1–0.24
Rice irrigation depth (m)	0.1–0.35	0.1–0.3	NA	NA
Pump efficiency multiplier	2	2	2	2
Cat 1 well depth (mBGL)	30	20	20	20
Cat 2 well depth (mBGL)	60	40	60	40
Cat 3 well depth (mBGL)	90	80	90	60
Range of initial savings[a]	50–500	50–500	50–500	50–500
Return flow	0.5	0.5	0.3	0.45
Irrigation efficiency	0.3	0.4	0.4	0.5
Canal leakage	NA	0.4	0.4	NA
Field capacity	0.1	0.3	0.2	0.3
Wilting point	0.05	0.12	0.12	0.12
Rooting depth wheat	1.5	1.25	1.25	1.1
Rooting depth rice	0.6	0.65	NA	NA
Rainfall runoff	0.95	0.95	0.95	0.9
Water stress coefficient: Min	0	0	0	0
Water stress coeff: Max	1	1	1	1
Yield response factor: wheat	0.6	0.8	0.65	0.9
Yield response factor: rice	1.2	1.3	NA	NA
Crop coefficient: wheat	0.80, 1.20, 1.30, 0.60	0.80, 1.12, 1.25, 0.46	1.00, 1.12, 1.25, 0.46	1.00, 1.12, 1.25, 0.46
Crop coefficient: rice	0.61, 0.80, 1.23, 0.74	0.61, 0.80, 1.23, 0.74	NA	NA

Note. mASL = meters above sea level; mBGL = meters below ground level.
[a]Initialization values.

Of the four districts studied, water levels in Hamirpur show the steepest decline under increased irrigation. Here water levels fall at approximately 1.3 m/year between 1971 and 2005; a reduction of 45 m when compared to model outputs driven by current practices, suggesting that water resources in Hamirpur are not capable of sustaining increased groundwater abstraction. Modeled outputs suggest that variations in predicted future climate will have little impact on water levels when increased abstraction is encouraged.

5.2. Farmer Income

Net farmer income is derived from the revenue generated from growing crops, less the expense of irrigation and fertilizer. The annual prices for fuel used for irrigation and fertilizer, along with the market prices for each crop were obtained from socioeconomic data sets (Government of India, Department of Fertilizers, Ministry of chemicals and fertilizers, 2015; ICRISAT-ICAR-IRRI Collaborative Research Project, 2012). The income values discussed are adjusted for inflation; an important factor to consider when assessing how farmer income has changed over the model run period. Inflation was accounted for using the consumer price index values (Triami, 2016), adjusting income to 1971 levels, providing a time series in constant rupees.

A comparison of farmer income under increased irrigation and increased irrigation when future climate scenarios is taken into account reveals little variation in any of the four districts (Figure 6). All outcomes are higher than under business as usual baseline conditions. Farmers who grow rice in addition to wheat (Sultanpur and Sitapur) receive higher income from the combined revenue generated by the two crops (Figure 6).
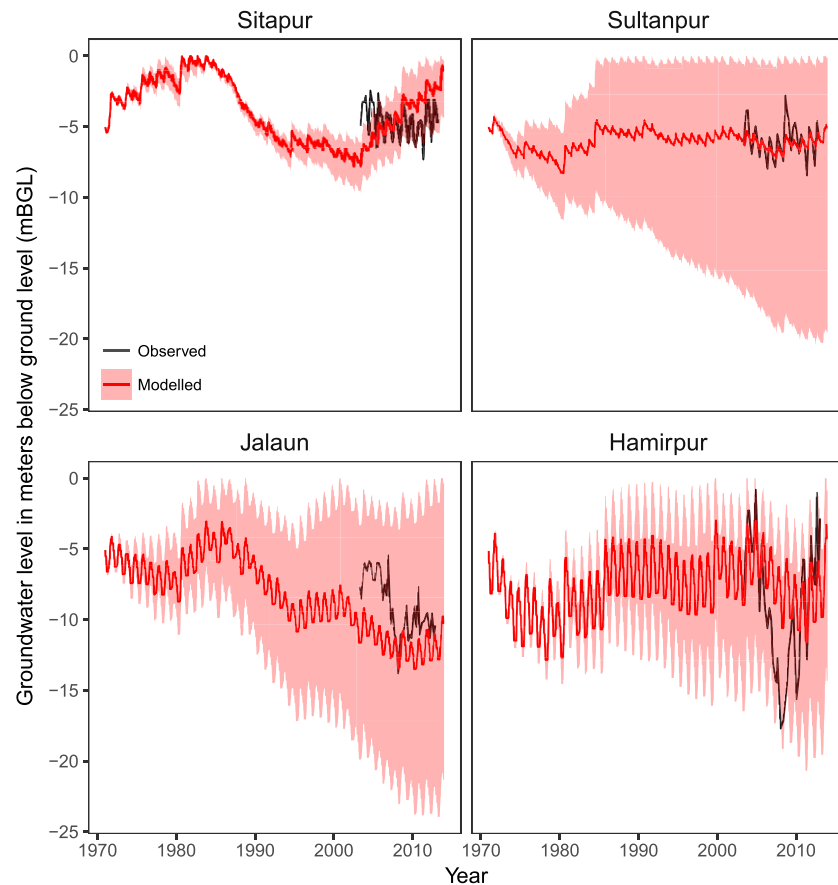
Figure 3. The range and median modeled groundwater level across the study areas between 1971 to 2013. The shaded area represents the range of values obtained from 50 model iterations within the scenario with variations depending on stochasticity of rainfall and irrigation application volumes. The red line represents the median groundwater level. Observed groundwater levels from 2002 to 2013 are shown in black. Water levels are in meters below ground level (mBGL).

