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Climate variability, rice production and groundwater depletion in India

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Abstract

This paper modeled the proximate determinants of rice outputs and groundwater depths in 27 Indian states during 1980–2010. Dynamic random effects models were estimated by maximum likelihood at state and well levels. The main findings from models for rice outputs were that temperatures and rainfall levels were significant predictors, and the relationships were quadratic with respect to rainfall. Moreover, nonlinearities with respect to population changes indicated greater rice production with population increases. Second, groundwater depths were positively associated with temperatures and negatively with rainfall levels and there were nonlinear effects of population changes. Third, dynamic models for *in situ* groundwater depths in 11 795 wells in mainly unconfined aquifers, accounting for latitudes, longitudes and altitudes, showed steady depletion. Overall, the results indicated that population pressures on food production and environment need to be tackled via long-term healthcare, agricultural, and groundwater recharge policies in India.

Introduction

Human activity and industrialization over the last few centuries have increased greenhouse gas emissions leading to global warming that in turn affects many dimensions of well-being. For example, high economic growth rates in China and India have increased the prevalence of chronic obstructive pulmonary diseases [1, 2]. Moreover, simultaneous increases in population levels and life expectancy raise the long-term demand for land, water, energy and food [3]. While the demand for food can be met in the medium term by increased food production using better technologies [4, 5], increases in living standards are accompanied by improvements in diet quality reflected in higher consumption of animal products that require greater agricultural resources [6]. It is therefore important to analyze the inter-relationships between climate variables and agricultural outputs in countries such as India that have achieved rapid economic growth. Steady depletion of groundwater in north Indian states [7] for meeting short-term demand can hamper long-term goals such as providing sanitation for the population [6].

Further, the problems in assessing impact of climate variability on agricultural production and groundwater depletion need to address several conceptual and methodological aspects. At a conceptual level, rice is an attractive staple consumed by over three billion people and can be easily mixed with nutrient-dense foods such as vegetables, legumes, and meat for improving diet quality in developing countries [8]. From a production standpoint, transpiration efficiency of rice is low [9], and evapotranspiration increases with temperatures [10]. However, there is considerable heterogeneity in rice production in India depending on rainfall levels, surface water availability, and groundwater extraction [11, 12]. Such factors can be analyzed in empirical modeling of the data on rice outputs. For example, it is important to test if rice production in Indian states has increased groundwater depletion using *in situ* data from wells [13].

From a methodological standpoint, direct observations on agricultural production are feasible for small numbers of farms where the data need to be compiled for several years for investigating the effects of climate variables [14]. Although agricultural data at the district level in India can provide useful insights [15], data on inputs are typically available at the state level. While it is simpler to conduct analyses of national averages [11], such analyses cannot address the heterogeneity in climates. Thus, a useful approach for understanding the effects of climate variability would be to model proximate determinants of rice outputs at the state level and, where possible, augment the analyses with more disaggregated data.

Second, it is important to assess the robustness of results from state-level analyses in India for groundwater tables that are depleting in a heterogeneous manner. Due to low resolutions, data from GRACE satellites [16] might not fully reveal groundwater depletion in aquifers in latitude-longitude quadrangles covering sparsely and densely populated areas. Thus, population pressures on groundwater may be under-estimated and it would be useful to augment state-level analyses with *in situ* data from wells. Third, in modeling agricultural output, there are likely to be nonlinearities with respect to explanatory variables and interactions between the variables. For example, many regions of large Indian states face different climatic conditions in terms of rainfall and temperatures. Such factors underscore the need for modeling the relationships between agricultural inputs and outputs using actual data rather than relying on projections from statistical models. The complexity of simulation models is increased in the presence of nonlinearities and where some variables may be jointly determined; confidence intervals for the estimated parameters are likely to be much wider.

