Chapter 9
Assessment of Agricultural Water Management in Punjab, India, Using Bayesian Methods

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Abstract The success of the Green Revolution in Punjab, India, is threatened by a significant decline in water resources. Punjab, a major agricultural supplier for the rest of India, supports irrigation with a canal system and groundwater, which is vastly overexploited. The detailed data required to estimate future impacts on water supplies or develop sustainable water management practices is not readily available for this region. Therefore, we use Bayesian methods to estimate hydrologic properties and irrigation requirements for an under-constrained mass balance model. Using the known values of precipitation, total canal water delivery, crop yield, and water table elevation, we present a method using a Markov chain Monte Carlo (MCMC) algorithm to solve for a distribution of values for each unknown parameter in a conceptual mass balance model. Model results are used to test three water management strategies, which show that replacement of rice with pulses may be sufficient to stop water table decline. This computational method can be applied in data-scarce regions across the world, where integrated water resource management is required to resolve competition between food security and available resources.

Keywords Agricultural water management • Punjab • India • Markov chain Monte Carlo • Groundwater overdraft • Mass balance model

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9.1 Introduction

9.1.1 The Green Revolution and Groundwater

India made tremendous strides toward self-sufficiency in food grains in the last half century. The Green Revolution, marked by higher-yielding varieties, chemical fertilizers and pesticides, and the provision of irrigation, are some of the key factors that contributed to a successful food grain economy and a transition to food self-sufficiency since the 1960s. The national food security goals have led to targeted regions for procurement of major food grains such as rice and wheat, with minimum guaranteed prices for the farmers, and a variety of subsidies for fertilizer, energy, and seeds. The success of the Green Revolution in India is now threatened by a significant decline in water resources. Punjab (Fig. 9.1), a major agricultural supplier for the rest of India, supports irrigation demand by overexploiting local groundwater resources. Competition between food security and water resources will only become more persistent with increasing populations and changing climate (Brahmanand et al. 2013; Sidhu et al. 2011). A solution is required that meets food security needs, uses water resources sustainably, and maintains farmer income.

Since the onset of the Green Revolution, the total area of irrigated agriculture as well as the intensity of agriculture as measured by the number of cropping seasons

Fig. 9.1 Map showing the location of Punjab in northwestern India and the districts of Punjab. The three districts analyzed in this study: Gurdaspur, Jalandhar, and Sangrur are shown in *gray*

per year has increased drastically. Most notably, the total area of high-water-demand crops has increased. Rice, a crop with a high water demand, typically requires ~1,800 mm in Punjab, while average annual rainfall is only ~650 mm. The area under rice increased from 7 % of the total Punjab land area in 1970 to 50 % in 2001, while gross cropped area increased from 95 % to 152 %, respectively (Takshi and Chopra 2004). Groundwater extraction rates exceed natural groundwater recharge rates, and as a result, water tables are decreasing on average at a rate of 0.4 m/year and up to 1.7 m/year locally (Kahn et al. 2007). In Punjab, the net annual groundwater availability is estimated to be 21.44×10^9 m^3, and the annual amount of groundwater extracted is 31.16×10^9 m^3 (Chatterjee and Purohit 2009). According to the Central Groundwater Board of India, the number of overexploited Blocks (subdistrict divisions) has increased from 53 in 1984 to 110 in 2009 of the total 138 Blocks in Punjab (CGWB 2012). Declining water tables can have negative consequences including increasing pumping costs and require a shift from centrifugal to submersible pump technology due to greater lifts (Samanpreet Kaur et al. 2011).

This study focuses on districts in Punjab that are experiencing groundwater overdraft and subsequent water table decline. Conversely, several districts in southwestern Punjab are experiencing rising water tables and water logging at the surface. Due to farming practices in these regions, soil water is highly saline and 50 % of the region reports saline groundwater deeper than 35 m (CGWB 2012), so irrigation water must come primarily from the canal system. Though not addressed in this study, water management in Punjab must ultimately accommodate both rising and falling groundwater, in addition to degradation of water resource quality from agricultural activity.