In Sitapur, increased irrigation does not result in additional farmer income as the revenue gain is matched by production costs. By 2005 with increased abstraction, income levels are simulated to remain similar to business as usual practices. Under RCP 4.5 and RCP 8.5, minimum and maximum income are simulated to reach 1,800 Indian rupees (INR)/year respectively, increasing at a rate of approximately 30 INR/year.

This is a similar level of increase to model predictions in Sultanpur. Under RCP 4.5 and RCP 8.5 income is expected to rise at approximately 40 INR/year; minimum and maximum income are predicted to reach 2,100 INR, and 2,500 INR/year, respectively, by 2005.

Farmers in Jalaun experience a slight benefit to increasing irrigation, with median income levels rising approximately 30 to 40 INR/ha/year. Modeled income levels in Jalaun show little variation between RCP 4.5 and RCP 8.5 where minimum and maximum income is predicted to be 1,400 INR and 1,600 INR, respectively, by 2005, increasing at a rate of approximately 50 INR/year. This is up to 100 INR greater than the median values expected under baseline conditions.

Modeled farmer income in Hamirpur under RCP 4.5 and 8.5 are approximately 100 INR/ha higher than under baseline conditions. From 2000 to 2005, overall income increases at a rate of 10 INR/year, peaking at close to 1,100 INR/ha in 2005. Simulated income levels in Hamirpur are the lowest of the four districts, ranging from 850 INR to 1,100 INR/year by 2005.
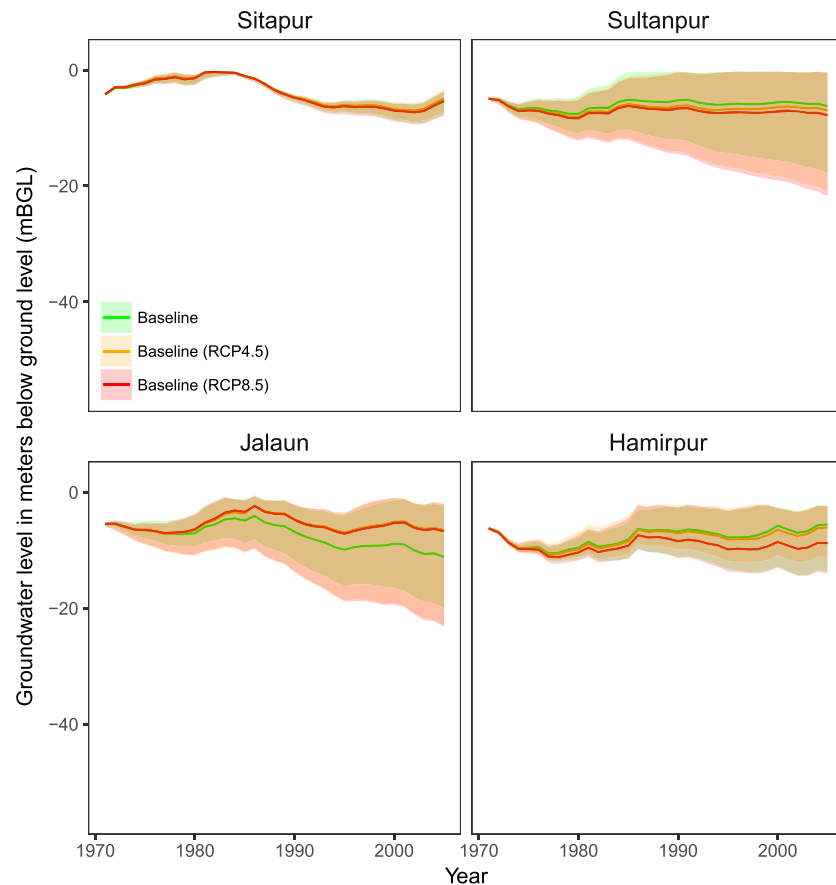
Figure 4. The median and range of modeled groundwater levels across the study areas between 1971 and 2005 under business as usual conditions, displayed in green, and under the same conditions driven by predicted future climate between 2005 and 2040. The shaded area represents the range of values obtained from 50 model iterations within the scenario with variations depending on stochasticity of rainfall and irrigation application volumes. The solid lines represent the median groundwater level. Water levels are in meters below ground level (mBGL). RCP = Representative Concentration Pathway.