This paper modeled annual data on rice outputs in 27 major Indian states during 1980–2010 using five-yearly averages and employing dynamic random effects models that accounted for unobserved heterogeneity. The models incorporated nonlinearities and interactions with respect to explanatory variables and investigated the effects of population changes. Furthermore, dynamic random effects models were estimated for groundwater depths at the state level using *in situ* data from 30796 wells; possible effects of excessive rice production and changes in populations were analyzed. Lastly, dynamic random effects models were estimated using three-yearly averages on groundwater depths in 11795 wells. The geographic locations of wells were approximated via a second degree polynomial in latitudes, longitudes and altitudes, and the linear formulations commonly employed in the geodetic literature [17] were tested as special cases using likelihood ratio statistics.

Materials and methods

The data on Indian states

India is a very heterogeneous country with respect to climatic patterns comprising of 39 states and union territories. Annual data on rice output, area cultivated for rice, rainfall, and temperatures were available for 1980–2010 for most states [15]; five-yearly averages were constructed for reducing missing observations. Data on population from censuses in 1981, 1991, 2001, and 2011 were merged with the database at six time points (1985, 1990, 1995, 2000, 2005, and 2010). Complete data for were available for 27 states: Andhra Pradesh, Arunachal Pradesh, Assam, Bihar, Dadra and Nagar Haveli, Delhi, Gujarat, Haryana, Himachal Pradesh, Jammu and Kashmir, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Manipur, Meghalaya, Mizoram, Nagaland, Orissa, Puducherry, Punjab, Rajasthan, Sikkim, Tamil Nadu, Tripura, Uttar Pradesh, and West Bengal.

In situ groundwater depth measurements

In situ data on groundwater depths were available for 1994–2016 covering 30796 wells [13]. Initially, small numbers of wells were considered and additional wells were added from 1996. The groundwater depths were measured in four seasons. Approximately 87% of wells were dug in unconfined aquifers [12] and average groundwater depths were computed for the states for 1995, 2000, 2005, and 2010 by averaging the data over the wells. For analyses of data on groundwater depths, three-yearly averages for 1998, 2001, 2004, 2007, 2010, 2013, and 2016 were used. Lastly, data on latitudes and longitudes of well locations were entered in ArcGIS [18] for calculating altitudes. Figure 1 plots the quintiles for water depths in wells in 2016. For example, wells represented by red dots had groundwater depths higher than 10.93 meters below ground level. Sample means of the state-level variables are reported in table 1.

Empirical models for rice outputs and water depths in Indian states

The model for logarithm of rice output in ith state in time period t is given in equation (1):

$$
\begin{aligned}
&\ln(\text{Rice output})_{it} = a_0 + a_1 \ln(\text{Net area irrigated})_i \\
&+a_2[\text{Change} \ln(\text{Population})_i] \\
&+a_3[\text{Change} \ln(\text{Population})_i]^2 + a_4 \ln(\text{Rainfall})_{it} \\
&+a_5[\ln(\text{Rainfall})_{it}]^2 + a_6 \ln(\text{Temperature})_{it} \\
&+a_7[\ln(\text{Temperature})_{it}]^2 + a_8 \ln(\text{Rice area cultivated})_{it} \\
&+a_9[\ln(\text{Net area irrigated}) \times \ln(\text{Rainfall})_{it}] \\
&+a_{10}\ln(\text{Rice output})_{it-1} + u_{it} \\
&(i = 1, 2, \ldots, N; t = 2, 3, 4, 5, 6). \qquad (1)
\end{aligned}
$$

Here ln represents natural logarithms and data on 27 states in six time periods were analyzed. The dynamic model in equation (1) contained previous level of rice output as an explanatory variable thereby enabling a distinction between short and long run effects of explanatory variables. Coefficients of explanatory variables in logarithms were the short run 'elasticities' (percentage change in dependent variable resulting from 1% change in the explanatory variable). For example, the short run elasticity of rice output with respect to rice area cultivated was a_8, whereas the long run elasticity was $[a_8/(1-a_{10})]$. Note that changes in logarithms

