

Groundwater depletion limits the scope for adaptation to increased rainfall variability in India

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Abstract Recent studies have found that increasing intra-seasonal precipitation variability will lead to substantial reductions in rice production in India by 2050, independently of the effect of rising temperatures. However, these projections do not account for the possibility of adaptations, of which the expansion of irrigation is the primary candidate. Using historical data on irrigation, rice yields, and precipitation, I show that irrigated locations experience much lower damages from increasing precipitation variability, suggesting that the expansion of irrigation could protect Indian agriculture from this future threat. However, accounting for physical water availability shows that under current irrigation practices, sustainable use of irrigation water can mitigate less than a tenth of the climate change impact. Moreover, if India continues to deplete its groundwater resources, the impacts of increased variability are likely to increase by half.

Keywords Agriculture · Climate change · Rainfall variability · Adaptation · Irrigation · Water Resources

1 Introduction

The importance of accounting for adaptation, and its limits, in projections of the impacts of climate change is widely recognized (Tol et al. 1998; Smit et al. 2000; Howden et al. 2007;

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Intergovernmental Panel on Climate Change 2014), but quantifying these limits empirically remains a challenge. In this paper, I use data on crop yields, precipitation, irrigation, and estimates of groundwater resources to demonstrate the extent to which the depletion of groundwater resources restricts the scope for irrigation to adapt Indian agriculture to increased precipitation variability.

Climate change is expected to shift precipitation patterns in ways that will threaten agriculture worldwide, especially in the semi-arid tropics. Precipitation is projected to decline in some areas and increase in others, but is likely to become more variable, within seasons, in most locations (Tebaldi et al. 2006; Meehl et al. 2000; Allan and Soden 2008; Min et al. 2011; Goswami et al. 2006; Meehl et al. 2005; Rajah et al. 2014; Krishnamurthy and Shukla 2000; Shukla 2003; Krishna Kumar et al. 2011; Trenberth et al. 2005; Hennessy et al. 1997). Relatively few studies have quantified the impacts on increasing intra-seasonal variability on crop yields, but both modeling (Wolf et al. 1996; Mearns et al. 1996, 1997; Olesen et al. 2000; Richter and Semenov 2005; Semenov and Porter 1995; Patil et al. 2012) and recent statistical analyses of historical rainfall and crop yields (Auffhammer et al. 2012; Fishman 2016) have found these impacts to be negative and large. However, these projections do not account for all possible adaptations, of which the expansion of irrigation is a primary candidate.

Irrigation has been used to buffer crop yields from precipitation shortages for millennia, since irrigation water can substitute for rainfall deficiencies in terms of both quantity and timing. The expansion of irrigated area is therefore often considered to be a promising adaptation strategy to climate variability and change (Rosenzweig and Parry 1994; Mendelsohn and Dinar 1999, 2003; Howden et al. 2007; Parry 2007) but the scope for irrigation as an adaptation strategy is constrained by physical water availability. This constraint is likely to become increasingly binding as renewable water supply is becoming exhausted and non-renewable resources, primarily groundwater aquifers, are becoming depleted (Konikow and Kendy 2005; Wada et al. 2010; Famiglietti 2014; Zaveri et al. 2016).

Numerous studies have used climate and crop modeling to simulate the future direct impacts of climate change on crop yields (Intergovernmental Panel on Climate Change 2014). Several studies have also evaluated the direct impacts of climate change on water availability for irrigation (Vörösmarty et al. 2000; Arnell 2004; Fischer et al. 2007; Konzmann et al. 2013; Haddeland et al. 2014) and the resulting impacts on agriculture (Elliott et al. 2014). However, as far as I am aware, the extent to which the depletion of water resources might limit the scope for *adapting to climate change* has not been quantified to date, especially on the basis of observed relationships between rainfall, crop yields and irrigation. This impact can be thought of as the *interaction* of the direct agricultural impact of climate change and of anthropogenic water resource depletion. Here, I perform such an analysis for the case of rice production in India.

Globally, rice is one of the three most important sources of energy for human consumption (Lobell et al. 2011). In India, it delivers about half of all calories obtained from cereals,¹ and occupies more than half the cultivated area in the rainy season.² Since India produces about a fifth of the world's rice crop, substantial losses in local yield will directly bear on global food grain prices.

¹Food and Agriculture Organization, <http://faostat3.fao.org/>

²Source: Agricultural Statistics at a Glance, Directorate of Economics and Statistics, Dept. of Agriculture, Govt. of India.

