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"Groundwater Depletion, Climate Variability and Agricultural Income in Western Uttar Pradesh: An Empirical Research Framework with a Regional Focus on Meerut and Neighboring Districts"

Dr. Salabh Mehrotra

Associate Professor NICE School of Business Studies- Shobhit university Meerut

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ABSTRACT

Western Uttar Pradesh combines high-value irrigated agriculture with a falling water table and a more variable climate, and this paper builds and demonstrates a framework to measure what that costs farmers. It studies Meerut and seven neighbouring districts (Baghpat, Muzaffarnagar, Shamli, Saharanpur, Ghaziabad, Hapur and Bulandshahr) using a block-level panel (16 blocks, 2010-2023) and a household survey (608 farm households). Four models are estimated: a two-way fixed-effects panel, a household Ricardian-type model, an instrumental-variable specification and a threshold model. On the simulated data used here to illustrate the framework, each additional metre of depth to water is associated with a 3.8-4.5 percent fall in net farm income per hectare in the panel and 4.9 percent in the household model; heat-stress days reduce income by about 1.1-1.2 percent each; and the penalty from depth is larger in drought years (an extra 1 percent per metre for every 10-point rainfall deficit). No significant threshold depth or farm-size gradient is detected, and irrigation cost does not statistically mediate the depth effect. Stressed blocks, where water tables fall 0.43 m a year against 0.17 m in safe blocks, earn about 13 percent less than safe blocks and spend about 15 percent more on irrigation. The paper concludes with policy implications for crop diversification, micro-irrigation, energy pricing and aquifer governance. All numerical results are simulated and must be replaced with real estimates before use.

Keywords: groundwater depletion; climate variability; farm income; Western Uttar Pradesh; Meerut; panel data; Ricardian model; sugarcane; paddy

JEL codes: Q25, Q54, Q15, Q12, O13

INTRODUCTION

India is the world's largest groundwater user, and irrigated agriculture accounts for the bulk of extraction. The Indo-Gangetic plains hold large alluvial aquifers, yet in their north-western parts extraction has for decades exceeded natural recharge. Western Uttar Pradesh sits at the eastern edge of this stressed belt. Its farmers combine canal water (notably the Upper Ganga Canal and Eastern Yamuna Canal systems) with millions of electric and diesel pumps, and the region's economy is anchored by sugarcane, wheat and paddy, with a significant dairy and agro-processing sector.

Two features make W-UP an important empirical setting. First, it is a region of *relative abundance turning into relative scarcity*: water tables were historically shallow, so the transition to deep and falling tables is recent and visible within the memory of living farmers. Second, the region's income base is concentrated in crops that are both profitable under assured irrigation and highly sensitive to water and heat stress. Climate variability, understood as the dispersion and timing of rainfall and temperature rather than just their mean, interacts with groundwater: in a poor monsoon farmers pump more, which lowers water tables, which raises pumping costs in subsequent seasons. This feedback loop means that the effects of depletion and climate variability on income cannot be studied in isolation.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

Problem statement

Existing work on Indian agriculture and climate tends to treat irrigation as a fixed control, while hydrogeological studies tend to measure water-table decline without linking it to farm economics. There is little district- and block-level evidence from W-UP that estimates, within a single framework, the income consequences of groundwater decline, climate variability and their interaction.

Research questions

1. How has groundwater availability (depth to water level, stage of extraction) evolved across Meerut and neighbouring districts, and where is stress concentrated?
2. How has climate variability (rainfall deviation, dry spells, heat stress) changed over the study period?
3. What is the effect of groundwater depletion on net farm income, holding climate and other factors constant?
4. Does climate variability amplify the income effect of depletion (an interaction effect)?
5. Which farm types and practices (small versus large holdings, sugarcane versus diversified systems, micro-irrigation adopters) are more or less resilient?

Objectives

- To map and describe spatio-temporal trends in groundwater levels and extraction stage.
- To construct indicators of climate variability from long-run gridded data.
- To estimate the elasticity of farm income with respect to groundwater depth and climate variability.
- To identify threshold depths beyond which pumping costs erode profitability.
- To recommend region-specific adaptation and governance measures.

Contribution

The paper contributes (a) a combined hydro-climatic-economic dataset design for W-UP, (b) an explicit treatment of the endogeneity of groundwater use, (c) a test for non-linear and threshold effects of water-table depth on income, and (d) heterogeneity analysis by farm size and crop system.

Study Area

The study region lies in the upper Ganga-Yamuna doab. Meerut is the focal district; the comparison set includes Baghpat, Muzaffarnagar, Shamli, Saharanpur, Ghaziabad, Hapur and Bulandshahr, selected because they share agro-climatic zone (sub-humid, Western Plain), alluvial aquifer characteristics and sugarcane-wheat-paddy cropping systems, while differing in canal access, urbanisation pressure and industrial water demand.

Key contextual features that the empirical design must account for:

- **Aquifer setting:** unconsolidated alluvium with multi-layered sand and clay; shallow unconfined aquifer used by most farm tubewells, with deeper confined layers tapped for urban and industrial supply.
- **Surface water:** canal commands vary across districts, so canal-fed and tubewell-dependent blocks differ in vulnerability.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

- **Cropping system:** kharif paddy and sugarcane; rabi wheat, potato and mustard in some pockets; strong sugar-mill procurement linkages.
- **Urban-industrial pressure:** the Delhi-NCR fringe (Ghaziabad, parts of Meerut and Hapur) competes for groundwater and converts farmland.
- **Energy:** a large share of tubewells run on electricity, with farm power tariffs and supply schedules shaping pumping behaviour.

LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

Groundwater and agricultural productivity

Studies of Indian groundwater economics show that private tubewell expansion raised productivity and incomes after the Green Revolution, but that open-access extraction creates a classic common-pool externality: each farmer's pumping lowers the water table for all. Falling tables raise lift costs, increase energy consumption, force well deepening, and eventually exclude poorer farmers who cannot afford deeper wells. Evidence from Punjab, Haryana and parts of Rajasthan and Gujarat documents these dynamics, while satellite gravimetry studies (such as those based on GRACE) have flagged north-west India as a major depletion hotspot.

Climate and Agriculture: The Ricardian Tradition

The Ricardian approach, introduced by Mendelsohn, Nordhaus and Shaw, regresses land value or farm net revenue on climate variables, implicitly capturing farmers' adaptation. Indian applications (for example Kumar and Parikh, and subsequent district-level studies) generally find that higher temperatures reduce net revenue while the effect of rainfall depends on irrigation access. Later work (Schlenker, Hanemann, Fisher; Auffhammer and others) stresses the importance of weather-variation identification with fixed effects and warns about omitted-variable bias in cross-sections.

Variability Versus Mean Climate

Farm incomes respond not only to changes in average climate but to its volatility. Rainfall deficits during critical stages (transplanting of paddy, tillering and grand growth of sugarcane), extreme heat during wheat grain filling, and unseasonal rain all produce income shocks. Irrigation acts as insurance, so depletion of groundwater erodes the buffer against climate shocks. This motivates the interaction hypothesis.

Conceptual framework

The framework links five blocks:

1. **Climate drivers** (rainfall deficit, rainfall coefficient of variation, dry-spell length, heat-stress days) reduce natural recharge and raise crop water demand.
2. **Groundwater state** (depth to water level, stage of extraction, well failure) responds to recharge and to pumping.
3. **Farm adaptation** (crop choice, pump deepening, micro-irrigation, canal use, laser levelling) mediates the effect.
4. **Production and cost outcomes** (yield, irrigation cost, energy use) determine **net farm income**.
5. **Institutional context** (power tariffs, canal management, sugarcane pricing, credit and insurance access) conditions all links.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

A feedback arrow runs from low income and climate shocks back to increased pumping, closing the loop.

Hypotheses

- **H1:** Greater depth to water level has a negative effect on net farm income per hectare, operating mainly through higher irrigation cost.
- **H2:** Higher rainfall variability and more heat-stress days reduce net farm income.
- **H3 (interaction):** The negative effect of climate variability on income is larger in blocks with deeper or faster-declining water tables.
- **H4 (non-linearity):** The income effect of depth is convex; beyond a threshold depth, losses rise sharply.
- **H5 (heterogeneity):** Small and marginal farmers and sugarcane-intensive households are more adversely affected than diversified or micro-irrigation-adopting households.

METHODOLOGY

Research Design

The study uses a mixed-methods design: a quantitative secondary-data panel at the district and block level, a primary household survey, and a short qualitative component (focus group discussions and key informant interviews with farmers, tubewell operators, mill officials and irrigation department staff) to interpret mechanisms.

Period of Study

The recommended window is 2000-2023 for climate and groundwater trends (long enough to separate trend from variability) and 2010-2023 for the economic panel, subject to availability of consistent agricultural statistics. Primary survey data refer to the most recent complete agricultural year.

Sampling for the Primary Survey

A multistage stratified design is proposed:

1. **Districts:** Meerut (focal) plus the seven neighbouring districts listed above.
2. **Blocks:** two blocks per district, one classified as over-exploited or critical and one as safe or semi-critical according to the latest CGWB/State assessment, giving 16 blocks.
3. **Villages:** two villages per block (32 villages).
4. **Households:** about 18-19 farm households per village, stratified by operational holding size (marginal below 1 ha, small 1-2 ha, medium and large above 2 ha), giving approximately 600 households.

Sample size can be checked with the standard formula $n = (Z^2 \cdot \sigma^2) / E^2$, adjusted by a design effect of roughly 1.5-2 for clustering. The final sample should be justified using pilot-survey variance of net income.

Variables and Measurement

Variable	Definition	Likely source
Net farm income (NFI)	Gross value of output minus paid-out costs (and optionally imputed family labour), per ha and per household	Household survey; district statistics
Depth to water	Mean pre-monsoon and post-monsoon depth in metres	CGWB / India-WRIS well

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

level (DTWL)	below ground level	network
Water-table trend	Slope of annual DTWL, metres per year	Computed
Stage of extraction	Ratio of annual extraction to net annual recharge (%)	Dynamic Ground Water Resources Assessment
Rainfall deviation	Seasonal rainfall minus long-term mean, as a percentage	IMD gridded data
Rainfall coefficient of variation	CV of rolling 10-year seasonal rainfall	IMD
Dry spells	Longest run of days below 2.5 mm rainfall in the monsoon	IMD daily data
Heat-stress days	Days with maximum temperature above crop-specific thresholds (for example 35 degrees C during wheat grain filling)	IMD
SPEI / SPI	Standardised drought indices	Computed from IMD data
Irrigation cost	Energy, diesel, pump repair, well deepening annualised	Household survey
Canal access	Share of area canal-irrigated	Land-use statistics
Crop pattern	Area shares of paddy, sugarcane, wheat, others; Herfindahl diversification index	Agricultural statistics
Controls	Fertiliser use, literacy, holding size, tenancy, credit, market distance, power supply hours	Survey / Census / statistical abstracts

Construction of Climate Variability Indicators

Using daily gridded rainfall (0.25 degree) and temperature (1 degree) data aggregated to district or block centroids:

- Compute seasonal means (kharif: June-October; rabi: November-March).
- Compute interannual CV, standardised anomalies, number of deficient-rainfall years (below 80 percent of normal) and extreme-event counts.
- Compute SPEI at 3- and 6-month scales.
- Test for trend with the Mann-Kendall test and estimate magnitude using Sen's slope; test for breakpoints with Pettitt's test.

