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Impact of temperature shocks on household water poverty in India

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Climate change-induced temperature shocks disrupt the natural water balance and consequently intensify households' water poverty. In this study, we examine the impact of temperature shocks on households' water poverty in India using household-level data from two rounds of the India Human Development Survey (IHDS) and climate data from the India Meteorological Department. We find that additional days above 9 °C, especially above 33 °C, significantly increase households' water poverty. Furthermore, the impact of temperature shocks on households' water poverty is less severe in regions with higher historical temperature variability as compared to other regions with less temperature variability. These results highlight the need for targeted policies to enhance water infrastructure and adaptive strategies in response to climate-induced temperature shocks.

Keywords Climate change, Temperature shock, Historical temperature variability, Water poverty, India

While the impact of the climate shocks on several economic indicators (like agricultural production, migration, economic growth, etc.) on water resources[1–6] are well-documented in the literature, very little is known about the impact of climate change on households' water poverty. Our study is the first of its kind to examine the impact of temperature shocks on households' multidimensional water poverty in India. This issue is particularly important to study given the intensifying impact of climate change on global water scarcity, which pose challenges to achieve United Nations Sustainable Development Goal 6. Moreover, the universal nature of climate change impacts vulnerable regions faster, despite regions like Africa and Nepal contributing minimally to global emissions. This creates a threat to freshwater resources[7,8]. In India, water demand is expected to rise by 20–40 per cent in the coming decades[9]. However, as climate change gets intensified, it worsens water poverty, affecting the poor disproportionately, particularly those living on less than two dollars a day[10]. This growing gap between demand for and supply of water, coupled with the impacts of climate change, poses a significant challenge for water resource management[11]. Therefore, using the household-level data from the India Human Development Survey (IHDS) and climate data from the India Meteorological Department (IMD), this study makes a novel attempt to first examines the impact of temperature shocks on households' water poverty and then explores whether water poverty in regions with a greater history of climate variation gets less impact from temperature shocks. While there is evidence in the literature that people exposed to more variable rainfall are less likely to diversify their income in response to rainfall shocks[12], there remains a critical gap in understanding the direct effects of temperature shocks on households' water poverty. Moreover, little is known about the role of historical climate variation in shaping regional adaptability. Previous research has demonstrated that climate variability contributes to production risk, and increased water demand[13,14], both of which have significant implications for water security. However, the implications of these dynamics for household water poverty have not been thoroughly explored. By estimating both the direct effects of temperature shocks on water poverty and the moderating role of historical temperature variability on water poverty, this paper contributes to a more nuanced understanding of how environmental stressors shape household vulnerability and adaptation in general, and household water poverty in particular.

Rising temperature and water poverty

Climate change, driven by the long-term rise in global temperatures and shifting weather patterns, has emerged as a significant disruptor of water resources across the globe. Climate change induced abnormal precipitation patterns, increase glacial melt, prolonged droughts, and intensifying floods, impact both the quantity and reliability of freshwater supply[15–18]. Rising temperatures and decreased precipitation are expected to reduce water availability by 30 to 40 per cent by mid-century, posing significant threat to regional water security[19]. Furthermore, observational records and projections increasingly highlight the growing pressure on freshwater resources, as changes in rainfall patterns and rising temperatures exacerbate water poverty issues globally[4,20,21]. Water poverty, defined as a lack of access to sufficient, safe, and affordable water for daily needs[22] is expected

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to worsen as a result of these significant climatic changes. On a global scale, the Intergovernmental Panel on Climate Change[23] estimates that between 62 and 76 per cent of the world's land area will experience increased water stress by 2030. This could leave 75 million to 250 million people facing heightened water poverty, where per capita water availability drops below 1700 m^3 annually. Furthermore, approximately two-thirds of the global population faces significant water shortages for at least one month each year, with half a billion people enduring severe water scarcity annually[24]. These challenges are further intensified by rapid urbanization, with 66 per cent of the world's population projected to reside in urban areas by 2050, primarily in Asia and Africa[25]. This brings additional pressure on water resources. In India, the effects of climate-induced water poverty are already visible. For instance, in the state of Sikkim, rising temperatures have led to a significant reduction in spring discharge during off-monsoon periods, reducing the availability of water sources[26]. Such disruptions to the spatial and temporal availability of water have far-reaching consequences, not only for environmental sustainability but also for human livelihoods[27]. The impact of these changes disproportionately falls on marginalized groups, particularly women, who are often responsible for water collection. They are being increasingly burdened by rising temperatures due to longer daily collection times[28]. This challenge is expected to worsen in India, as projections indicate that by 2050, India's per capita water availability could fall to as low as 1140 m^3 per year[29].