The high variability and uneven temporal distribution of rainfall in India, both within and across years, has made irrigation essential for agricultural productivity and food security, and its expansion has been one of the central pillars of India's agricultural development policy for decades. India is now the world's third largest dam builder, with over 4000 large dams, and the world's largest consumer of groundwater, with over ten million wells. Groundwater is estimated to support 70% of agricultural production and more than 50% of the Indian population (World Bank 1998; Shah 2008). India is probably also the country most vulnerable to the threat of groundwater depletion. Over-extraction of groundwater (in excess of natural recharge) is widespread (Rodell et al. 2009; World Bank 1998; Livingston 2009; Shah 2008; Fishman et al. 2011) and the rates of water table declines across the country are alarming (Aeschbach-Hertig and Gleeson 2012; Rodell et al. 2009; Tiwari et al. 2009; Livingston 2009).

My approach is based on a recent statistical analysis of historical rice yields and precipitation in almost 500 locations across India in the period 1970–2003, that estimates the impact of rainfall variability on rice yields (Fishman 2016). Statistical analyses are widely used, alongside those based on crop models, to project climate change impacts (Lobell and Burke 2010). Both approaches have their strengths and weaknesses. One particular advantage of statistical models, which is especially important in developing countries, is that they base their estimates on observed crop production achieved by farmers that often employ sub-optimal cultivation practices that can be quite different than those used in controlled agronomic conditions or assumed in crop models (Mondiale 2008).

Numerous such statistical analyses of historical crop-weather relationships have estimated the impact of rising temperatures on crop yields, in India and elsewhere (Schlenker and Lobell 2010; Schlenker and Roberts 2009; Deschenes and Greenstone 2007; Fisher et al. 2012; Welch et al. 2010; Peng et al. 2004; Nelson et al. 2009; Guiteras 2008; Krishna Kumar et al. 2004; Dinar 1998; Rosenzweig et al. 2013). However, reference (Fishman 2016) has for the first time used this approach to show that increasing rainfall variability (measured by the number of rainy days in the season) also has large negative impacts on crop yields. Applying the estimates to a climate change projection showed that by 2050, increasing variability will more than offset the beneficial impacts of increased precipitation totals, and result in a net 10% decline in rice yields. These impacts are independent of and additional to the well-documented effects of rising temperatures.

Here, I build on this analysis and assess the degree to which irrigation reduces the impact of precipitation variability on crop yields. Basing this assessment on empirical estimates derived from observed yields is important, because farmers are likely to be applying irrigation water in sub-optimal ways due to various hydrological and economic constraints, and may adjust to the availability of irrigation in additional ways (Taraz 2017).

I then apply these estimates to a number of stylized integrated climate-groundwater scenarios that combine projections of precipitation variability to 2050 with several possible trajectories for India's irrigation expansion and its groundwater aquifers. These highly stylized simulations are not meant to provide an accurate and comprehensive projection that accounts for all factors impacting rice production in India in mid-century. Rather, they are meant to illustrate the interplay between the impacts of climate change and the ongoing depletion of India's water resources. In particular, they provide novel quantification of the extent to which groundwater availability limits the future prospects of adaptation to climate change. The effects of these two independent threats to Indian agriculture have until now been mostly subject to separate analyses.

2 Methods

Data sources I use the same weather and agriculture data sets employed in reference (Fishman 2016) and repeat its description here. Daily gridded ($1^\circ \times 1^\circ$) precipitation and temperature data (Rajeevan et al. 2005; Srivastava et al. 2009) for the period 1970–2004 are modified to represent 2001 Indian district boundaries through weighted spatial averaging (Devineni et al. 2013). Additional modifications are made to account for district splits during the period (Kumar and Somanathan 2009). Daily mean temperatures during the rainy season (June–September) are used to calculate the growing season *degree days*, a measure of heat often used in phenological studies (Schlenker et al. 2006). Daily precipitation data is used to calculate total seasonal rainfall and several other indicators of intra-seasonal rainfall variability, including the number of days with rainfall in excess of 0.1 mm (see the results section). Rainy season rice yields, cropped areas and gross (annually totaled) irrigated areas, at the district level, are obtained from the Indian Harvest Data set of the Center for the Monitoring of the Indian Economy (CMIE). In total, 6,432 annual weather and agricultural observations in 485 districts (covering 18 Indian states) are available. Table S1 reports the mean and standard deviation of the main variables used in the analysis.