9.1.2 Institutional and Economic Obstacles

The two major incentives for growing rice and wheat in Punjab are the guaranteed purchase prices set by the central government and a fixed connection charge for electricity with no per unit charge. The policy of electricity subsidies adopted by the state government permits farmers to freely pump groundwater required to irrigate their crops without a concern for efficiency or conservation (Sidhu et al. 2011). As a result, almost 97 % of the total agricultural land in Punjab is now irrigated, and agricultural pumping accounts for 40–60 % of the total electricity consumption and leads to unreliable electricity for all uses. Electricity supply to agricultural areas is intermittent and unpredictable, often on for only a few hours per day. To overcome the unreliability, farmers commonly leave their pumps on all the time leading to over-irrigation.

Driven by a national food security concern, the central government established procurement and price support systems for selected grains to protect producers against sudden price declines in the unregulated market. Government procurement policies have shifted the major crops in Punjab from vegetables, pulses, and oil seeds to rice and wheat. Punjab, which accounts for only 1.5 % of India's land area, now supplies 40–50 % of the rice and 60–65 % of the wheat that India consumes (Aggarwal et al. 2009). Farmers have little incentive to grow low-water-demand crops because of the subsidized electricity and the guaranteed market price provided by government procurement programs. This scenario is typical in much of the country. A recent study shows that the major regions that contribute to the food security of the country are chronically falling short of water and are under severe stress (Devineni et al. 2013). Theoretically, replacing rice with a cash crop like vegetables or flowers, which also require less irrigation, benefits the hydrologic balance as well as farmer income. However, most farmers are hesitant to switch to cash crops due to the high market price variability.

Many authors have suggested a variety of adaptation strategies to mitigate groundwater overdraft in Punjab (Aggarwal et al. 2009; Ambast et al. 2006; Hira 2004; Humphreys et al. 2010; Shah 2009), though most lack rigorous quantitative analysis or simulation of proposed management strategies due to an overall lack of access to hydrogeologic and water consumption data. In lieu of a dynamic numerical model, a hydrologic mass balance approach can provide initial results to inform water management decisions. In this study, we developed a Bayesian approach to constrain the mass balance while estimating the probability density for unknown parameters. Bayesian methods are becoming increasingly common for hydrologic system modeling (e.g., Engeland and Gottschalk 2002; Winslow et al. 2013).

The objectives of this study are to address the following questions: (1) How do we estimate the unknown hydrogeologic and agricultural parameters in the hydrologic mass balance equation? (2) How and why might these parameters vary within the state of Punjab? (3) Which types of irrigation management reduce or reverse groundwater elevation decline? While we focus on Indian Punjab, our methodology is transferrable to similar data-scarce regions around the world.

9.2 Study Location and Data

9.2.1 Study Area

The state of Punjab located in northwestern India has an area of 50,362 km^2 (Fig. 9.1). The state is underlain by Quaternary alluvium eroded from the Himalayas and contains clay, loam, and silt. Secondary porosity in the alluvium comes from buried channels within the greater alluvial deposits. The alluvium is bounded in the northeast by the Sivalik formation, primarily the Tertiary period sandstone and conglomerate. The region is known for particularly fertile soils and is a critical agricultural region within India.

Average annual precipitation in Punjab ranges between 360 and 1,120 mm/year, with wetter areas in the northeast and dryer areas in the southwest. Even in the wettest areas, the monsoon rainfall is not sufficient to support current year-round rice-wheat agriculture; therefore, irrigation is required. Irrigation water can be sourced from a network of surface canals or groundwater wells. Canals are supplied by the Bhakra reservoir, the second largest in India, which holds up to 9.34 billion cubic meters (bcm), and diversions from the Ravi River which supplies water to the districts of Gurdaspur and Amritsar. Despite the large canal network, use of surface water has been surpassed by groundwater due to unreliable surface flows (Tyagi et al. 2005) and because many farmers are not directly adjacent to a canal.

We focus on three districts for which agricultural and hydrologic data were available: Gurdaspur, Jalandhar, and Sangrur (Fig. 9.1). The three districts are all intensively farmed and have differing water table depths and average precipitation (Table 9.1). In 1973, the average depth to groundwater was between 5 and 7 m for all three districts (Fig. 9.2). By 2010, the depth ranged from 8 to 23 m. The regional variability in water table elevation change over time is due to differences in irrigation requirements, climate, aquifer properties, and recharge parameters.