Groundwater Analysis

- Interpolate well-level data to block averages using kriging or inverse-distance weighting, with well-count weights.
- Compute pre- and post-monsoon levels and the seasonal fluctuation (recharge proxy).
- Classify blocks by CGWB category (safe, semi-critical, critical, over-exploited) and map change over successive assessments.
- Use Mann-Kendall and Sen's slope for trend significance.

Econometric Models

Model 1: Two-way fixed-effects panel (district or block level)

$$\ln(NFI_{it}) = a + b1 \cdot DTWL_{it} + b2 \cdot ClimVar_{it} + b3 \cdot (DTWL_{it} \times ClimVar_{it})$$
$$+ b4 \cdot Canal_{it} + b5 \cdot X_{it} + \mu_i + \tau_t + e_{it}$$

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

where *i* indexes blocks or districts, *t* years, μ_i are unit fixed effects absorbing time-invariant geology, soils and culture, and τ_t are year effects absorbing national price and policy shocks. The hypotheses map as follows: H1 is b1 < 0; H2 is b2 < 0; H3 is b3 < 0. Standard errors are clustered at the district level (with wild-cluster bootstrap given the small number of clusters).

Model 2: Household Ricardian-type model

$$\ln(NFI_h) = g0 + g1 \cdot DTWL_v + g2 \cdot ClimMean_d + g3 \cdot ClimVar_d + g4 \cdot Irrig_h + g5 \cdot Z_h + \theta_b + u_h$$

where *h* is a household, *v* village, *d* district and θ_b block fixed effects. The model includes quadratic terms in temperature and rainfall to capture non-linear climate response. Because household data are cross-sectional, climate effects are identified from within-block variation and should be interpreted cautiously; Model 1 provides the panel-based check.

Model 3: Threshold (non-linear) model

$$\ln(NFI_it) = a + d1 \cdot DTWL_it \cdot 1(DTWL_it \le \gamma) + d2 \cdot DTWL_it \cdot 1(DTWL_it > \gamma) + controls + \mu_i + \tau_t + e_it$$

The threshold γ is estimated using Hansen's panel threshold regression, with bootstrap p-values for the null of no threshold. H4 is supported if |d2| > |d1| and the threshold is statistically significant. A simpler alternative is a quadratic specification in DTWL.

Model 4: Mechanism (mediation) analysis

Irrigation cost and yield are examined as mediators in a stepwise approach: first regress cost and yield on DTWL and climate variables; then add them to the income regression and examine how b1 changes.

Model 5: Heterogeneity

Interact DTWL and climate variability with farm-size class, sugarcane share, and a micro-irrigation-adoption dummy; alternatively use quantile regression to see whether effects are larger in the lower tail of the income distribution.

Endogeneity and Identification

Groundwater depth is not exogenous: richer or higher-yield areas pump more, and income can affect pumping. Three responses are proposed.

1. **Fixed effects and lags:** use lagged DTWL and unit fixed effects to reduce simultaneity and remove time-invariant confounders.

2. **Instrumental variables:** instrument current DTWL with (a) lagged monsoon rainfall deficit (a recharge shifter affecting income only through water availability and, separately, controlled direct rainfall effects), (b) distance to the nearest canal or river, or (c) hydrogeological variables such as aquifer transmissivity or specific yield. Instrument validity is discussed explicitly because rainfall can affect income directly; hence a combination of recharge-oriented instruments (lagged multi-year rainfall) and geological instruments is preferred, with overidentification (Hansen J) and weak-instrument (Kleibergen-Paap F) tests reported.

3. **Spatial spillovers:** because aquifers cross administrative lines, include a spatial lag or spatial-error term and test with Moran's I; estimate a spatial Durbin model as a robustness check.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

Diagnostics and Robustness

- Unit-root tests (Im-Pesaran-Shin, Levin-Lin-Chu) and cointegration tests (Pedroni, Kao) where long panels are used.
- Hausman test for fixed versus random effects; Wooldridge test for serial correlation; modified Wald test for heteroskedasticity; Pesaran CD test for cross-sectional dependence, with Driscoll-Kraay standard errors if needed.
- Variance inflation factors for multicollinearity (rainfall and SPEI are likely correlated, so they are entered separately).
- Alternative income definitions (with and without imputed family labour), alternative climate measures, exclusion of Ghaziabad (urban-fringe outlier), and leave-one-district-out estimation.
- Real-income deflation using appropriate agricultural price indices, and sensitivity to sugarcane State Advised Price changes.
- Placebo tests, for example regressing income on future (not current) groundwater depth.

Qualitative Component

Two focus group discussions per district (one with sugarcane-dominant, one with diversified farmers) and key informant interviews are analysed thematically, focusing on well deepening decisions, borrowing, crop switching, perceptions of rainfall change, and awareness of schemes. These are triangulated with econometric findings.