Weather-yield analysis The impacts of climatic variability on rice yields are estimated using a multivariate log-linear regression model that controls for growing season heat exposure, measured by *degree days* (Schlenker et al. 2006); total seasonal rainfall; and the number of rainy days (May 2004) as a measure of intra-seasonal variability (Summary statistics for these variables are reported in Table S1).

$$\log Y_{sdt} = \mathbf{v} \cdot \mathbf{W}_{sdt} + f_s(t) + p_d + \epsilon_{sdt} \quad (1)$$

where Y_{sdt} is the crop yield in district d , state s and year t ; \mathbf{W}_{sdt} is a vector of weather variables including total Monsoon rainfall, seasonal degree days, and the number of rainy days. The three coefficients contained in the vector \mathbf{v} represent the impact of deviations in these three weather indicators on rice yields. The model follows standard practices in the literature and includes unobserved, time-invariant factors, p_d , that are specific to each district such as soil types, water resources availability and other geographical or time invariant socio-economic characteristics; and state-specific quadratic time trends $f_s(t)$ to reflect the substantial variation in agricultural technological progress across Indian states. By including these controls, the estimation is based on random deviations of weather from its long-term mean within each district, and thus facilitates causal inference. Additional details are provided in reference (Fishman 2016).

Heterogenous impacts by irrigation cover The CMIE dataset does not report irrigated and unirrigated yields separately, making it impossible to directly estimate whether irrigated yields are less sensitive to weather patterns. However, the dataset does report the seasonal rice cropped area GA and gross (annually totalled) rice cropped irrigated area GIA (where water was applied at least once during the growing season). I use the fraction of gross area irrigated $FIA_{sdt} = GIA_{sdt}/GA_{sdt}$ as a measure of irrigation cover in each state, district and year.

To estimate the degree to which the impacts of weather deviations on rice yields differ between irrigated and non-irrigated areas, I estimate a regression model, similar to Eq. 1, that also includes interaction terms between irrigation cover and the weather variables:

$$\log Y_{sdt} = (\mathbf{v}_0 + FIA_{sdt} \times \boldsymbol{\delta}) \cdot \mathbf{W}_{sdt} + f_s(t) + \pi_d + \epsilon_{sdt} \quad (2)$$

In this model, the three coefficients contained in the vector \mathbf{v}_0 represent the impact of deviations of the three weather indicators on rice yields in completely non-irrigated districts (where irrigation cover equals zero). The three coefficients in the vector δ represent the change in the sensitivity of crop yields to the three weather variables, as irrigation cover increases (continuously) from 0 (no irrigation) to 1 (fully irrigated).

One possible concern in interpreting estimates of regression (2) lies with the possibility of un-observed variables that might be correlated with irrigation cover and are the ones responsible for reducing the impacts of rainfall variability. In such a case, a causal interpretation of the results that implies that increasing irrigation cover will reduce the future impacts of rainfall variability can be misleading. While I am unable to fully address these concerns, I can separate the effects of irrigation from those of any unobservable confounder operating at the state level by estimating a model:

$$\log Y_{sdt} = (\mathbf{v}_0 + FIA_{sdt} \times \delta + \mu_s I_s + \nu_s I_s \times t) \cdot \mathbf{W}_{dt} + f_s(t) + \pi_d + \epsilon_{sdt} \tag{3}$$

which also controls for interactions between all weather variables and state-specific linear time trends (obtained as products of 18 state level binary indicators I_s with state specific constants and time trends). This range of 36 controls will capture all potential confounders whose variation is well captured at the state level, or by state dependent linear time trends. These would include time-invariant attributes such as institutional or geographical state attributes, and variables that change linearly over time, even if the rate of change differs across states. The resulting estimate of the coefficient δ is therefore based only on variation in irrigation cover that occurs *within* states and is also orthogonal to arbitrary state level linear trends in time.

I further estimate an additional variant of the interaction model

$$\log Y_{sdt} = (\mathbf{v}_0 + FIA_{sdt} \times \delta + \mu_{s,D} I_{s,D}) \cdot \mathbf{W}_{dt} + f_s(t) + \pi_d + \epsilon_{sdt} \tag{4}$$

in which the 54 binary indicators $I_{s,D}$ (18 states times 3 decades) represent more flexible interactions of the weather variables with arbitrary state decade combinations and therefore capture all slow moving (decadal) processes occurring at the state level.

Additional robustness tests are discussed and reported in the Results section, below.

Climate change simulations To perform simple climate change impact simulations, I multiply projected changes in total precipitation and the number of rainy days ΔW from an illustrative climate change scenario for South Asia by the estimated coefficients relating rice yields to changes in these weather variables.³ The climate change scenario used in this projection is taken from reference (Fishman 2016) and includes a 100 mm increase in total precipitation (inspired by the IPCC’s A1B, South Asia, 2080–2099 median projection of a 10% increase in precipitation) and a decrease of 15 rainy days by 2050 cited by IPCC AR4 (Solomon 2007; Krishna Kumar et al. 2003).