9.2.2 Data Sources

Groundwater elevation data were obtained from the Central Groundwater Board. Crop area and yield records were obtained from colleagues at the Punjab Agricultural University. Daily release values from the Bhakra Dam were obtained from Bhakra Beas Management Board. We assume the magnitude of flow from the Bhakra reservoir to correlate with flows in the Bari Doab canal system in Gurdaspur. Gridded daily rainfall data from 1971 to 2005, available at $1^\circ \times 1^\circ$ spatial resolution from Indian Meteorological Department (IMD) (Rajeevan and Bhate 2008), were spatially averaged over each district using the geographic information system (GIS). Gridded daily temperature data (at 6 hourly time step) from 1948 to 2000, available at the spatial resolution $1^\circ \times 1^\circ$ from National Centers for Environmental Prediction/National Center for Atmospheric Research (Ngo-Duc et al. 2005), is used in this study to estimate the potential evapotranspiration. Crop water requirements were determined from crop data provided by colleagues at the Punjab Agricultural University and annual potential evapotranspiration. Specific yield (S_y) of the aquifer was assumed to be 0.15 for all districts (MWR 1997). The intersection of all available data sets spans from 1973 to 2002, which were used as model input for the Bayesian model.

Table 9.1 Geographic, agricultural, and hydrologic data for each study district

	Gurdaspur	Jalandhar	Sangrur
Area (km^2)[a]	3,513	2,662	3,737
Gross irrigated area (km^2)[a]	4,270	4,137	5,754
Average annual rainfall (mm)[b]	831	654	522
Average depth to GW, 2011 (m)	8.2	17.8	22.4

[a]Values from Central Groundwater Board district reports (2007)
[b]Average calculated from IMD gridded precipitation data, 1979–2012 (Rajeevan and Bhate 2008)

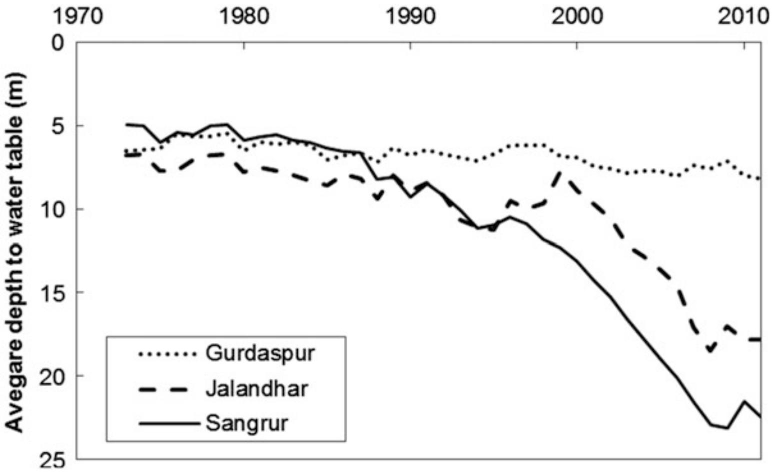

Fig. 9.2 Annual average water table elevation between 1973 and 2011 for Gurdaspur (*dotted line*), Jalandhar (*dashed line*), and Sangrur (*solid line*) districts

9.3 Methods

9.3.1 Parameter Estimation: Markov Chain Monte Carlo Method

We use a Bayesian method to estimate parameters in the under-constrained hydrologic mass balance for each study district in Punjab. Groundwater inputs to Punjab include recharge from precipitation and leakage from the canal network. Groundwater outputs include evapotranspiration and extraction for irrigation. We use the following groundwater mass balance equation:

$$R + L - ET - X - \Delta S = 0 \tag{9.1}$$

where R is recharge from precipitation, L is canal leakage, ET is evapotranspiration, X is total groundwater pumped for irrigation, and ΔS is change in groundwater storage which includes lateral groundwater flow in and out of the district. For this study, we account for ET in irrigation requirements (X) and assume additional

Table 9.2 List of known and unknown agricultural, hydrologic, and climate variables