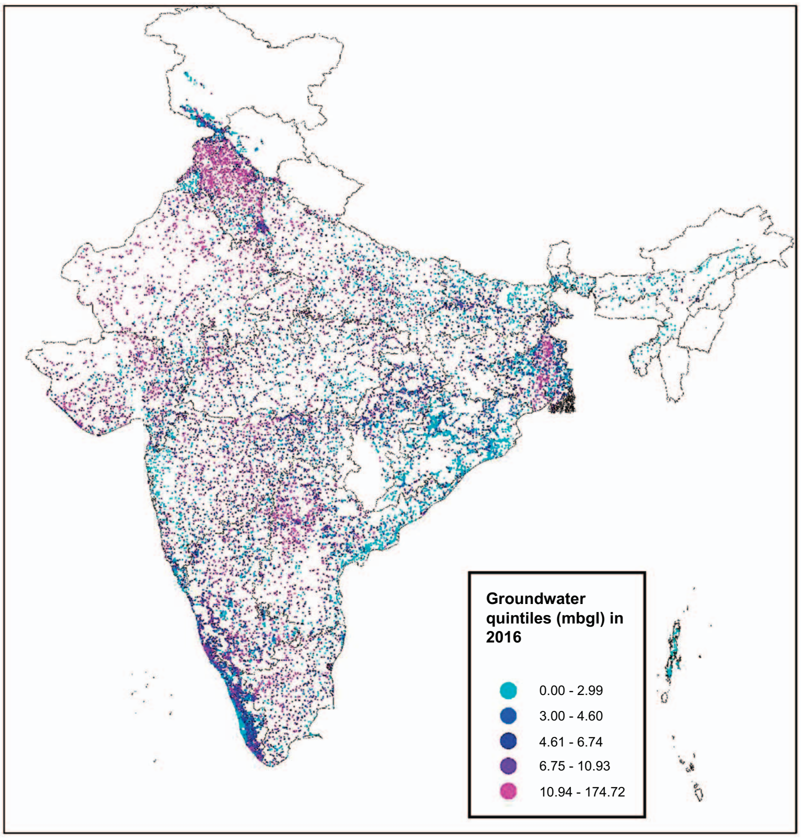

Figure 1. Geographical location of wells in India with quintiles for groundwater depths in 2016.

Table 1. Sample means and standard deviations of five-yearly averages of agricultural and climate variables for Indian states during 1985–2010.[a]

Year:	1985		1990		1995		2000		2005		2010	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Net area irrigated[b], km^2	2169	2946					—	—	—	—	—	—
Population[c], 1000's	23859	26269	—	—	29543	32640	35912	40133	—	—	42186[e]	47708
Rice output, 1000s tons	2088	2488	2479	3130	2215	2737	2683	3405	2804	3826	3002[e]	4093
Rainfall, mm	1515	810	1562	905	1546	822	1533	813	1479	804	1508	727
Temperature, °C	21.70	6.74	21.85	6.80	21.76	6.76	22.00	6.66	22.18	6.60	22.45[e]	6.55
Rice area cultivated, km^2	1486	1898	1524	1961	1573	1991	1597	1994	1387	1778	1417	1787
Groundwater depth[d], mbgl	—		—		6.399	4.36	6.493	4.76	7.453	4.99	7.855[e]	5.09

[a] Longitudinal data on 27 Indian states were used; see text for the state names.

[b] Irrigation data were available after 2000 and were averaged over time.

[c] Population data from census were matched to the nearest time point.

[d] Data on groundwater depths in meters below ground level were available from 1995.

[e] Changes from 1985–2010 were significant at 5% level using paired t-tests.

of population from 1981–2011 were approximations for population growth in the states. Lastly, owing to the modest number of states in India, two specifications were estimated for the model in equation (1), i.e. where squared temperatures were included and where this variable was dropped from the model.