In each district, changes in rice yields are calculated on the basis of the sensitivity of (log) rice yields to weather fluctuations in that district, v_d , which is in turn determined by

³My analysis is focused on the effects of precipitation and I therefore omit the impacts of temperature increases from the analysis. To first order, the impacts of the shifts in the three weather indicators are linearly separable, so that the impact of temperature increases, which have been investigated in other studies, are, to first order, independent of and additional to those at the focus of the analysis.

the irrigation cover FIA_d in that district, according to the estimated coefficients of Eq. 2, i.e.,:

$$v_d = v_o + \delta FIA_d \quad (5)$$

where FIA_d is the irrigation cover in district d in the irrigation scenario in question (see below), and v_o and δ are the estimated obtained from regression (2).

Calculated yields y_d in each district are then multiplied by mean rice cropped areas A_d in each district (1980–2000), which is assumed to remain unchanged, and aggregated production losses ΔP are aggregated across India:

$$1 + \frac{\Delta P}{P} = \frac{\sum_d A_d y_d \exp(v_d \Delta W)}{\sum_d A_d y_d} \quad (6)$$

Groundwater scenarios To incorporate the effect of irrigation expansion into a climate change impact projection, and illustrate the interaction between climate change and water resource availability, I couple the above climate change scenario with five stylized irrigation-groundwater scenarios that capture different possible trajectories of groundwater irrigation in India. Each scenario projects the future irrigation cover in each district FIA_d on the basis of current irrigation cover (leftmost map in the top panel of Fig. 2) and different stylized assumptions. These values are then plugged into Eq. 5 to produce a simulation of future rice yields.

Five irrigation scenarios are considered. In the benchmark scenario, irrigation cover is maintained at current levels (1980–2000 means). In this scenario, FIA_d is given by its current value FIA_d^C (displayed in the left most map in the top panel of Fig. 2). In the *full irrigation* scenario, it is assumed that $FIA_d = 1$ everywhere.

To calculate the fraction of area irrigated in the *sustainable expansion* scenario, I use data on the fraction of overall irrigated area that is irrigated by groundwater GW_d^4 and X_d , the *stage of groundwater development*, provided by the Indian government (Central Ground Water Board 2004), and defined as the ratio of extraction to renewable natural recharge (Fig. S1). In districts where this parameter exceeds 100%, extraction already exceeds recharge and is therefore un-sustainable. Note that this data is only available at the aggregate level across all crops, so I assume the rice specific figures are similar to the aggregate ones. In making the projection, I assume that the area served by surface irrigation does not change, and allow the area served by groundwater to adjust to sustainable levels:⁵

$$FIA_d^S = FIA_d^C \times (GW_d/X_d + (1 - GW_d)) \quad (7)$$

In the *mild depletion* scenario, the area irrigated by groundwater it is assumed to reduce to zero in districts where it is currently unsustainable. In the *severe depletion* scenario, it is assumed to reduce to zero everywhere. In all scenarios, cropped areas and areas irrigated by other (surface) sources are assumed to remain unchanged

3 Results and discussion

The effect of intra-seasonal precipitation variability on rice yields Estimates of regression (1) (essentially identical to those in (Fishman 2016)) are reported in Column 1 of

⁴Source: Agricultural Statistics at a Glance, Directorate of Economics and Statistics, Dept. of Agriculture, Govt. of India.

⁵I force the resulting irrigation cover remain below 1

Table 1, with coefficients presented in terms of 0.01 logarithmic units, so that they can be approximately interpreted as the number of percentage points by which rice yield are estimated to change per unit increase in the respective weather variable. The estimates reveal the large effect of intra-seasonal variability. They imply that each additional rainy day, keeping heat exposure and total precipitation fixed (which amount to a more even intra-seasonal distribution), increases rice yields by an estimated 0.78% ($p < 0.01$). In comparison, an additional 10 mm of total precipitation, roughly the amount of precipitation in an average rainy day, increases yields by 0.11% (while keeping the number of rainy days fixed). Heat has a negative effect: each additional degree-day reduces yields, on average, by 0.11%.

Difference in effects in irrigated and non-irrigated areas The impacts estimated above represent an India-wide average. However, significant heterogeneity exists in cultivation practices across the country, particularly with respect to irrigation cover. Across the entire sample, the mean irrigated fraction of the area cultivated with rice is 55% but it exhibits a substantial degree of spatial variation (rightmost map in the top panel of Fig. 2). To estimate the degree to which irrigation is associated with a lower sensitivity of rice yields to weather fluctuations, I estimate regressions that includes interactions between all three weather variables and irrigation cover (share of rice cultivated land which is irrigated).