5.3. Crop Yield

As expected, the introduction of an additional irrigation event for wheat results in an increase in yield, ranging from 0.2 to 0.6 tonnes/ha across the four districts (Figure 7 where the black line represents recorded annual crop yields [ICRISAT-ICAR-IRRI Collaborative Research Project, 2012]).

Under increased irrigation the model results show that farmers in Sitapur will receive median wheat yields approximately 0.2 tonnes/ha larger than those under baseline conditions, while yield values in Sultanpur are expected to increase by up to 0.5 tonnes/ha.

Simulated wheat yield for farmers in Jalaun and Hamirpur also increases, up to 3.2 tonnes/ha in Jalaun, or 0.2 tonnes/ha more than under baseline conditions, and a median yield increase of up to 0.5 tonnes/ha in Hamirpur resulting in approximately 2.4 tonnes/ha by the end of the model run. As irrigation practices are not changed for rice cultivation there is little difference in yield, with overall values matching those produced during the baseline run (Figure 7).

The increase in crop yield as a result of an additional irrigation event is maintained under future climate scenarios RCP 4.5 and RCP 8.5 (Figure 7). There is only a marginal change in rice yields, which remain similar to baseline model outputs throughout (Figure 7).

6. Discussion

This paper explores the integration of water user behavior in a sociohydrological modeling framework in order to simulate the feedbacks between anthropogenic and environmental variables. Model development
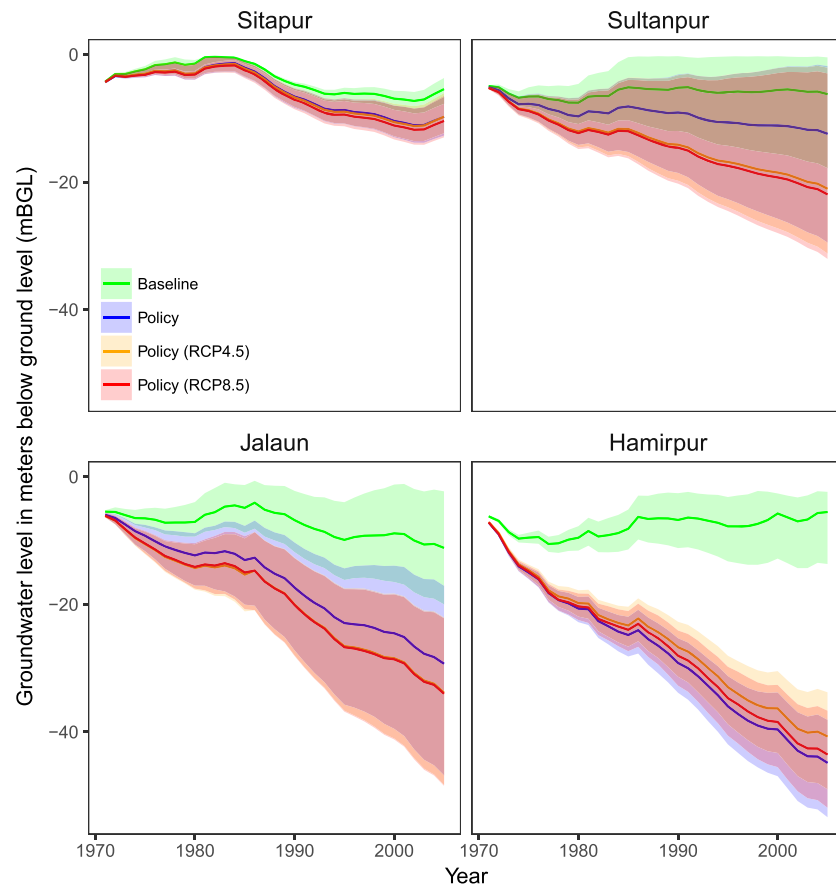
Figure 5. The median and range of modeled groundwater levels across the study areas between 1971 and 2005 under increased groundwater abstraction and under the same behavior driven by predicted future climate between 2005 and 2040. Modeled income levels under historic business as usual conditions are also displayed in green. The shaded area represents the range of values obtained from 50 model iterations within the scenario with variations depending on stochasticity of rainfall and irrigation application volumes. The solid lines represent the median groundwater level. Water levels are in meters below ground level (mBGL). RCP = Representative Concentration Pathway.