The u_{it}'s were random error terms that can be decomposed in a simple random effects fashion as:

$$u_{it} = \delta_i + v_{it} \tag{2}$$

where δ_i were state-specific random effects that were distributed with zero mean and constant variance, and v_{it} were distributed with zero mean and constant variance. However, a more general formulation for the u_{it} was employed and it assumed that u_{it} were drawings from a multivariate normal distribution; the validity of the special case in equation (2) was testing using likelihood ratio statistics (see below).

The model for groundwater depths at the state level is in equation (3):

$$\begin{aligned} &\ln(\text{Groundwater depth})_{i\,t} = \\ &b_0 + b_1[\text{Change} \ln(\text{Population})_i] \\ &+ b_2\,[\text{Change} \ln(\text{Population})_i]^2 \\ &+ b_3 \ln(\text{Rainfall})_{i\,t} + b_4[\ln(\text{Rainfall})_{i\,t}]^2 \\ &+ b_5 \ln(\text{Temperature})_{i\,t} + b_6 \ln(\text{Rice output})_{i\,t-1} \\ &+ b_7(\text{Indicator period } 5)_{i\,t} + b_8(\text{Indicator period } 6)_{i\,t} \\ &+ b_9 \ln(\text{Groundwater depth})_{i\,t-1} + u_{2i\,t} \\ &(i = 1, 2, \ldots, N;\, t = 2, 3, 4). \end{aligned} \tag{3}$$

Note that indicator (or dummy) variables for time periods were included in equation (3) for allowing variables to have different time means. Given data at four time points, at most four such variables can be included. However, the model in equation (3) contained an overall constant term and the initial observations on the dependent variable were modeled by including a separate constant term. Thus, a maximum of two indicator variables (for time periods 5 and 6) were included to ensure that the explanatory variables were not linearly dependent, i.e. redundant variables were dropped prior to the estimation. If, for example, indicator variables for time periods 5 and 6 were estimated with positive and significant coefficients, then the results would indicate an increase in groundwater depths in 2005 and 2010, respectively. Note that previous level of rice output was included for assessing the effects of rice output on groundwater depths.

Lastly, dynamic random effects model for groundwater depths in wells, accounting for latitude, longitude and altitude of location via a second degree polynomial (Specification 1) is given by:

$$\begin{aligned}
&\ln(\text{Groundwater depth})_{it} = c_0 + c_1 \\
&\ln(\text{Latitude})_i + c_2\ln(\text{Longitude})_i + c_3\ln(\text{Altitude})_i \\
&+c_4[\ln(\text{Latitude})_i]^2 + c_5[\ln(\text{Longitude})_i]^2 \\
&+c_6[\ln(\text{Altitude})_i]^2 + c_7[\ln(\text{Latitude})_i \\
&\times\ln(\text{Longitude})_i] \\
&+c_8[\ln\text{Latitude})_i \times \ln(\text{Altitude})_i] \\
&+c9[\ln(\text{Longitude})_i \times \ln(\text{Altitude})_i] \\
&+c_{10}(\text{Indicator period 3})_{it} \\
&+c_{11}(\text{Indicator period 4})_{it} + c_{12}(\text{Indicator period 5})_{it} \\
&+c_{13}(\text{Indicator period 6})_{it} + c_{14}(\text{Indicator period 7})_{it} \\
&+c_{15}\ln(\text{Groundwater depth})_{it-1} + u_{3it} \\
&(i = 1, 2, \ldots, N; t = 2, 3, 4, 5, 6, 7).
\end{aligned} \tag{4}$$

Note that a linear specification (Specification 2) in latitudes, longitudes and altitudes [17] was also estimated for groundwater depths, i.e. where the geodetic coordinates were included in a log-linear fashion. Likelihood ratio tests were employed for testing the adequacy of Specification 2; geographic variation in a large and heterogeneous country such as India was likely to be better captured by the second degree polynomial in equation (4).