Furthermore, historical climate variability, in addition to long-term climate trends, plays a critical role in shaping water insecurity and livelihood vulnerability, particularly in low and middle-income countries. Previous research shows that climate variability can significantly affect agricultural livelihoods and household well-being, especially where farming is the primary source of income[12]. Regional differences further influence how households adapt. For instance, farmers from regions with historically high climate variability are generally more resilient to rainfall shocks, having developed adaptive practices over time, whereas those in areas with more stable weather patterns tend to be more susceptible to such shocks[2,30]. Similarly, in Zimbabwe's Save Valley, repeated flooding has eroded agricultural land, compromised food security, and hindered market access[31]. These findings point to the necessity of designing context-sensitive adaptation policies that account for local climatic histories and the differential capacities of households to withstand environmental stressors[12,32]. Building on this, the study examines whether households in regions with greater historical temperature variability are more resilient to current temperature shocks in terms of water poverty. The underlying hypothesis is that repeated exposure to climate uncertainty fosters adaptive responses that may reduce the adverse effects of rising temperatures to some extent. This study contributes to broader insights on how climatic variability shapes household vulnerability, particularly in the domain of water security.

Data
To build our sample, we combine household level data obtained from the India Human Development Survey (IHDS)[33,34] and climate data from the India Meteorological Department (IMD)[35,36].

Household data
We collect household-level data from IHDS, which is a longitudinal nationally representative dataset of 41,554 households and 215,754 individuals in two rounds: 2004–2005 (IHDS-I) and 2011–2012 (IHDS-II). Drawn from 1503 villages and 971 urban neighborhoods across 33 states and union territories of India. Data collection was jointly carried out by the University of Maryland and the National Council of Applied Economic Research (NCAER) in India. We use household level water poverty data from Nongbri and Mandal[37]. Household water poverty index is constructed using the Alkire-Foster approach. The index is developed from seven indicators: source, sanitation, supply, time taken to fetch water, treatment, storage, and adequacy of water. These indicators are grouped under four dimensions—access, stress, quality, and capacity—to capture different aspects of household water deprivation. Each indicator is coded as binary (1 = deprived, 0 = not deprived) based on standard deprivation thresholds (See supplementary text Table S1 for details). These binary indicators are first assigned general weights and then aggregated to generate a household-level water poverty score, which ranges from 0 to 1 (0 indicates no water poverty and 1 represents the highest level of deprivation across all considered indicators). To capture the heterogeneity in household characteristics and provide a broader socio-economic context, we incorporate a set of demographic and economic variables derived from IHDS. Specifically, we control for household head age, and education, and household dependency ratio and economic status were captured using the yearly income (log). Corresponding descriptive statistics are shown in the supplementary text Table S2.

Climate data
For the climate data, we use IMD data, which comprises real-time weather monitoring and extensive data from numerous weather sensors, covering wind speed, temperature, precipitation, and humidity. Given that IHDS provides district names without geocoordinates, we manually extracted latitude and longitude for each district using Google Earth to align the IMD data with our study. To ensure precise alignment with the IMD grid, we adjusted these coordinates by adding 0.5 degrees to both latitude and longitude values. This adjustment was necessary to match the spatial resolution and grid structure of the IMD dataset, ensuring accurate data integration and analysis. Specifically, we calculate temperature shocks using district-level IMD data, including daily high and low temperatures and precipitation. Averages are computed from $0.25° \times 0.25°$ rainfall and $1° \times 1°$ temperature grids spanning 1970 to 2011. We use district-level temperature records spanning 34 years prior to each survey year. Specifically, the period from 1970 to 2003 and 1977 to 2010 for IHDS-I and IHDS-II surveys, respectively. Using this district-level climate data, we constructed our key explanatory variable, temperature shock.