5. Data Sources and Management

Data	Institution	Notes
Groundwater levels (wells, pre/post-monsoon)	Central Ground Water Board; India-WRIS portal	Check well-network continuity and station changes
Groundwater resource assessment (extraction stage, block categories)	CGWB with State Ground Water Department	Periodic assessments; harmonise methodology changes
Rainfall (0.25 degree gridded, daily)	India Meteorological Department	Aggregate to block or district
Temperature (1 degree gridded, daily)	India Meteorological Department	Coarse resolution; note measurement error
Crop area, production, yield	Directorate of Economics and Statistics, UP; Agricultural Statistics at a Glance	District level
Cost of cultivation	Comprehensive Scheme for Studying Cost of Cultivation of Principal Crops	State-level benchmarks
Farm household income	NSS Situation Assessment Survey of Agricultural Households	Benchmark for primary survey
Land use, irrigation sources	District Statistical Handbooks; Agricultural Census	Canal versus tubewell shares
Energy	UP power utilities, Rural Electrification Corporation data	Tubewell connections, supply hours, tariff
Satellite proxies	GRACE/GRACE-FO terrestrial water storage; NDVI from MODIS	Cross-validation and yield proxy
Primary data	Household survey and FGDs	Own collection

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

Data management: build a district-and-block crosswalk because administrative boundaries have changed (for example the creation of Shamli and Hapur districts), and harmonise to constant boundaries. Document all imputation, and archive code and cleaned data for replication.

Results and Analysis (Simulated Data)

On the simulated data, groundwater depth is the strongest and most robust correlate of lower farm income, and it hurts more in dry years. Everything in this section was produced by running the models of Section 4 on a synthetic dataset; Appendix C describes how the data were generated, so the exercise can be reproduced and then repeated with real data.

Data used

Dataset	Structure	Size
Block panel	8 districts x 2 blocks (one stressed, one safe) x 14 years (2010-2023)	224 block-years
Household survey	16 blocks x 2 villages x 19 households	608 households

The panel dependent variable is the log of net farm income per hectare in constant 2010-11 prices. The household variable is net farm income per hectare in current rupees, so levels are not comparable across the two datasets, but proportional effects are.

Descriptive Statistics and Trends

Depth to water averages 16.4 m across the panel and varies widely, from 9.4 m to 27.2 m.

Variable (block panel)	Mean	Std. dev.	Min	Max
Depth to water level (m)	16.38	3.90	9.39	27.21
Rainfall deviation from normal (%)	-0.47	15.91	-49.58	34.27
Heat-stress days per season	10.61	3.24	2.61	20.25
Rainfall coefficient of variation (%)	21.96	2.58	15.09	28.10
Canal-irrigated area share	0.39	0.08	0.20	0.55
Log net farm income per ha	10.01	0.16	9.48	10.43

Across districts, mean depth over 2010-2023 ranges from 13.4 m in Saharanpur to 22.9 m in Ghaziabad, with Meerut at 16.7 m and Hapur at 18.3 m.

Water tables are falling in every block, but at very different speeds: stressed blocks lose 0.43 m a year on average against 0.17 m in safe blocks. Mann-Kendall tests on regional annual means confirm significant upward trends in depth ($Z = 4.93$, $p < 0.001$, Sen's slope 0.31 m a year), heat-stress days ($Z = 2.96$, $p = 0.003$, 0.25 days a year) and rainfall variability ($Z = 2.85$, $p = 0.004$, 0.32 percentage points a year). Mean rainfall deviation shows no trend ($Z = 0.77$, $p = 0.44$), so climate change in this dataset operates through heat and variability rather than a drying mean.

Panel Results (Model 1)

Once block and year effects are controlled, one extra metre of depth to water cuts net farm income per hectare by about 3.8 to 4.0 percent.

Dependent variable: ln net farm income per ha	(1) Pooled OLS	(2) Two-way FE	(3) FE with interaction
Depth to water (m)	-0.0101 (0.0096)	-0.0397*** (0.0080)	-0.0379*** (0.0050)
Rainfall deviation (%)	0.0043*** (0.0005)	0.0047*** (0.0007)	0.0038*** (0.0007)
Heat-stress days	-0.0090**	-0.0113***	-0.0119*** (0.0012)

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

	(0.0032)	(0.0013)	
Canal share	0.5154 (0.4082)	0.4224*** (0.0923)	0.5157*** (0.1108)
Rainfall deficit (% below normal)			-0.0002 (0.0009)
Depth (centred at 14 m) x deficit			-0.0010*** (<0.0001)
Block and year fixed effects	No	Yes	Yes
R-squared	0.392	0.868	0.914
Observations	224	224	224

Standard errors clustered by district in parentheses; * p<0.10, ** p<0.05, *** p<0.01. With only eight clusters, wild-cluster bootstrap p-values should be added for real data.

Three points stand out. First, pooled OLS badly understates the depth effect (-0.010 and insignificant) because deep-water blocks are also the more productive, better-connected ones; fixed effects remove that confounding and the coefficient quadruples. Second, rainfall helps (0.4 to 0.5 percent per percentage point of rainfall above normal) and heat hurts (about 1.1 to 1.2 percent per heat-stress day). Third, the rainfall coefficient on its own does not capture drought damage that depends on groundwater, which is the interaction below.

Depth and drought interact (Hypothesis H3)

Deep water tables make drought years much more costly. In column (3) the penalty from depth rises by 0.10 percentage points for every metre beyond 14 m and every point of rainfall deficit. At a 20 percent deficit, one extra metre of depth then lowers income by about 5.8 percent (3.8 plus 20 x 0.10 -> roughly 5.8), against 3.8 percent in a normal year. A block 5 m deeper than 14 m facing the same deficit loses about 10 points more income than a shallow block. This is the simulated version of the claim that groundwater works as insurance, and the insurance thins as the table falls.

Using a rainfall-variability measure (the coefficient of variation) in place of the deficit variable gives a depth coefficient of -0.0378 ($p < 0.01$) and a small, insignificant variability effect of -0.0031 ($p = 0.28$), so in this dataset it is the interaction of specific deficit years with depth, not long-run variability alone, that carries the damage.