Known variable	Unknown variable
Precipitation, $P(t)$	Precipitation recharge, $\beta P(t) = R$
Canal discharge from Bhakra reservoir, $B(t)$	Canal leakage, $\varepsilon B(t) = L$
Total area, A_T	Pumped irrigation, $x_i(t)$
Crop area, $A_i(t)$	Net groundwater influx, γ
Crop water requirements, $\mathrm{CWR}_i(t)$	
Maximum yield, $Y_i^{\max}$	
Crop yield, $Y_i(t)$	
Groundwater elevation change, $\Delta\mathrm{GW}$	
Specific yield, S_y	

groundwater loss is equal to zero, because the average groundwater depth is greater than the expected evapotranspiration extinction depth (Shah et al. 2007). Both annual precipitation and canal discharge are known, and we assume a constant coefficient to represent the percentage of each source that reaches the groundwater. Net groundwater flow into the district is unknown but is assumed to originate as recharge in the Sivalik foothills in and northeast of Punjab.

The coefficients for precipitation recharge (R), canal leakage (L), and net groundwater influx (γ), and volumes of pumped irrigation (X), were estimated using a Markov chain Monte Carlo (MCMC) method. For each individual district (Gurdaspur, Jalandhar, and Sangrur), we use the MCMC method to simulate the complete posterior distribution of values for each unknown model parameter (Table 9.2). Uniform prior distributions based on physical properties constrain acceptable values for each unknown parameter.

The two governing equations of the MCMC algorithm are shown in Eqs. (9.2) and (9.3). Every iteration proposes new values for the unknown parameters, which are accepted or rejected, based on the prior constraints and the assumption that the known values are normally distributed about the mean, and have a variance with a prescribed distribution. Equations (9.2) and (9.3) describe the relationship between the parameters of the mass balance equation and two known values, change in water table elevation and observed annual yield, respectively:

$$\Delta\mathrm{GW}(t) \sim N\left(\gamma\left(\frac{\beta p(t) A_T(t) + \varepsilon B(t) - \sum_{i=1}^{n}\left(x_i(t) A_i(t)\right)}{S_y A_T}\right), \tau_{gw}^2\right) \tag{9.2}$$

$$Y_i(t) \sim N\left(\frac{x_i(t)}{\mathrm{CWR}_i(t)} Y_i^{\max}(t), \tau_y^2\right) \tag{9.3}$$

where t is simulation year, i refers to each of the eight most common crops in Punjab (rice, wheat, groundnut (peanut), maize, sugarcane, potato, and two varieties of cotton), and all other variables are defined in Table 9.2. We assume non-informative prior distributions for each unknown variable are as follows:

$$\beta \sim U(0, 0.7) \tag{9.4}$$

$$\varepsilon \sim U(0, 0.7) \tag{9.5}$$

$$\gamma \sim U(0, 5) \tag{9.6}$$

$$x \sim U(0, \mathrm{CWR}_i(t)) \tag{9.7}$$

$$\tau_{gw} \sim U(0, 1000) \tag{9.8}$$

$$\tau_y \sim U(0, 400) \tag{9.9}$$

The joint posterior distribution $p(\boldsymbol{\theta}/y)$ of the complete parameter vector $\boldsymbol{\theta}$ (that includes β,ε, γ, X, and τ) is derived by defining the posterior distribution function as follows:

$$\begin{aligned}
&p(\Delta\mathrm{GW}, Y) \quad \propto \\
&\prod_{t=1}^{T} N\left(\Delta\mathrm{GW}(t)|\gamma\left(\frac{\beta p(t)A_T(t) + \varepsilon_B(t) - \sum_{i=1}^{n}(x_i(t)A_i(t))}{S_y A_T}\right), \tau_{gw}^2\right)\cdot \\
&N\left(\mathrm{Y}_i(t)|_{\frac{x_i(t)}{\mathrm{CWR}_i(t)}}\mathrm{Y}_i^{\max(t)}, \tau_y^2\right)\cdot U\left(\beta\middle|0, 0.7\right)\cdot \\
&U\left(\varepsilon\middle|0, 0.7\right)\cdot U\left(\gamma\middle|0, 5\right)\cdot U\left(x\middle|0, \mathrm{CWR}_{i(t)}\right)\cdot \\
&U\left(\tau_{gw}\middle|0, 1000\right)\cdot U\left(\tau_y\middle|0, 400\right)
\end{aligned} \tag{9.10}$$