Firstly, to estimate the direct impact of temperature shocks on water poverty using Eq. (1), we calculate temperature shock variable following Churchill et al.[38]. The construction involves the following steps:

Step 1: Calculation of long-run temperature statistics

To estimate the long-run mean temperature, we use $\overline{X}_{dt} = \frac{\sum \overline{x}_{dt}}{No.of years}$, where $\sum \overline{x}_{dt}$ is the mean of the mean annual temperatures of *d* district and *t* year (t = 2004 & 2011) and $\overline{x}_{dt}$ denotes the yearly average of the minimum and maximum temperatures of *d* district from 1970 to 2010. Based on the annual averages, we have also calculated the long-run standard deviation (σ).

Step 2: Calculation of adjusted daily average temperature

Next, the observed daily maximum and minimum temperature for district *d* in year *t* (t = 2004 & 2011) are adjusted using the long-run mean temperature statistics of step 1. Thus, the newly adjusted daily maximum and minimum temperatures are estimated as $xnewmax_{dt} = \frac{xmax_{dt} - \overline{X}_{dt}}{\sigma}$ and $xnewmin_{dt} = \frac{xmin_{dt} - \overline{X}_{dt}}{\sigma}$. The $xnewmax_{dt}$ and $xnewmin_{dt}$ is calculated for the days of the year 2004 and 2011, respectively. Using adjusted maximum and minimum temperatures for 2004 and 2011, we then calculate the adjusted daily average temperature as $\overline{xnew}_{dt} = \frac{xnewmax_{dt} + xnewmin_{dt}}{2}$.

Step 3: Calculation of Temperature bin

To accurately determine the temperature bins, we first estimated the average minimum and maximum temperatures for each state in India. After obtaining these estimates, we identified the lower bound or the starting point of our first bin as, $minimum\,(minaveragetemperatureofallstates)$. Similarly, we determined the endpoint for our last bin as, $maximum\,(maxaveragetemperatureofallstates)$. This approach led us to adjust the temperature range into 10 bins, each with a 3-degree Celsius interval, ranging from below 9 °C to above 33 °C. The choice of a 3 °C bin width was made to capture finer variations in temperature that could influence water poverty, allowing us to observe the potential impacts of even small fluctuations. To ensure robustness, we have also tested a 5 °C bin width. By constructing our bins on the actual minimum and maximum temperatures across Indian states, we ensured that the temperature categories more accurately represent the regional climatic variations. We take a temperature range below 9 °C as our reference point, as it offers a clear baseline where temperature-induced stress on water resources is expected to be minimal. For instance, lower temperatures, such as those below 9 °C, correlated with reduced evapotranspiration and water demand, minimizing stress on water resources. Given India's climate diversity across regions, 9 °C serves as a conservative yet practical threshold. This temperature accommodates cooler conditions in northern and high-altitude regions where water stress is historically lower. While India lacks a standardized baseline for such studies, our approach aligns with Churchill et al.[38], who defined context-specific temperature ranges for energy poverty analysis, using average temperature of Australia to define a comfortable temperature range.

Step 4: Counting the number of days in each temperature bin

Next, using the adjusted daily average temperature; $\overline{xnew}_{dt}$, we count the number of days that fall into each bin, denoted by $\sum_{j=1}^{10} T_{djt}$ where,T_{djt} is the measure of temperature shock which captures number of days fall into each bin for district *d* in the year *t* and *j* captures the number of bins. This approach is used as it captures the differential effects of temperature shocks, allowing us to examine the heterogeneous impact across different temperature ranges.

Secondly, to estimate the role of historical climate variability using Eq. (2), we adopt an alternative measure of temperature shocks following Chuang[12]. The temperature shock is specified as $TempShock_{dt} = \log(x_{dt}) - \log(\overline{X}_{dt})$. This measure helps mitigate potential outliers' influence, ensuring that temperature shock values do not disproportionately influence the results. Secondly, it facilitates easier interpretation by converting the variables into a form that reflects proportional changes, rather than absolute differences. Finally, the logarithmic transformation reduces the variability of the independent variable with respect to the dependent variable, contributing to more stable and robust model estimates.