Endogeneity checks (Hypothesis H1 robustness)

The depth effect survives lags and instrumenting, and the instrumented estimate is slightly larger. Using depth lagged one year, the coefficient is -0.0269 (se 0.0074, $p < 0.01$, $N = 208$), smaller but still clearly negative. For two-stage least squares, depth is instrumented with the mean rainfall deviation of the previous three years (a recharge shifter) and with a stressed-block time trend.

Statistic	**Value**
First-stage coefficient, 3-year lagged rainfall	0.0149 ($p = 0.052$)
First-stage coefficient, stressed-block trend	0.2513 ($p < 0.001$)
F-statistic on excluded instruments (conventional)	184.5
2SLS coefficient on depth	-0.0449 (se 0.0060)
Sargan overidentification test	$J = 1.29$, $p = 0.26$

The 2SLS estimate (-4.5 percent per metre) is close to the fixed-effects estimate (-4.0 percent), which suggests simultaneity bias is modest here, and the Sargan test does not reject the instruments. Two cautions apply. The F-statistic is conventional rather than cluster-robust, and the stressed-block trend is a strong instrument by construction in synthetic data; with real data its exclusion restriction (the trend affects income only through depth) would need a convincing argument, and geological variables such as aquifer transmissivity would be preferable.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

Is there a threshold depth? (Hypothesis H4)

No statistically significant threshold is found, so the income loss per metre does not accelerate at a critical depth. The best-fitting break is at 15.5 m, with a slope of -0.0613 below it and -0.0397 above it (116 of 224 block-years lie above the break). The sup-F statistic is 4.50 with a residual-bootstrap p-value of 0.24 (99 replications). The slope is if anything steeper at shallower depths, the opposite of the convex pattern predicted, and the null of a single linear slope is not rejected. In the simulation, then, the case for "depth tipping points" is not supported, and any threshold in real data would need to be shown, not assumed.

Heterogeneity across block types (Hypothesis H5, panel)

Per-metre damage is similar in stressed and safe blocks, but stressed blocks are exposed to far more depth change.

Subsample (two-way FE)	Depth	Rainfall deviation	Heat days	Canal share
Safe blocks (8 blocks)	-0.0770** (0.0315)	0.0042*** (0.0010)	-0.0082** (0.0032)	0.1888 (0.1034)
Stressed blocks (8 blocks)	-0.0756*** (0.0117)	0.0061*** (0.0009)	-0.0109*** (0.0014)	0.6602* (0.3112)

The two depth coefficients are almost identical, so vulnerability per metre does not differ; the income gap between block types arises because stressed blocks sink 2.5 times faster (0.43 against 0.17 m a year). Canal access is worth far more in stressed blocks (about 0.66 in log income per unit share against 0.19), consistent with canal water substituting for scarce groundwater. Subsample depth coefficients (about -0.076) are larger than the pooled -0.04 because year effects are estimated separately in each group, absorbing group-specific trends, so the subsample figures are best read comparatively rather than as levels.

6.8 Household survey results (Models 2, 4 and 5)

Farmers in stressed blocks earn about 13 percent less per hectare and pay about 15 percent more for irrigation than farmers in safe blocks.

Group	Households	Mean net income (Rs/ha)	Mean irrigation cost (Rs/ha)	Mean depth (m)
Safe blocks	304	69,556	9,672	14.3
Stressed blocks	304	60,516	11,159	17.2
Marginal farms (< 1 ha)	216	60,641	10,507	15.6
Small farms (1-2 ha)	223	64,699	10,599	15.8
Medium and large farms (> 2 ha)	169	71,098	10,058	15.8
All households	608	65,036	10,416	15.8

Micro-irrigation adoption rises with farm size, from 6 percent of marginal farms to 14 percent of small and 28 percent of medium and large farms. Marginal farms make up 36 percent of the sample but 48 percent of the lowest-income quarter of households (73 of 152), against 14 percent for medium and large farms.

Ricardian-type income model (Model 2)

ln net income per ha	(1) Base	(2) Cane interaction	(3) Farm-size interaction
Depth to water (m)	-0.0489** (0.0119)	-0.0652** (0.0194)	-0.0437 (0.0249)
Sugarcane area share	-0.0628 (0.0458)	-0.1341 (0.0744)	-0.0598 (0.0513)
Cane share x (depth - 14 m)		0.0412 (0.0401)	
Marginal farm x (depth - 14 m)			-0.0349 (0.0246)
Small farm x (depth - 14 m)			0.0134 (0.0219)

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

Micro-irrigation adopter	0.0659 (0.0593)	0.0625 (0.0618)	0.0631 (0.0574)
ln farm size (ha)	0.0992*** (0.0232)	0.0993*** (0.0231)	0.1292 (0.0741)
Years of schooling	0.0086** (0.0026)	0.0084** (0.0026)	0.0081** (0.0026)
Canal access (0/1)	0.1442*** (0.0277)	0.1449*** (0.0275)	0.1458*** (0.0268)
Block fixed effects	Yes	Yes	Yes
R-squared	0.182	0.183	0.193

Observations 608; standard errors clustered by district.

The household model gives a depth effect of about -4.9 percent per metre (-6.5 percent when the cane interaction is included), close to the panel estimates. At the sample mean of Rs 65,036 per hectare, one metre of extra depth is worth roughly Rs 3,200 a year. A farmer in a stressed block, sitting about 2.9 m deeper than one in a safe block, therefore loses on the order of 13 to 14 percent, matching the raw gap. Canal access adds about 15 percent, schooling about 0.9 percent a year, and larger farms earn more per hectare (elasticity 0.10).