The unknown parameters are estimated using WinBUGS (Lunn et al. 2000; Spiegelhalter et al. 1996). WinBUGS employs the Gibbs sampler, an MCMC method for simulating the posterior probability distribution of the parameters conditional on the current choice of parameters and the data. The Gibbs sampler sequentially samples one parameter from the conditional distribution of that parameter relative to the others and provides an effective sampling-based numerical solution for parameter estimation (Gilks et al. 1996). We simulated three chains starting from random initial values for the parameters to verify the convergence of the posterior distribution based on the shrink factor (Gelman and Rubin 1992). The shrink factor compares the variance in the sampled parameters within and across the chains to describe the improvement in the estimates for an increasing number of iterations. For this application, each chain was run for a 1,000 cycle burn-in to discard the initial state, followed by 2,000 simulations of model parameters until the shrink factor was <1.1.

9.3.2 *Model Projections: Evaluation of Water Management Scenarios*

To make projections about future water management scenarios, we use the resulting parameter distributions from the MCMC algorithm to solve for the distribution of water table change. We simulate three management scenarios for 30 years to estimate the cumulative influence on water table elevation of each strategy: (1)

continue current irrigation practices, (2) reduce irrigation by 30 %, and (3) replace all rice crops with pulses. The first scenario assumes that crop areas and irrigation practices remain constant from 2002 through the end of the 30-year simulation. The second scenario represents expected irrigation savings if farmers use soil moisture sensors to inform irrigation timing and duration. Previous experiments carried out by the Punjab Agricultural University demonstrated savings as high as 30 % using a low-cost soil tensiometer (Perveen et al. 2012). The third management scenario represents irrigation requirements if each district replaced high-water-demand rice crops with lower-water-demand pulses. Precipitation and evapotranspiration values from the original model (1973–2002) are repeated in order for the management scenario simulations.

9.4 Results and Discussion

9.4.1 Model Results: Variability Across Districts

The model parameters were fit using observed groundwater and yield data. Annual groundwater elevation changes were summed to give each the cumulative water table elevation change for each simulation year (Fig. 9.3). The modeled and observed water table elevation levels are given for each study district. As expected, 50–56 % of the observations are within the 50 % confidence interval of the modeled values for each district.

The three study districts vary in climate and cropping patterns, in addition to geologic properties and density of surface canals. Theoretically, the latter two should control β and ε, while γ depends on both aquifer transmissivity and hydraulic gradient between the district and neighboring regions. The medians of each distribution of values for Gurdaspur, Jalandhar, and Sangrur are as follows: $\beta = 0.25$, 0.39, and 0.23; $\varepsilon = 0.039$, 0.017, and 0.12; and $\gamma = 0.060$, 0.086, and 0.058, respectively (Fig. 9.4). The distribution and median vary across districts for each unknown parameter.

Groundwater recharge comprises a percentage of annual precipitation and a percentage of total water release from the irrigation canals. Recharge from precipitation ranges between 20 and 40 % of total annual rainfall, which is reasonable for subhumid to humid regions. The drier climate in Sangrur theoretically should have a lower recharge coefficient, and though it has the lowest median recharge value, the posterior distribution of values does not differ significantly from those of Gurdaspur or Jalandhar. Model results suggest that seepage to groundwater from canals accounts for 20–50 % of total average surface recharge. Gurdaspur has the greatest total recharge from canal leakage, which may come from the major branch of the Upper Bari Doab canal, the oldest canal network in Punjab. Sangrur is relatively far from the Bhakra headwaters and may have a smaller amount of recharge from the canals because less water reaches the district.