Column 2 of Table 1 reports estimates of the basic interaction model, Eq. 2. The results can be interpreted to mean that in the absence of irrigation, an additional rainy day increases yields by 1.36% ($p < 0.01$), but as irrigation cover increases, this impact eventually decreases by 0.96 percentage points ($p < 0.01$). They are represented by the light blue line in Fig. 1, which depicts the change in the estimated impact of an additional rainy day on rice yields (vertical axis) as irrigation cover continuously increases from 0 to 100% (horizontal axis). In the bottom two rows of the Table 1 report the point estimate and P value of the impact of rainy days on rice yields in completely irrigated districts, which I define as the sum of the coefficients $v_0 + \delta$.

Columns 3–8 of the same table report estimates of a range of alternative specifications and robustness checks that aim to improve the interpretation of the results. These estimates are also summarized in Fig. 1

Columns 3 and 4 report results of robustness tests (Eqs. 3 and 4) that address concerns about a biased interpretation of the effect of irrigation by including flexible controls for interactions between weather deviations and unobservable factors varying at the state and time level, as described in the methods section. The estimated coefficients of interest remain remarkably similar in magnitude and statistical significance to those obtained using the basic interaction model. Note that unlike the estimates reported in column 2, in the case of columns 3 and 4, one may not interpret the coefficient of the un-interacted weather terms as capturing the effect of these weather fluctuations in completely un-irrigated districts, because of the presence of interaction terms between weather variables and state specific intercepts in the regressions.

A second potential concern with model (2) is that irrigation cover is itself endogenous (responsive) to weather anomalies in a particular district and year, leading to biased estimates. To partially address this concern, I also estimate a model in which I use the time-invariant long-term average of irrigation cover in each district in place of its contemporaneous level, i.e., I use $FIA_{sd} = \overline{GIA_{sdt}}/\overline{GA_{sdt}}$. The results, reported in column 5 of Table 1, remain extremely similar. In column 6 I add interactions between weather variables and state specific fixed effects to the same model, so that the estimates are based only on variation between districts in the same state, for the same reasons discussed above.

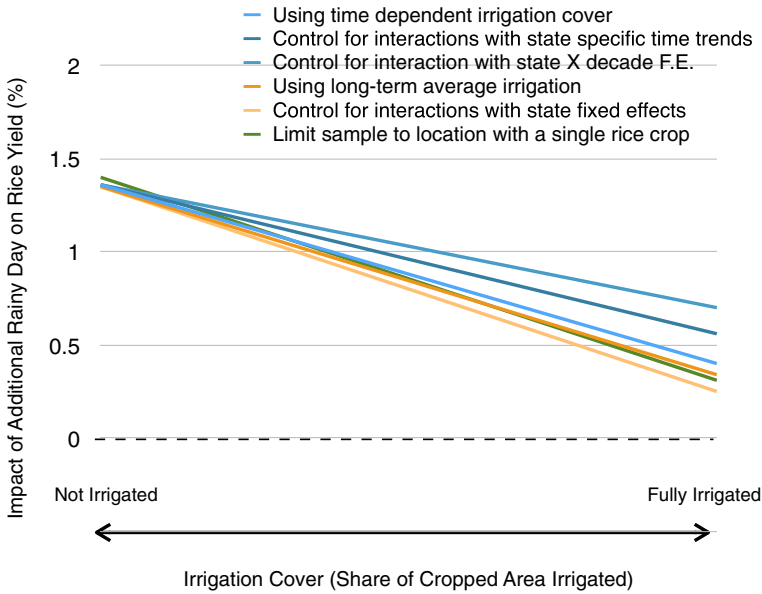


Fig. 1 Graphical representation of the estimated effect of irrigation cover (the share of area cultivated with rice which is irrigated) on the sensitivity of rice yields to increases in the number of rainy days. Each line traces the effect of each additional rainy day on (Log) rice yields as irrigation cover increases from 0 (left end, no irrigation) to 1 (right end, full irrigation), as estimated by a separate regression model. The slope of each line is the estimated coefficient of the interaction term in Eq. 2, i.e. the parameter δ , whereas the intercept represents the un-interacted term, i.e., the parameter v_0 , which captures the effect of rainy days in completely un-irrigated districts. Lines in blue shades represent estimates from models which use time-varying irrigation data (columns 2, 3, 4 in Table 1). The intercept for these lines is taken from column 2 of Table 1 (the intercepts estimated in columns 3 and 4 of Table 1 cannot be interpreted in the same way because these regressions include interactions of weather with state fixed effects). Lines in orange shades represent estimates from models which use time-invariant irrigation data (columns 5,6 in Table 1). The intercept for these lines is taken from column 5 of Table 1. The green line represents an estimate from a regression that limits the sample to locations where a single rice crop is cultivated per year (column 8 in Table 1, see text). The intercept in for this line is also taken from column 8. Standard errors are not shown for clarity (they are reported in Table 1), but all intercepts and slopes are statistically significant at the 5% level. The various regression models are explained in greater detail in the main text (methods section)

In columns 7 and 8 I repeat the estimation reported in Columns 5 and 6 in a sub-sample of the data in which rice is only cultivated in the rainy season. My main motivation for doing so lies in the concern that the definition of irrigation cover may be skewed in such locations, because it divides the gross irrigated area, i.e. the annual irrigated area, by the rainy season cropped area. If rice is cultivated outside the rainy season, this measure could be misleading. However, I find that the results remain similar to those obtained with the full sample.