Heterogeneity and Mechanism

- Sugarcane: the cane share has a negative, imprecise coefficient and its interaction with depth is not significant (0.0412, $p = 0.34$), so the simulated data do not show cane-intensive farms suffering more per metre.
- Farm size: implied depth slopes are -7.9 percent per metre for marginal farms, -4.4 for medium and large and -3.0 for small, but none of the differences is significant (marginal x depth $p = 0.20$).
- Micro-irrigation: adopters cut irrigation cost by about 22 percent (coefficient -0.2438, $p < 0.01$) but the direct income gain (6.6 percent) is not statistically distinguishable from zero.
- Mechanism: each extra metre of depth raises irrigation cost by 4.2 percent ($p < 0.01$). However, adding log irrigation cost to the income equation leaves the depth coefficient unchanged (-0.0490 against -0.0489) and the cost term insignificant (-0.0471, $p = 0.47$), so measured pumping cost does not statistically explain the income loss; other channels such as yield stress or crop switching must be carrying it.

Summary of Hypothesis Tests

Three of five hypotheses are supported on the simulated data, one is not, and one is only suggested by the point estimates.

Hypothesis	Verdict	Key evidence
H1: depth lowers net farm income	Supported	-3.8 to -4.5% per metre (panel FE, IV); -4.9% (household)
H2: climate variability lowers income	Largely supported	Heat days -1.1 to -1.2% each; rainfall deficit hurts; rainfall CV not significant ($p = 0.28$)
H3: variability effect larger where depth is greater	Supported	Interaction -0.0010, $p < 0.01$; about 5.8% loss per metre at a 20% deficit
H4: convex threshold effect of depth	Not supported	Break at 15.5 m, bootstrap $p = 0.24$; slope not steeper above it
H5: small and cane-intensive farms more exposed	Suggestive only	Marginal-farm slope -7.9% vs -4.4%, $p = 0.20$; cane interaction $p = 0.34$; marginal farms 48% of lowest-income quarter

DISCUSSION

The central message is that depth to water is a first-order driver of farm income and that it compounds weather risk. The effect size, roughly 4 to 5 percent of income per metre, is large relative to the 0.43 m a year at which

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

stressed blocks are sinking: after a decade that is more than four metres, or about a fifth of income, before any climate shock. This figure is consistent across a block panel, a household cross-section and an instrumented model, which is the kind of triangulation the framework was designed to deliver.

The interaction result matters most for policy. Because the damage from a dry year grows with depth, protecting aquifers is a form of climate adaptation and not only a resource issue. Insurance, canal access and recharge all work by restoring the buffer that falling tables erode; in the simulation canal access was worth far more in stressed than in safe blocks.

The null results are also informative. No threshold means there is no safe "last metre" to wait for, so interventions justified by a tipping point would have weak support; and no significant farm-size or cane gradient means targeting rules should not rest on those characteristics alone without real evidence. That marginal farmers are overrepresented in the bottom income quarter is a distributional warning, but it reflects their lower average income level, not demonstrably higher sensitivity to depth.

The failure of irrigation cost to mediate the depth effect is a methodological flag: either cost is measured with error in the survey, or most of the income loss comes through yield, area abandoned or forced crop changes. A real survey should therefore record well failures, deepening events, irrigation counts per crop and area left fallow, so these channels can be separated.

Finally, every figure here comes from a synthetic dataset. The signs and sizes are by construction, so they show that the estimators recover relationships when these exist, not that Meerut's farmers face a 4.5 percent loss per metre. The statements to carry forward are the specifications, the diagnostic sequence and the way results are interpreted.

Policy Implications

The policy discussion below is conditional on findings but follows from the framework.

1. **Crop diversification and water-efficient practices:** incentives for shifting part of paddy and cane area to maize, pulses, oilseeds, vegetables and fodder; direct-seeded rice, alternate wetting and drying, trench or furrow planting and drip irrigation in sugarcane.

2. **Micro-irrigation scale-up:** subsidies under national micro-irrigation programmes need to reach small farmers through credit and service support; evidence on actual water savings (not just area covered) should be tracked.

3. **Energy-water nexus:** metered or rationalised farm power, feeder separation and solar pump schemes designed so that they do not simply lower marginal pumping costs and accelerate extraction; consider payments for energy not used.

4. **Canal and surface-water management:** rehabilitation of distributaries and conjunctive use planning in canal commands to reduce tubewell dependence.

5. **Aquifer recharge:** managed aquifer recharge, restoration of ponds and drains, rainwater harvesting, and treated wastewater reuse, prioritising blocks identified as critical or over-exploited.

6. **Governance:** participatory groundwater management at village or aquifer level, enforcement of State groundwater regulation, and publicly accessible well-level monitoring data.

7. **Risk management:** index-based weather insurance linked to SPEI or rainfall deficits, with premiums and triggers calibrated to local conditions.

8. **Urban-agriculture coordination:** in NCR-fringe districts, planning that accounts for competing urban and industrial demand and protects recharge zones.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

9. **Extension and information:** advisory services using seasonal forecasts and groundwater bulletins to guide crop and irrigation decisions.

LIMITATIONS

- Well networks are sparse and irregular, so block-level interpolation involves error.
- Gridded temperature data are coarse relative to block size, introducing measurement error that tends to bias climate coefficients towards zero.
- Household income is self-reported and subject to recall bias; consumption or asset cross-checks are advisable.
- Short and unbalanced panels reduce power to detect thresholds.
- Hydrogeological heterogeneity within blocks and aquifer-wide spillovers are only partly captured.
- Results from the eight districts may not generalise to Eastern or Bundelkhand UP.
- **Synthetic data:** the numerical results in Section 6 are generated, not observed, so none of them can be cited as evidence about Western Uttar Pradesh. The simulated dataset is also cleaner than real data: it has no missing wells, no boundary changes and no measurement error in climate variables.
- Only eight districts act as clusters in the panel, so conventional cluster-robust inference is likely to be unreliable and wild-bootstrap inference is advisable.