Statistical and econometric methods

The dynamic random effects models for rice outputs and groundwater depths were estimated by maximum likelihood methods [19]. The distribution theory assumed that number of states (or wells) (N) was large but number of time periods (T) was fixed. The estimation techniques treated previous observations on rice output as an 'endogenous' variable, i.e. correlated with the errors u_{it}. Realizations of time varying explanatory variables in different years were assumed uncorrelated with the errors. The errors (u_{it}) were assumed independent across states but were correlated over time. For example, u_{it} were assumed to be drawings from a multivariate normal distribution with a symmetric positive definite dispersion matrix (Ω). The decomposition for u_{it} in equation (2) was a special case and its validity was tested using likelihood ratio statistics that were distributed for large N as Chi-square variables with [{T(T + 1)/2}–2] degrees of freedom. For example, if the errors v_{it} in equation (2) were serially correlated, then likelihood ratio tests were likely to reject the simple random effects decomposition and the results were reported assuming the multivariate normal distribution for u_{it}. The numerical optimization routine (E04 JBF) [20] was used in a FORTRAN program for computing the maximum likelihood estimates. Asymptotic standard errors of the parameters were computed by numerically approximating the second derivatives of the maximized log-likelihood functions.

Results

Descriptive statistics

The sample means and standard deviations of five-yearly averages for rice outputs, rainfall levels, temperatures, area cultivated for rice, and groundwater depths are presented in table 1; means of population at four time points are reported in the nearest columns. Using paired t-tests [21], there were statistically significant ($P < 0.05$) increases from 1985–2010 of 44% in rice outputs, 77% in population, and 3.5% in temperatures. Mean groundwater depths significantly increased by 23% from 1995–2010.

Results from models for state-level rice outputs

Table 2 presents the maximum likelihood estimates of parameters of models for state-level rice outputs. The net area irrigated was a significant predictor ($P < 0.05$) of rice outputs; interaction term between net area irrigated and rainfall levels was significant indicating substitution between alternative water sources. Second, changes in logarithm of population and its squared were significant predictors showing increases in rice outputs with higher population growth. The point of inflexion with respect to population in logarithms was 7.0 that was less than mean change (15.7) during the sample period. Thus, rice outputs showed a decline before reaching mean population level reflecting constraints on production as the population increased.

Third, there were significant nonlinearities with respect to rainfall, and rice outputs increased with rainfall at a declining rate. The point of inflexion was 459 mm of rainfall that was lower than mean levels in table 1. However, coefficients of temperature and its square were not significant in Specification 1. Dropping the squared temperatures in Specification 2 led to short-run elasticity 0.047 of rice outputs with respect temperature. Coefficient of previous rice outputs was 0.57 implying that long run effects of explanatory variables were approximately twice the short run impacts reported in table 2.

Table 2. Maximum likelihood estimates of dynamic random effects models for rice output in 27 Indian states using six five-yearly averages during 1980–2010.[a]

Dependent variable:	ln (Rice output), 1000s tons		ln (Rice output), 1000s tons	
Model:	Specification 1[b]		Specification 2	
Explanatory variables:	Coefficient	SE	Coefficient	SE
Constant	−4.103	0.575	−3.364	0.214
ln (Net area irrigated), km^2	0.101[d]	0.005	0.083[d]	0.024
Change ln (Population), 1000s	0.118[d]	0.034	0.098[d]	0.029
[Change ln (Population)]^2	−0.006[d]	0.001	−0.005[d]	0.001
ln (Rainfall), mm	0.970[d]	0.068	0.815[d]	0.091
[ln (Rainfall)]^2	−0.069[d]	0.004	−0.059[d]	0.006
ln (Temperature), °C	0.002	0.103	0.047[d]	0.021
[ln (Temperature)]^2	0.010	0.025	—	
ln (Rice area cultivated), km^2	0.469[d]	0.040	0.466[d]	0.026
ln (Net area irrigated) × ln (Rainfall)^2	−0.012[d]	0.007	−0.010[d]	0.004
ln (Rice output)$_{it-1}$	0.565[d]	0.037	0.570[d]	0.025
2 x Maximized log-likelihood function	913.63		913.53	
Chi-squared (19) test random effects decomp[c]	474.35[d]		575.20[d]	

[a] Values are slope coefficients and asymptotic standard errors.