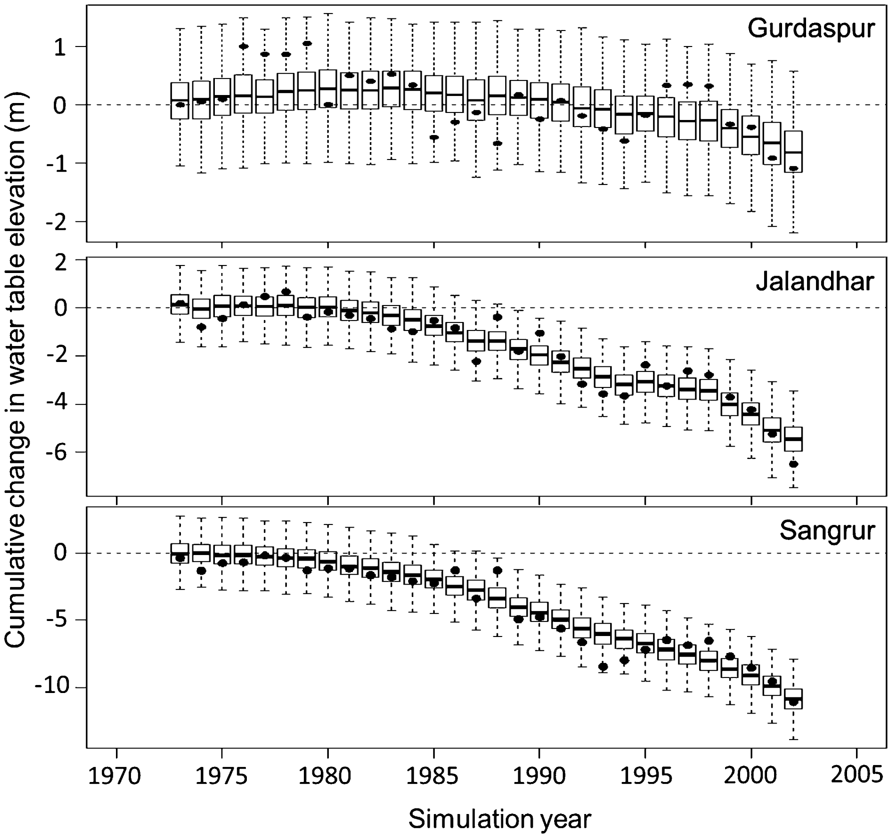

Fig. 9.3 Observed and modeled water table elevations for Jalandhar, Sangrur, and Gurdaspur districts. The *boxplots* show the calculated distribution of water table elevations for each simulated year, and the *filled circles* represent observations

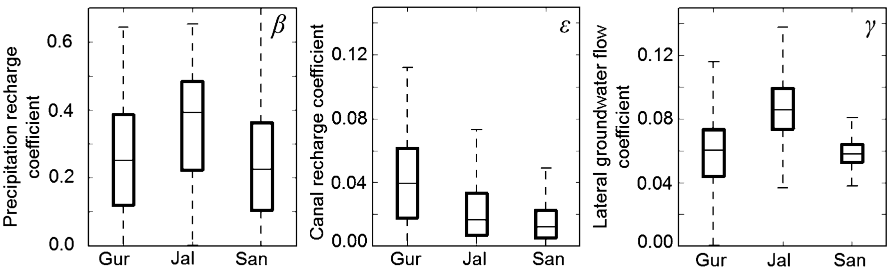

Fig. 9.4 *Boxplots* show the first and third quartiles of each distribution of coefficients for precipitation recharge (β), canal seepage (ε), and lateral groundwater flow (γ) for Gurdaspur, Jalandhar, and Sangrur districts

Gamma, representing the net contribution of lateral groundwater flow to the district, has similar medians for Gurdaspur and Sangrur and a higher value for Jalandhar. Values less than one indicate a net groundwater inflow, where a value of 1 means groundwater inflow equals outflow. Theoretically, gamma represents an external source for the net volume change of groundwater and should be quantified as an additive term in the numerator of Eq. (9.2). However, due to a lack of physical constraints on the value, the model was not able to converge with γ in the numerator. Therefore, γ is represented as a multiplier of the estimated change in water table elevation, which implies that net lateral flow to a district will be a function of current groundwater overdraft. For all districts, the mass balance cannot be completed without net groundwater inflow. The median simulated volume of groundwater inflow is similar to recharge from precipitation. Gurdaspur may have high inflow due to its proximity to the high surface recharge region in the Sivalik foothills, while Sangrur is experiencing the greatest groundwater overdraft; therefore, the gradient drawing groundwater in is high.