has been informed by interviews conducted with over 200 farmers in Uttar Pradesh, northern India, providing field level insight on the operation and challenges behind water use. The model is applied to four districts representative of conditions across the Indo-Gangetic plain and is used to investigate the impacts increased groundwater abstraction and changes in future climate may have on water resources and farmer livelihood. Our results show that the impacts of predicted future climate alone may not substantially impact water resources. Nevertheless, climate change may indirectly affect variables outside the modeled environment such as energy price and availability or the cost of fertilizer, leading to uncertainty and market volatility. It is possible, however, that future socioeconomic factors will lead to additional water abstraction. Results suggest that increasing irrigation prior to the onset of the monsoon, such as those suggested by Amarasinghe et al. (2016b) and Revelle and Lakshminarayana (1975), is potentially viable in Sitapur and Sultanpur. This is not the case in Jalaun or Hamirpur, however, where an unsustainable depletion in groundwater levels is likely under the same behavior. The variability of results between the study districts highlights the importance of collecting data that are relevant to the inferences made and the potential decisions that may be taken, as actions which are applicable in one location may not work in another despite their relative proximity.

The scenarios and results described highlight the ability of the model to show how changes in anthropogenic or environmental conditions can impact farmer livelihood and water resources. Due to limited data, however, this model is necessarily a simplified representation of reality, which leads to a number of limitations. Groundwater is represented within the model as a single cell where inflows are supplied by rainfall and canal flow.
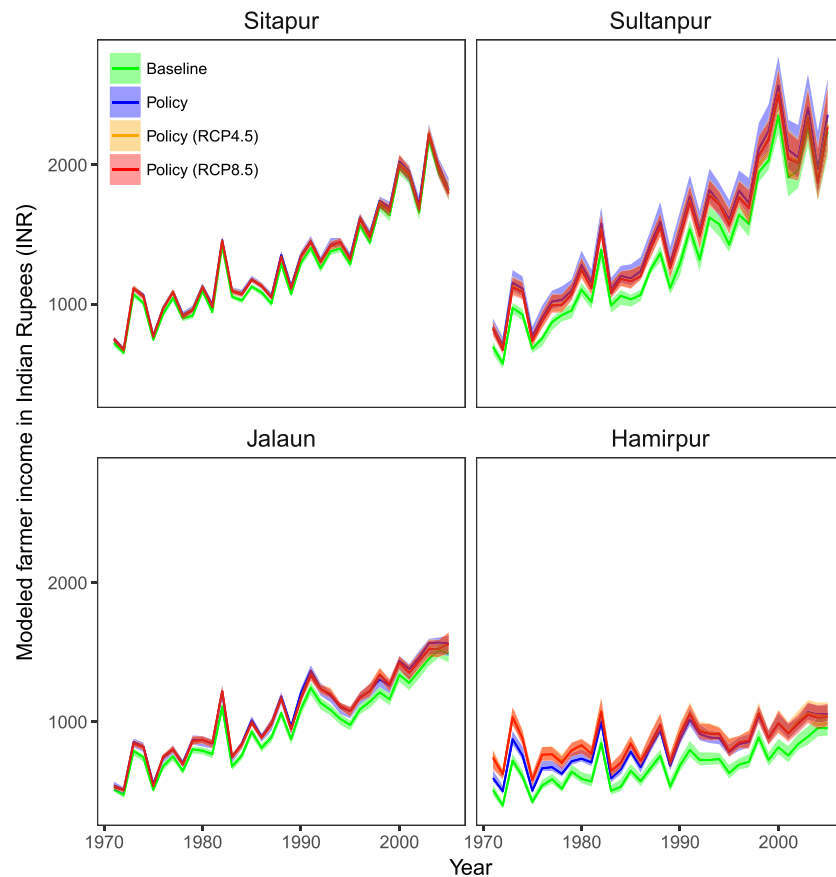
Figure 6. The median and range of modeled farmer income levels adjusted for inflation across the study areas between 1971 and 2005 under increased groundwater abstraction and under the same behavior taking predicted future climate between 2005 and 2040 into account. Modeled income levels under historic business as usual conditions are also displayed in green. The shaded area represents the range of values obtained from 50 model iterations within the scenario with variations depending on stochasticity of rainfall and irrigation application volumes. The solid lines represent the median income level. Income levels are in Indian rupees (INR). RCP = Representative Concentration Pathway.