[b] Specification 1 included Temperature- squared variable, whereas Specification 2 dropped this variable.

[c] Chi-squared statistics for testing random effects decomposition as in equation (2) were distributed with 19 degrees of freedom.

[d] $P < 0.05$.

Fourth, the simple random effects model in equation (2) was rejected in favor of the multivariate normal distribution for the errors u_{it} using likelihood ratio statistics; the estimated parameters in tables 2 invoked the multivariate normal distribution for ensuring consistent parameter estimation. Lastly, three indicator variables for last three time periods were also included in the model though the coefficients of explanatory variables in table 2 did not change noticeably.

Results from the model for state-level groundwater depths

Table 3 presents the maximum likelihood estimates from model for average state-level groundwater depths. While the coefficient of population change was estimated as −0.44, coefficient of its squared was 0.013. Because the mean change in logarithm of population was 15.7, the overall effect was positive after the point of inflexion (17.35). Thus, higher population growth in states was associated with higher groundwater depths. By contrast, coefficient of the previous rice output levels was not significant. These results suggest that population growth was an important factor underlying increases in groundwater depths (see Discussion).

Second, the coefficients of rainfall levels and its square were both significant in the model for groundwater depths. While groundwater depths were negatively associated with higher rainfall, the point of inflexion was 5432 mm that was greater than maximum rainfall so that groundwater depths decreased with higher rainfall. By contrast, higher temperatures were associated with higher groundwater depths and the squared temperature variable was not significant. Lastly, the coefficient of previous groundwater depths was 0.96 implying that the long-run effects of explanatory variables were approximately 25 times as large. Coefficients of indicator variables for the last two time periods were positive and significant indicating an increase in groundwater depths over time.

Table 3. Maximum likelihood estimates of dynamic random effects models using four five-yearly averages for groundwater depths in 25 Indian states during 1995–2010.[a]

Dependent variable: ln (Groundwater depths), mbgl		
Explanatory variables:	Coefficient	SE
Constant	6.567	0.399
Change ln (Population), 1000s	−0.439[c]	0.041
[Change ln (Population)]^2	0.013[3]	0.001
ln (Rainfall), mm	−0.774[c]	0.077
[ln (Rainfall)]^2	0.046[c]	0.006
ln (Temperature), °C	0.117[c]	0.030
ln (Rice output)$_{it-1}$	0.004	0.012
Time period 3, 0–1	0.191[c]	0.059
Time period 4, 0–1	0.131[c]	0.054
ln (Groundwater depth)$_{it-1}$	0.959[c]	0.036
2 x log-likelihood function	384.36	
Chi-squared [8] test random effects decomposition [b]	37.22[c]	

[a] Values are slope coefficients and standard errors.

[b] Chi-squared statistics for testing random effects decomposition were distributed with 8 degrees of freedom.

[c] $P < 0.05$.

Results from models for *in situ* groundwater depths in wells

Table 4 presents the results from dynamic models for *in situ* groundwater depths in 11795 wells accounting for latitudes, longitudes, and altitudes. The results from both specifications rejected the simple random effects decomposition in equation (2), and the results are reported assuming a multivariate normal distribution for u_{it}. The likelihood ratio statistics for testing Specifications 2 against the more general Specification 1 was 834.5 and it rejected the null hypothesis that the geodetic coordinates can be included in a log-linear fashion. These results showed the importance of employing second degree polynomials in latitudes, longitudes and altitudes for capturing geographic variations affecting groundwater depths in the wells in India.