9.4.2 Model Assumptions and Limitations

Limitations of the study stem from uncertainty in the data, assumptions made about individual parameters, and assumptions in the underlying model. Assumptions made about variables in the mass balance equation include simplification and lumping of parameters that may not accurately represent the heterogeneity of the system. However, these assumptions and the use of Bayesian methods are opportune given the lack of hydrogeologic data and observations. We assume that the aquifer is continuous and has uniform storage properties. We also assume that irrigation application (X) is 100 % efficient, meaning there is no return flow to the aquifer of excess irrigation water. Actual pumping volumes may be greater in practice, with some of the surplus water consumed by ET and some of it recharging the aquifer. Our model does not simulate extraction of groundwater for irrigation that immediately returns to the aquifer, because it is not required for the mass balance to agree. However, our estimates must be conservative because we do not account for extra losses due to ET on the flooded fields. The use of constant coefficients to represent recharge from precipitation and the canals is another simplification of the system. Actual coefficient values will change seasonally and with long-term changes in climate and land use.

Our assumptions combined with the macro-level aggregated model structure will not capture each interannual water table fluctuation (Fig. 9.3). This is primarily because the model time step is 1 year; therefore the resolution at that time step is coarse. However, the model capacity for representing the decadal-scale trend in groundwater depletion implies that we have accounted for the major components of the mass balance correctly. This model should not be used to estimate groundwater response to water management strategies on short time scales, such as 1–3 years, unless more frequent water table elevation data can be found to reduce the model time step length. The range of each parameter distribution can be used to inform future field data collection efforts to constrain the most uncertain parameters.

9.4.3 Hydrologic Response to Management Scenarios

Water management strategies often involve widespread political change and economic investments and may take several years to evaluate the benefit. Modeling offers a quick and low-cost platform for systematic evaluation of the solutions for estimating the influence of agricultural water management strategies on water table elevation and should be used as a preliminary step to inform management decisions. We calculate the cumulative groundwater response to three water management scenarios over 30 years for each of the three study districts (Fig. 9.5).

The three strategies are not intended to represent easily implementable management strategies, but rather to illustrate the type and extent of change required in order to reduce the groundwater deficit in each district. The first strategy is essentially what the farmers are doing now, though may underestimate current (2013) irrigation requirements due to increases in rice area since 2002. The second strategy will require extensive outreach to farmers, likely a combined effort by the Punjab Agricultural University, extension programs, farmer cooperatives, and government programs (Humphreys et al. 2010; Kaur 2009; Sidhu et al. 2011). Funding for such a program could come from electricity cost savings due to reduced groundwater pumping; for example, the government would save over 150 million USD per year with a 30 % decrease in groundwater pumping. The third strategy will require a change in the government procurement program, which we show to be the most effective method for mitigating groundwater overdraft in Punjab (Devineni and Perveen 2012).

In all cases, the first management scenario (no change) results in further water table decline, with the median rate of decline varying between 0.16 and 0.43 m/year across the three districts (Fig. 9.5). Groundwater extraction is unsustainable in scenario 1 because more water is pumped for irrigation than enters the system via surface recharge (from precipitation and canal leakage) and lateral groundwater inflow. The second management scenario (30 % irrigation savings) results in a slower water table elevation decline (0.07 to 0.28 m/year) compared to the first management strategy. In Jalandhar and Gurdaspur, the third management scenario (replacing rice crops with pulses) has a median result of sustainable water consumption, with greater uncertainty in Jalandhar. In Sangrur, scenario 3 is not sufficient to balance water supply and consumption; however, the median water table decline is ~60 % less than for scenario 1. Scenario 3 represents the most effective of the three simulated management strategies for mitigating damage and potentially restoring depleted aquifers.