I also subject the results to a number of variations of the specification of the basic weather model, that consist of inclusion of year fixed effects, a quadratic expression in total precipitation, and replacing degree days as my measure of heat exposure by a flexible model relying on the number of days in various temperature ranges. The main results remain robust to these alternative specifications (see the SOI and Table S2 for more details).

It is interesting to note that I only find robust and statistically significant evidence that irrigation cover reduces the impacts of changes in the intra-seasonal variability of precipitation, and not the impacts of changes in *total* precipitation. Previous statistical estimates

Table 1 (Log) Rice yields

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Precipitation (10 mm)	0.11*** (0.03)	0.18*** (0.06)	0.22 (0.18)	0.33 (0.21)	0.15*** (0.05)	0.17 (0.11)	0.15*** (0.04)	0.25*** (0.06)
Degree days (Monsoon)	- 0.11*** (0.03)	- 0.09*** (0.03)	- 0.05 (0.04)	- 0.06 (0.05)	- 0.10*** (0.03)	- 0.06 (0.05)	- 0.12*** (0.03)	- 0.08** (0.03)
Rainy days	0.78*** (0.14)	1.36*** (0.28)	1.19** (0.51)	0.59 (0.50)	1.35*** (0.23)	1.26*** (0.28)	0.88*** (0.17)	1.40*** (0.23)
Precipitation X Irrigation		-0.08 (0.08)	0.06 (0.10)	0.05 (0.10)	-0.11 (0.08)	0.00 (0.10)		-0.28*** (0.09)
Degree days X Irrigation		- 0.04* (0.02)	- 0.02 (0.02)	- 0.02 (0.02)	- 0.01 (0.04)	- 0.01 (0.04)		- 0.08* (0.04)
Rainy days X Irrigation		- 0.96*** (0.27)	- 0.80*** (0.25)	- 0.66*** (0.22)	- 1.01*** (0.24)	- 1.10*** (0.25)		- 1.09*** (0.26)
Observations	6432	4124	4124	4124	6046	6046	4285	4285
Adjusted R ²	0.752	0.754	0.781	0.798	0.757	0.775	0.743	0.750
Rainy days (full irrigation)		0.40			0.34			0.31
P value		0.01			0.01			0.08

Dependent variable: the logarithm of rice yield in units of 0.01. Each column represent a separate regression model. Standard errors are displayed in parentheses and are robust to heteroskedasticity and arbitrary correlation within the same state in a given year. Stars indicate statistical significance: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. All models include district fixed effects and state specific quadratic time trends. Column 1 reports estimates of the basic model, Eq. 1. Column 2 reports estimates from a model which includes interaction of all weather variables with the contemporaneous extent of irrigation cover, Eq. 2. Column 3 reports parallel estimates from a model which also includes interactions of all weather variables with state specific intercepts and linear time trends, as in Eq. 3. Column 4 reports parallel estimates except that the model includes fixed effects for a combination of state and decade, as in Eq. 4. Column 5 reports estimates obtained from a model like that reported in column 2, except that the long-term mean of irrigation cover in each district is used instead of the contemporaneous extent of irrigation cover. Column 6 reports parallel estimates, except that the model also includes interactions of all weather variables with state specific fixed effects. Columns 7 and 8 report similar estimates to those reported in columns 5 and 6 except that the sample is restricted to districts in which rice is only grown in the rainy season. The two bottom rows of the table report, for columns 2, 6 and 8, the point estimate and the P value of the impact of rainy days on yields in fully irrigated locations, defined as the sum of the coefficients of the un-interacted effect of rainy days (which captures the effect in entirely un-irrigated locations) and the interaction of rainy days with irrigation cover

of Indian agricultural data did find evidence that irrigation reduces the impacts of total precipitation on agricultural production (Duflo and Pande 2007; Taraz 2017), but they did not control for intra-seasonal variability. When I only include total precipitation in the regressions, I find similar results to these studies, but once I control for intra-seasonal variability, the interaction estimates between total precipitation and irrigation cover become smaller,

statistically insignificant and less robust. This disparity can be understood to reflect the particular effectiveness of irrigation in compensating for intra-seasonal variability in rainfall, more than for shortages in the overall amount of rainfall, since irrigation itself relies on water resources whose recharge also often depends on total rainfall amounts. Similarly, I do not find evidence that irrigation reduces the negative impacts of heat exposure. This, too, is broadly consistent with simple phenological considerations, since the impacts of high temperatures on crop growth are not limited to increased evapo-transpirative water demands, and several studies have observed strong temperature effects on irrigated rice crops in Asia (Peng et al. 2004; Welch et al. 2010; Nelson et al. 2009).