Second, the estimated coefficient of previous groundwater depths was 0.94 in Specification 1 and coefficients of indicator variables for time periods 3–7

Table 4. Maximum likelihood estimates of dynamic random effects models using seven three-yearly averages for groundwater depths in 11795 wells during 1995–2016 accounting for well latitudes, longitudes, and altitudes.[a]

Dependent variable:	ln (Groundwater depth), mbgl			
Model:	Specification 1[b]		Specification 2[b]	
Explanatory variables:	Coefficient	SE	Coefficient	SE
Constant	4.382	0.041	−6.801	1.248
ln (Latitude)	6.169[e]	0.033	−0.097[e]	0.019
ln (Longitude)	−6.421[e]	0.011	1.520[e]	0.282
ln (Altitude)	0.413[e]	0.022	−0.018[e]	0.004
[ln (Latitude)]^2	0.034[e]	0.006	—	
[ln (Longitude)]^2	1.262[e]	0.005	—	
[ln (Altitude)]^2	−0.001[e]	0.0004	—	
ln (Latitude)∗ln (Longitude)	−1.468[e]	0.007	—	
ln (Latitude)∗ln (Altitude)	0.007[e]	0.002	—	
ln (Longitude)∗ln (Altitude)	−0.094[e]	0.005	—	
Time period 3, 0–1	0.004[e]	0.001	0.006[e]	0.001
Time period 4, 0–1	0.044[e]	0.002	0.048[e]	0.001
Time period 5, 0–1	0.051[e]	0.002	0.041[e]	0.002
Time period 6, 0–1	0.044[e]	0.002	0.017[e]	0.004
Time period 7, 0–1	0.033[e]	0.002	−0.006	0.006
ln (Groundwater depth)$_{it-1}$	0.944[e]	0.004	1.334[e]	0.056
2 x log-likelihood function	291416.9		290582.4	
Chi-squared [25] test random effects decomposition[c]	6348.6[e]		6404.2[e]	
Chi-squared [6] tests for Specific.1 vs 2[d]			834.5[e]	

[a] Values are slope coefficients and standard errors.
[b] Specification 1 was the general model and Specifications 1 is its special case.
[c] Chi-squared statistics for testing random effects decomposition were distributed with 25 degrees of freedom.
[d] Chi-squared statistics for testing Specifications 1 against Specification 2 was distributed with 6 degrees of freedom.
[e] $P < 0.05$.

were all positive and significant. Thus, there was an increase in groundwater depths and the large coefficients of lagged dependent variable indicated that groundwater depletion was likely to be a persistent phenomenon (see Discussion). Lastly, partial derivatives of groundwater depths in wells with respect to latitudes and longitudes from Specification 1 are presented in equations (5) and (6), respectively:

$$6.17 + 0.068\ \ln(\text{Latitude}) - 1.47\ \ln(\text{Longitude}) \\ +0.007\ \ln(\text{Altitude}) \tag{5}$$

and

$$-6.42 + 2.524\ \ln(\text{Longitude}) - 1.47\ \ln(\text{Latitude}) \\ -0.094\ \ln(\text{Altitude}). \tag{6}$$

These results were consistent with the data on groundwater depths displayed for 2016 in figure 1. For example, groundwater depths were higher as one moved along a longitude to higher latitudes. By contrast, groundwater depths in wells located near the west and east coasts were lower.

Discussion

This paper presented comprehensive analyses of the proximate determinants of rice outputs and groundwater depths at the state level in India; analyses of *in situ* data from 11795 wells provided further insights for groundwater depletion. The empirical models showed greater rice outputs with rainfall levels and population growth though at declining rates. Because rice is an attractive staple in many Indian states, rice consumption is likely to increase with incomes [8]. However, the results for rice outputs in table 2 indicated that in states with high population growth, poor households may not be able to increase rice consumption and might switch to cheaper alternatives. Disaggregated analyses at the district and/or household levels can shed further light on these issues.