Though we show that irrigation efficiency measures and crop replacement are not sufficient to balance and restore aquifer levels in all districts, they can be significant components of a multifaceted management plan. Other options for

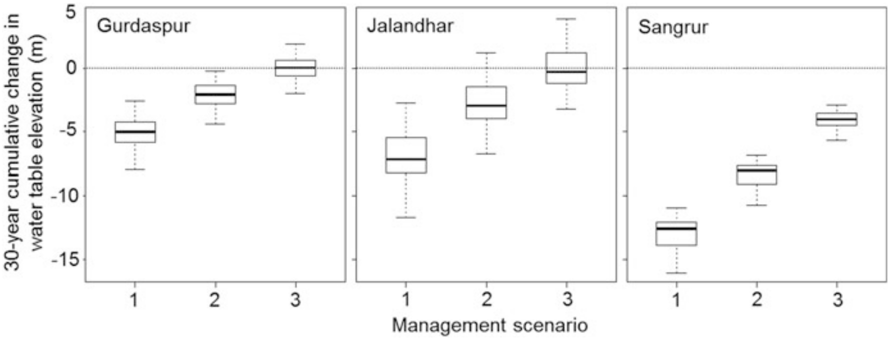

Fig. 9.5 Simulated 30-year-cumulative water table response to three management strategies in Gurdaspur, Jalandhar, and Sangrur. *Strategy 1* represents continuing current practices; *Strategy 2* represents 30 % reduction in irrigation consumption; and *Strategy 3* represents replacement of rice with pulse crops

management include more aggressive crop shifting, such as replacement of rice, sugarcane, and cotton, and a combination of irrigation efficiency with crop replacement. Alternatives to pulses include other low-water-demand crops such as maize, millet, gram (chick pea), and barley (Jalota and Arora 2002). In addition to water conservation methods like scenarios 2 and 3, balance can be attained by enhancing local water supply. Strategies that enhance water supply include managed aquifer recharge and water harvesting.

Model projections do not account for changes in rainfall patterns and temperature in Punjab. Changes in rainfall will impact irrigation requirements and groundwater recharge rates, while temperature will influence *ET* and yields. Intensity and frequency of extreme precipitation events decreased in eastern Punjab between 1951 and 2003, while much of eastern and central India experienced increases (Goswami et al. 2006; Krishnamurthy et al. 2009). Assessment of rainfall changes should be conducted at the district scale, rather than state scale to capture local heterogeneities (Ranade and Singh 2013; Russo et al. 2013). Future work should include projected climate changes when evaluating future agricultural management strategies, especially crop shifting scenarios that utilize local precipitation in lieu of irrigation.

9.5 Conclusion

We present a method using an MCMC algorithm to solve for a distribution of values for each unknown parameter in an under-constrained hydrologic mass balance. The model accounts for variation in observed groundwater overexploitation, climate, crop patterns, and surface and lateral groundwater recharge parameters. The MCMC method quantifies unknown hydrogeologic and agricultural parameters, which vary across districts. Parameter distributions provide estimates of hydrologic fluxes through the ground surface and laterally into each district. We found that the observed water table elevation changes could not be explained by pumping extraction and surface recharge alone, and therefore the system must include a net lateral groundwater inflow approximately equivalent to the flux received from precipitation recharge. We attribute this source to be lateral flow that recharges in the Sivalik foothill range of the Himalayas and flows to the southeast through Punjab.

The model provides quantitative estimates of projected groundwater pumping and water table change under specified water management scenarios. Calculated posterior distributions are used to evaluate three water management scenarios: continuing current practices, reducing irrigation by 30 %, and replacing high-water-consuming rice with low-water-consuming pulses. Projected water table responses to the three scenarios show that replacement of rice crops with pulses may be sufficient to balance or restore the depleted groundwater in Gurdaspur and Jalandhar.

This paper illustrates the hydrologic benefit associated with each strategy, but the results could also be used as input to a cost-benefit analysis, further optimizing management decisions. The feasibility and cost to implement each scenario must be considered in future work. There are economic, political, and cultural elements embedded in agricultural management actions. Changing decisions will require consent and effort from local and regional politicians, farming cooperatives, and agricultural extension services. Results of this study can be used to inform and motivate the management changes required to ensure sustainable agricultural production in Punjab.

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