The statistically significant negative sign of the estimated interaction term between precipitation variability and irrigation cover indicates that the negative impacts of rainfall variability are lower in more highly irrigated districts. However, it does not necessarily imply a causal relationship, strictly speaking, since in principle, other, unobserved factors correlated with irrigation might be responsible for the reduced impact. While I am unable to fully account for this possibility, I subject the regression results to a range of robustness tests that include separating the effects of irrigation from any potential confounders operating at the state level in increasingly demanding specifications (see the methods section for details), at which most water and irrigation related policies are determined (including, for example, water tariffs and subsidies on power used for irrigation). Estimates of the interaction term of interest remain stable and statistically significant across this range of alternative model specifications, reported in columns 2–8 of Table 1 and depicted in Fig. 1 using lines of different colors. While I avoid making causal claims, I assume these estimates to be illustrative of the impact of irrigation on the sensitivity of yields to increased variability, and make use of them in the projections that follow.

Simulation of climate change impacts Figure 2 depicts simulated future irrigation cover in each of the five groundwater-irrigation scenarios and the associated projected losses in rice production in 2050.

In the first scenario, irrigation cover remains at its current levels indefinitely. In this scenario, the negative effect of the decrease in the number of rainy days on 2050 rice yields is estimated at -11% , large enough to offset a small positive gain (2%) resulting from the increase in total precipitation, and result in a net 10% decline in rice yields (Fishman 2016) (this effect is independent of and additional to the impact of increasing temperatures).

The first scenario fails to account for the possibility of adapting through the expansion of irrigation. As I found above, the impact of variability in irrigated areas is much lower than in non-irrigated areas, suggesting that an expansion of irrigation could substantially reduce the resulting climate change impact in 2050. In the second scenario, I allow irrigation to expand so as to cover all area cropped with rice, and estimate that such an expansion would reduce the impact of changing precipitation patterns by about a half (from 10% loss to 6%).

Given current limitations on India's water resources, however, neither current irrigation cover nor a full expansion are sustainable using current irrigation practices. While more than half of India's irrigated area is irrigated by groundwater, unsustainable over-exploitation (relative to natural recharge) and falling water tables are already pervasive (Shah 2008; Rodell et al. 2009; Fishman et al. 2011).

The third scenario I consider is a scenario of *sustainable expansion*, in which groundwater usage is everywhere brought to levels of natural recharge. This involves an expansion of groundwater irrigation in areas where resources are not fully utilized, and a shrinking of the area irrigated by groundwater in locations in which they are fully utilized or over-extracted. In this scenario, the impact of climate change is little changed, and turns out to be reduced