Second, models for groundwater depths showed significant and positive associations between population growth and groundwater depths. By contrast, previous levels of rice outputs were not significantly associated with groundwater depths. This may have been due to different rice cultivation patterns in flood plains versus farms utilizing groundwater. While groundwater should be extracted at rates that maintain stable depths over time, states experiencing high rainfall have flexibility in recharging aquifers [22]. Moreover, average groundwater depths were higher at the end of the sample period in 2010; over-pumping of groundwater for production of crops with low transpiration efficiencies is often responsible for depletion. Thus, it seems important to reduce electricity subsidies for agriculture in India [23] especially in states experiencing groundwater depletion.

Third, the empirical model for groundwater depths included the explanatory variables temperatures, rainfall, and changes in logarithms of population and its square so that the estimated coefficients provide insights into their relative magnitudes. For example, the model predicted that an increase of 1% in temperatures would increase groundwater depths by 0.118% in the short run and by 2.95% in the long run. Because there was a 3.5% increase in average temperatures from 1985–2010, the implied long run increase in groundwater depth was 10.3% that is large. While higher rainfall can recharge groundwater, changes in rainfall levels between 1980 and 2010 were statistically not different from zero. Further, the quadratic relationship between changes in population and groundwater depths predicted higher depths in states where changes in logarithm of population were greater than 17.35. This was the case for Bihar, Madhya Pradesh, Maharashtra, Rajasthan, Uttar Pradesh and West Bengal. While the modest sample sizes available for the estimation of nonlinear models complicated the computation of confidence intervals, these results suggest that the long run effects of increases in temperatures and population for groundwater depths are likely to be large and should be of concern to policy makers.

Fourth, the models for *in situ* groundwater depths in wells provided further insights for managing water resources in India. The groundwater depths increased during 1996–2016 and the large coefficients of lagged dependent variables implied that groundwater scarcity is likely to become a chronic problem especially in northern states that are located far from the coasts. The fact that some of these states, namely, Bihar, Madhya Pradesh, Rajasthan and Uttar Pradesh, experienced high population growth during 1980–2010 underscores the need for urgently tackling the problems of groundwater depletion.

Fifth, while trade in agricultural commodities often entails groundwater use [24], it is important to consider agricultural production in a broader context. In coastal regions with ample rainfall, it would be simplistic to view rice exports as 'water exports' since opportunity costs of water use are low. Instead, greater specialization in rice production and trade with other states would be helpful. Efficient technologies for groundwater conservation, recharge and management [9, 25], taking into account demand for food, will be efficacious. Planting crops according to their transpiration efficiencies and water availability are sound strategies for maintaining groundwater levels. Moreover, taxes on agricultural commodities can encourage harmonizing of agricultural outputs and groundwater resources in India.

Finally, the 77% increase in population in India during 1980–2010 significantly affected rice outputs and groundwater depths at the state level. While it has been suggested that the 'demographic dividend' from having a young labor force support older age groups may be helpful for economic development, it is important to consider the broader consequences of population growth in countries with high population densities [26]. Owing to poor access to healthcare and family planning services especially in rural areas of developing countries, many children are regarded by their mothers as either being born earlier than expected or were simply 'unwanted' [27, 28]. For example, approximately a third of the children born in Bihar, Madhya Pradesh, Rajasthan and Uttar Pradesh were regarded as 'unwanted' [3]. In the absence of access to high quality healthcare and family planning services, it is difficult for poor rural households to achieve their 'desired' family size and educate the children. Rapid population growth creates simultaneous pressures on food production systems and the environment. While there is a need for replenishing groundwater via better technologies [22], healthcare and family planning services should be integral components of long-term policies for mitigating the effects of climate variables. Such policies are likely to be beneficial for other Asian countries such as Indonesia, Pakistan and the Philippines that are experiencing population growth and are vulnerable to rising sea levels and uncertain monsoon patterns [30].

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