Work Plan and Ethics

A realistic schedule is: months 1-3, literature and data compilation; months 4-5, survey design, pilot and enumerator training; months 6-9, field survey and qualitative work; months 10-12, analysis, writing and validation workshops with stakeholders. Surveys require informed consent, anonymisation of respondents, secure data storage and institutional ethics clearance. Well-level and village-level identifiers should be masked in published outputs to avoid stigmatising specific communities.

CONCLUSION

Groundwater depletion and climate variability are two faces of one water-security problem in Western Uttar Pradesh: groundwater has cushioned farmers against rainfall shocks, and as it declines the cushion thins. This paper set out a replicable framework to measure that link for Meerut and neighbouring districts and demonstrated it on a synthetic dataset. In the demonstration, one extra metre of depth to water lowered net farm income per hectare by about 4 to 5 percent, heat-stress days lowered it by a further 1 percent each, and the loss from depth was substantially larger in drought years; no threshold depth, farm-size gradient or cost-mediation channel reached significance. The framework's value lies in its design: block-level panel plus household survey, fixed-effects and instrumental-variable estimation, explicit threshold and heterogeneity tests, and a disciplined sequence of diagnostics. The next steps are to assemble the real CGWB, IMD and agricultural data, run the pilot survey, re-estimate every model and replace the simulated tables in Section 6. Policy should then be drawn only from those real estimates, with their uncertainty and robustness checks reported.

REFERENCES

1. Abadie, A., Athey, S., Imbens, G. W., & Wooldridge, J. M. (2023). When should you adjust standard errors for clustering? Quarterly Journal of Economics, 138(1), 1-35.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

2. Asoka, A., Gleeson, T., Wada, Y., & Mukherjee, V. (2017). Relative contribution of monsoon precipitation and pumping to changes in groundwater storage in India. Nature Geoscience, 10(2), 109-117.
3. Auffhammer, M., Ramanathan, V., & Vincent, J. R. (2012). Climate change, the monsoon, and rice yield in India. Climatic Change, 111(2), 411-424.
4. Bhattarai, N., Lobell, D. B., Balwinder-Singh, Fishman, R., Kustas, W. P., Pokhrel, Y., & Jain, M. (2023). Warming temperatures exacerbate groundwater depletion rates in India. Science Advances, 9(35), eadi1401. https://doi.org/10.1126/sciadv.adi1401 (checked)
5. Birthal, P. S., Khan, M. T., Negi, D. S., & Agarwal, S. (2014). Impact of climate change on yields of major food crops in India. Agricultural Economics Research Review, 27(2), 145-155.
6. Burke, M., & Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture. American Economic Journal: Economic Policy, 8(3), 106-140.
7. Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. Review of Economics and Statistics, 90(3), 414-427.
8. Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. Journal of Human Resources, 50(2), 317-372.
9. Central Ground Water Board. (2024). National compilation on dynamic ground water resources of India, 2024. Ministry of Jal Shakti. (checked: national figures)
10. Dangar, S., Asoka, A., & Mishra, V. (2021). Causes and implications of groundwater depletion in India: A review. Journal of Hydrology, 596, 126103.
11. Deschênes, O., & Greenstone, M. (2007). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. American Economic Review, 97(1), 354-385.
12. Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. Review of Economics and Statistics, 80(4), 549-560.
13. Fisher, A. C., Hanemann, W. M., Roberts, M. J., & Schlenker, W. (2012). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather: Comment. American Economic Review, 102(7), 3749-3760.
14. Frontiers in Water. (2025). Impact assessment of different water management technologies on regional groundwater ecosystem service. Frontiers in Water, 7, 1654541. https://doi.org/10.3389/frwa.2025.1654541 (checked; complete the author list from the DOI record)
15. Gordon, H. S. (1954). The economic theory of a common-property resource: The fishery. Journal of Political Economy, 62(2), 124-142.
16. Hamed, K. H., & Rao, A. R. (1998). A modified Mann-Kendall trend test for autocorrelated data. Journal of Hydrology, 204(1-4), 182-196.
17. Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. Journal of Econometrics, 93(2), 345-368.
18. Hardin, G. (1968). The tragedy of the commons. Science, 162(3859), 1243-1248.
19. Kendall, M. G. (1975). Rank correlation methods (4th ed.). Griffin.
20. Khan, M. M. A., & Umar, R. (2008). Implications of Kali-Hindon inter-stream aquifer water balance for groundwater management in western Uttar Pradesh. Journal of Earth System Science, 117(1), 69-78. (checked)
21. Kleibergen, F., & Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. Journal of Econometrics, 133(1), 97-126.
22. Kumar, K. S. K., & Parikh, J. (2001). Indian agriculture and climate sensitivity. Global Environmental Change, 11(2), 147-154.
23. MacDonald, A. M., Bonsor, H. C., Ahmed, K. M., Burgess, W. G., Basharat, M., Calow, R. C., et al. (2016). Groundwater quality and depletion in the Indo-Gangetic Basin mapped from in situ observations. Nature Geoscience, 9(10), 762-766.
24. Mann, H. B. (1945). Nonparametric tests against trend. Econometrica, 13(3), 245-259.
25. Mendelsohn, R., Nordhaus, W. D., & Shaw, D. (1994). The impact of global warming on agriculture: A Ricardian analysis. American Economic Review, 84(4), 753-771.
26. Olea, J. L. M., & Pflueger, C. (2013). A robust test for weak instruments. Journal of Business & Economic Statistics, 31(3), 358-369.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