Outflows occur through abstraction, evaporation, and transpiration. Lateral subsurface groundwater flow into or out of the cell is not taken into account. A single water level is applied to all farmers across the cell, and the model does not account for well interaction. While this approach is less of an issue in unconsolidated alluvial aquifers, such as those found in the Ganges Basin, model uncertainty will increase when applied to hard rock aquifers. Crop production is determined through the relationship between evapotranspiration and yield (see Doorenbos & Kassam, 1979; Smith & Steduto, 2012). While the model accounts for the impact of water availability on crop production, it does not explicitly account for the biophysical impacts derived from fertilizer application or improvements in seed variety, except through the reported increase in observed yield, which is used in equation (8). Representation of socioeconomic conditions was a major challenge during this study. In reality, the way in which farmers save and spend their income is highly variable and depends on a range of factors which are outside the scope of this work. The model assumes that individual farmers will retain savings for investment in their water security and does not take into account the many other options, for example, their children's education or investment in aspects of their farm besides irrigation. It is also assumed that all farmers sell their crops for the same price and that indeed there is a market for their produce. It does not take into account that a proportion of crops grown are for personal consumption, a common practice among interview participants. Loans, repayments, supplementary farmer income, or water markets were not directly considered, elements that can lead to changes in farmer behavior including, but not limited to, drilling additional tube wells.
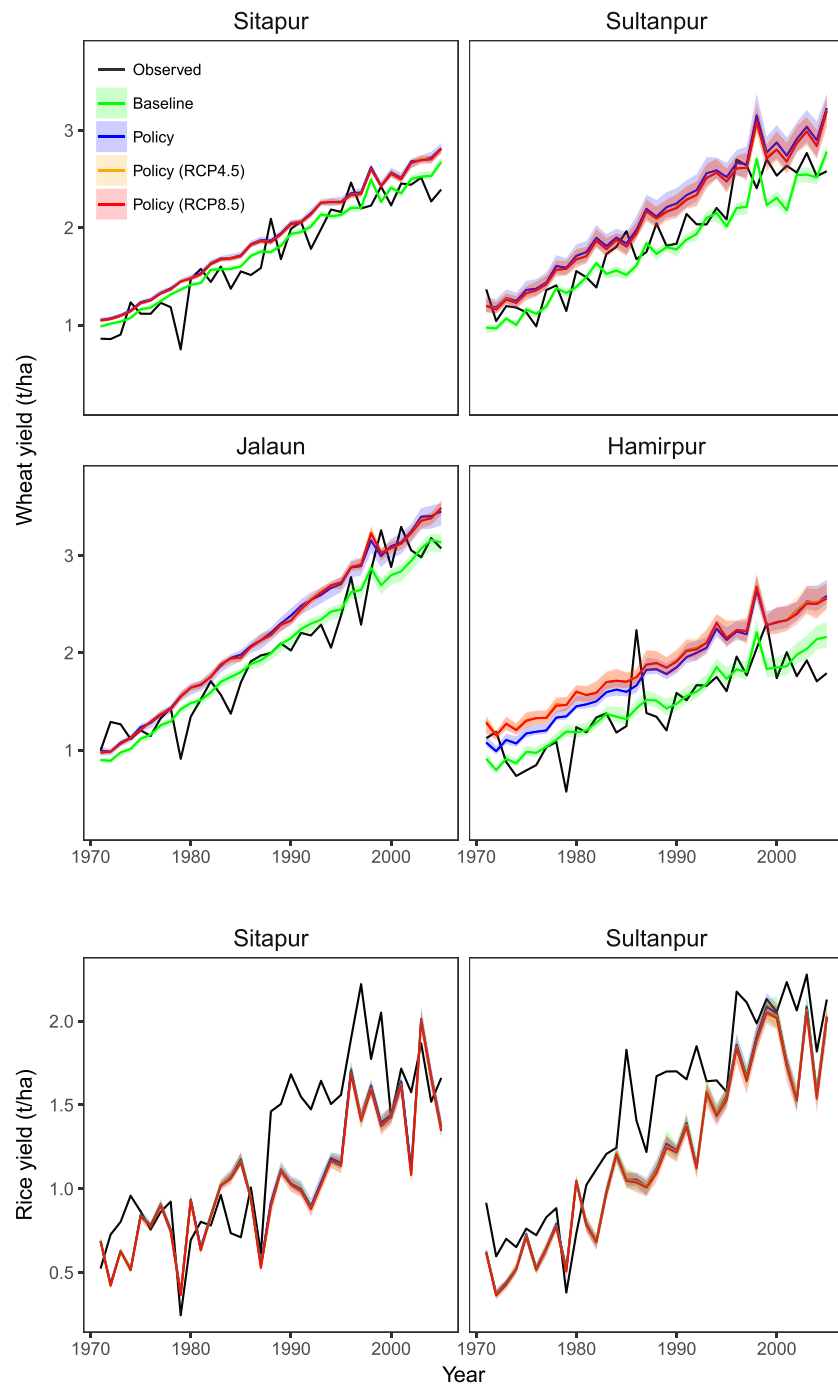
Figure 7. The median and range of modeled wheat and rice yields from 1971 to 2005 under increased groundwater abstraction and under the same practices driven by predicted future climate from 2005 to 2040 (1971 to 2005 used on *x* axis throughout). Rice is typically not grown in Jalaun or Hamirpur. Units are in tonnes per hectare (t/ha). RCP = Representative Concentration Pathway.