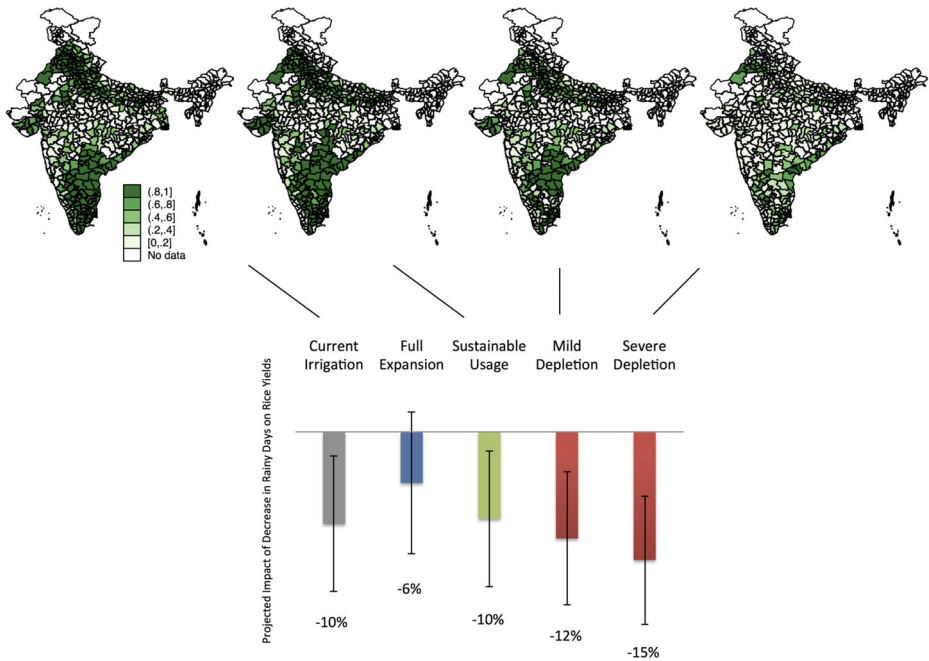


Fig. 2 Simulation of Climate Change impacts on rice yields in India resulting from the decrease in the number of rainy days at 2050 in various scenarios for future irrigation cover. The top panel depicts maps of projected irrigation cover (share of cultivated area which is irrigated) in each the scenarios: current coverage, sustainable expansion, mild and severe depletion (see text for definitions). The bottom panel plots the resulting projected losses in rice production in each of the scenarios (as well as in a scenario of full irrigation expansion). Error bars indicate changes resulting from using coefficient estimates for the impact of the rainfall variable which are higher or lower by one standard deviation from their mean values

by less than a tenth (from 11 to 10%). This reduction is mostly a result of the fact that both the associated increases and declines in production losses are modest and tend to offset one another.

I next calculate climate change impacts in two scenario of “business as usual” in which groundwater resources are exhausted in areas in which they are currently being unsustainably depleted (“mild” depletion) or everywhere (“severe” depletion). Climate change impacts in these scenarios are found to be larger (worse) by a factor of about 1.2 (12%) and 1.5 (15%), respectively, as compared to the benchmark scenario (which ignores water resources limitations).

Using estimates from the alternative regression specifications discussed above leads to results that are broadly similar in pattern (see Fig. S2).

4 Conclusions

Increasing rainfall variability is projected to have large negative impacts on crop production in the semi-arid tropics. The expansion of irrigation, a primary adaptation strategy, is shown here to have a large theoretical potential to reduce future climate change impacts, but a much more limited scope for mitigating this impact if physical constraints on future groundwater

availability are taken into account. Continuing the current un-sustainable use of groundwater in much of India is likely to lead to a shrinking of irrigation in over-exploited areas by the time climate change impacts manifest, and my estimates show that if this results in a decline in irrigation cover, climate change impacts will be substantially amplified in comparison to those estimated on the basis of current irrigation cover. On the other hand, the maximal sustainable use of groundwater, which involves shrinking irrigation cover in some areas and expanding it in others, is shown to have little potential to reduce climate change impacts (but also to avoid enlarging them). These findings demonstrate an additional pathway through which growing water scarcity will impact future crop yields, above and beyond its direct impacts on agriculture or on water resources (Tilman et al. 2002; Gleick 2000; Elliott et al. 2014).

Agricultural systems are increasingly exposed to multiple environmental stresses (Godfray et al. 2010). Acting together, such stresses can interact in unexpected ways, resulting in losses that exceed the linear total of their separate impacts. For example, the North American “Dust Bowl” exemplifies how one form of stress (intensive land use) can exacerbate a system’s susceptibility to another (drought) (Worster 1982; Cook et al. 2009). This paper demonstrates another important example of such a coupling. It is shown how the depletion of groundwater resources constrains the capacity of India’s agriculture to adapt to increasing precipitation variability. Thus, in this case, the degradation of a natural resource reduces a system’s capacity to *adapt* to environmental change.

The approach used in this paper is limited in several ways. First, like other statistical models, it is unable to account for the fertilisation impact of higher CO_2 concentrations on crop yields, which may also depend on irrigation. Second, it does not attempt to account for adaptations other than the expansion of irrigation. For example, my model assumes rice cropped areas will remain unchanged. Lower availability of irrigation water may also lead to reductions in rice cultivation. Since the areas most dependent on groundwater irrigation tend to have higher productivity, such reductions are likely to further decrease nationally averaged rice yields, meaning my estimates are conservative. On the other hand, shifts to less water intensive crops may potentially help buffer overall productivity (across the entire crop mix) from losses in rice yields. My model also does not currently account for possible shifts in irrigation practices (Gleick 2003; Fishman et al. 2015). Third, the irrigation scenarios considered here are simplistic and are only meant to highlight the importance of accounting for physical constraints on adaptation. Future studies should also take into account the direct impacts of climate change on water supplies, such as the direct impacts of precipitation shifts on groundwater recharge, and those of Himalayan glacial and snow melt on downstream river flow and surface irrigation (Shukla 2003; Immerzeel et al. 2010).

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