27. Ostrom, E. (1990). Governing the commons. Cambridge University Press.
28. Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels (CESifo Working Paper No. 1229).
29. Pettitt, A. N. (1979). A non-parametric approach to the change-point problem. Journal of the Royal Statistical Society: Series C, 28(2), 126-135.
30. Rodell, M., Velicogna, I., & Famiglietti, J. S. (2009). Satellite-based estimates of groundwater depletion in India. Nature, 460(7258), 999-1002.
31. Roodman, D., Nielsen, M. Ø., MacKinnon, J. G., & Webb, M. D. (2019). Fast and wild: Bootstrap inference in Stata using boottest. Stata Journal, 19(1), 4-60.
32. Schlenker, W., Hanemann, W. M., & Fisher, A. C. (2005). Will U.S. agriculture really benefit from global warming? American Economic Review, 95(1), 395-406.
33. Sekhri, S. (2014). Wells, water, and welfare: The impact of access to groundwater on rural poverty and conflict. American Economic Journal: Applied Economics, 6(3), 76-102.
34. Sen, P. K. (1968). Estimates of the regression coefficient based on Kendall's tau. Journal of the American Statistical Association, 63(324), 1379-1389.
35. Shah, T. (2009). Taming the anarchy: Groundwater governance in South Asia. Resources for the Future.
36. Taraz, V. (2017). Adaptation to climate change: Historical evidence from the Indian monsoon. Environment and Development Economics, 22(5), 517-545.
37. Taylor, R. G., Scanlon, B., Doll, P., Rodell, M., van Beek, R., Wada, Y., et al. (2013). Ground water and climate change. Nature Climate Change, 3(4), 322-329.
38. Wada, Y., van Beek, L. P. H., van Kempen, C. M., Reckman, J. W. T. M., Vasak, S., & Bierkens, M. F. P. (2010). Global depletion of groundwater resources. Geophysical Research Letters, 37, L20402.
39. Zaveri, E., Grogan, D. S., Fisher-Vanden, K., Frolking, S., Lammers, R. B., Wrenn, D. H., Prusevich, A., & Nicholas, R. E. (2016). Invisible water, visible impact: Groundwater use and Indian agriculture under climate change. Environmental Research Letters, 11(8), 084005. https://doi.org/10.1088/1748-9326/11/8/084005 (checked)
40. Zaveri, E., & Lobell, D. B. (2019). The role of irrigation in changing wheat yields and heat sensitivity in India. Nature Communications, 10, 4144.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

APPENDIX A: DRAFT HOUSEHOLD SURVEY MODULES

1. Household roster and demographics.
2. Landholding, tenure and land use by season.
3. Crop-wise area, inputs, yields, output prices and sales channels.
4. Irrigation sources, pump type and horsepower, well depth history, deepening events and costs, hours of electricity supply, canal access and water-sharing arrangements.
5. Climate shocks experienced and coping strategies; insurance and credit.
6. Adoption of micro-irrigation, laser levelling, direct-seeded rice and crop diversification.
7. Non-farm and livestock income.
8. Perceptions of groundwater and rainfall change; participation in water institutions.

APPENDIX B: VARIABLE CODING NOTES

- Convert all monetary values to constant prices using an appropriate agricultural deflator.
- Express DTWL in metres below ground level; larger values mean deeper (worse) water tables.
- Define kharif and rabi climate indicators separately and match to crop calendars.
- Treat blocks reclassified between CGWB assessments carefully; use a harmonised classification or note the revision year.

APPENDIX C: HOW THE SIMULATED DATA WERE GENERATED

The synthetic data follow the study design so that every model in Section 4 can be run and read, with a fixed random seed for reproducibility.

Block panel (224 observations). Sixteen blocks (two per district, one stressed and one safe) are observed for 2010-2023. Baseline depth differs by district (9 to 18 m) and is 3 m deeper in stressed blocks. Depth then drifts downward by about 0.45 m a year in stressed blocks and 0.18 m a year in safe blocks, rises slightly in rainfall-deficit years, and carries small random noise. A common regional rainfall shock is drawn for each year, with block-level noise added; heat-stress days trend upward by about 0.25 a year; canal share is set by district. Log income per hectare is generated from a block-specific level, a negative effect of depth, a positive effect of rainfall deviation, a negative effect of heat-stress days, an additional penalty that grows with depth beyond 14 m in rainfall-deficit years, a positive canal effect, a small positive time trend and random noise (standard deviation 0.05).

Household survey (608 observations). Nineteen households are drawn in each of 32 villages (two per block). Farm-size class (marginal 38 percent, small 34 percent, medium and large 28 percent), sugarcane share, micro-irrigation adoption (rising with farm size), canal access and schooling are assigned at random with these tendencies. Village depth is the block level plus a village effect and household noise. Income per hectare is log-linear in depth, farm size, schooling, canal access and micro-irrigation, with noise (standard deviation 0.35); irrigation cost rises with depth and falls with micro-irrigation.

Estimation. Models were estimated with block and year dummies (panel) or block dummies (households), district-clustered standard errors, Mann-Kendall and Sen's slope tests on regional annual means, manual two-stage least squares with a Sargan test, and a grid-search threshold model with a residual-bootstrap sup-F test. When real data replace these, the same code structure applies; add wild-cluster bootstrap inference, cluster-robust first-stage F-statistics and the spatial and unit-root diagnostics listed in Section 4.9.