Despite some limitations, the framework captures the most important aspects of the farmers' environment and represents an advancement in hydrological modeling by directly including human behavior. The modeling framework is capable of identifying trends and tipping points, providing a useful tool for policy analysis, planning, and resource management. The model is adaptable and can be used as the basis for studies across a wide variety of locations and environments to represent a range of scenarios as well as socioeconomic and biophysical conditions.

7. Conclusions

This paper describes the development of a modeling framework, which directly includes water user behavior through a set of built in rules. Field collected insights are used to produce a tool, which is rooted in reality, capable of examining the impacts of changes in environmental and anthropogenic conditions on farmer irrigation behavior. The framework is adaptable and capable of incorporating a wide variety of farmer behavior across a range of socioeconomic and biophysical conditions.

The model is applied to four districts in Uttar Pradesh, North India, to investigate the effect of changes in policy and climate on farmers and water resources. Model results highlight that changes in human behavior may have a larger impact on water security and stakeholder livelihood than changes in climate. In addition, increased irrigation under predicted future climate may be possible in Sitapur and Sultanpur. However, in the southern districts of Jalaun and Hamirpur, similar practices are unlikely to be sustainable as all scenarios involving increased abstraction predict groundwater levels falling to unsustainable levels. Predicted climate change alone is unlikely to adversely impact water resources, crop yields, or farmer income, although any potential increase in the costs of energy or fertilizer as a result of climate change are not accounted for. Under scenarios in which irrigation is increased, the water levels in all districts show a decline from the baseline, along with an increase in wheat yield. This results in increased income for farmers in Jalaun and Hamirpur but not for Sitapur or Sultanpur, where the production costs outweigh the advantages of more irrigation. The results show the importance of conjunctive use of groundwater and surface water and that under certain conditions an increase in groundwater abstraction may be feasible.

The modeling framework developed is necessarily a simplified version of reality. As limited data exist in the study region, parametrization and calibration is difficult. Consequently, the model is not intended to be fully predictive but rather a tool than can be used to highlight trends and tipping points and understanding the outcomes of stakeholder practices.

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