Thirdly, for the robustness analysis, we adopt a more conventional method of measuring temperature shocks by taking the absolute deviation of annual average temperature from the long-term historical mean ($TempShock_{dt} = \left|x_{dt} - \overline{X}_{dt}\right|$)[39–41]. This measure captures the overall impact of temperature shocks.

Furthermore, as a control variable, we construct rainfall data by counting the days of rainfall above 0.1 mm per year for each district and computed their average annual rainfall in millimeters[42]. Corresponding descriptive statistics are shown in the supplementary text (Table S2).

Empirical strategy

Baseline model: Impact of temperature shocks on household water poverty

Given that our dependent variable (Household water poverty) is a censored variable—meaning it is bounded within a certain range—we employ a Double-Bounded Tobit model for the analysis. The model is specified as follows:

$$WP_{idt} = \sum_{j=1}^{10} \alpha_1 T_{djt} + \alpha_2 R_{dt} + \alpha_3 Y_{idt} + \varepsilon_{idt} \tag{1}$$

where WP_{idt} is the water poverty score of the *i* household in *d* district for the year *t*. T_{djt} is the measure of temperature shock which captures number of days fall into each bin for district *d* in the year *t* and *j* captures the number of bins. R_{dt} measures average annual rainfall for district *d* in the period *t*. Y_{idt} are the household covariates (Household head age and education, household log annual income, and dependency ratio), and ε_{idt} denotes the error term.

Furthermore, in our sensitivity analysis, we further examine the robustness of our findings by considering alternative measures of temperature bins. Specifically, we test seven temperature bins and also analyze the effects of absolute mean temperature and rainfall (see supplementary text Robustness check 2 for details) over specified periods on different thresholds of water poverty. This comprehensive approach allows us to assess the consistency and reliability of our results across various model specifications.

Heterogeneity analysis: Role of historical climate variability

In this paper, we have two broad objectives. Firstly, to estimate the impact of temperature shocks on water poverty. This is achieved through Eq. (1) above. The second objective of our paper is to check whether the impact of temperature shocks on water poverty is heterogeneous across regions depending on their climate history captured by variability in temperature. We do this because historical climatic conditions may influence household responses to contemporary temperature shocks, making them less impacted. To address this, we introduce Eq. (2) as a heterogeneity analysis, following Chuang's[12] approach. Unlike the approach that categorizes temperatures into bins, capturing immediate temperature effects, this specification allows us to assess whether regions with greater historical temperature fluctuations experience different levels impact of water poverty. Specifically, we include an interaction between the standardized temperature shock and the district-level standard deviation of historical temperatures in Eq. (2) to assess whether long-term exposure to climatic variability moderates the effect of short-term temperature shock on household water poverty. This moderation framework enables a more nuanced understanding of climate impacts, moving beyond average effects to uncover conditional relationships. Our approach draws conceptual support from prior studies that apply similar moderation strategies to capture interaction effects in environment and development contexts[43], where background structural variation alters the strength of primary relationship. The heterogeneity analysis is specified as follows:

$$
\begin{aligned}
WP_{idt} = {} & \beta_1 TempSD_{dt} + \beta_2 TempShock_{dt} + \beta_3 \left(TempShock_{dt} * TempSD_{dt}\right) \\
& + \beta_4 \left(TempShock_{dt} * TempSD_{dt} * Year11\right) + \beta_5 Temp_{dt} + \beta_6 Rain_{dt} \\
& + \beta_7 H\_AvgTemp_{dt} + \beta_8 H\_AvgRain_{dt} + \beta_9 Y_{idt} + \epsilon_{idt}
\end{aligned} \tag{2}
$$

Here, $TempSD_{dt}$ captures the temperature variability of district *d*, measured by the long-run standard deviation from 1970 to *t* years (t = 2004 and 2011). $TempShock_{dt}$ is calculated as the difference between the logarithm average temperature of the *t* year and the logarithm of the long-run average temperature in *d* district for *t* year. $Temp_{dt}$ and $Rain_{dt}$ denotes the average temperature and rainfall in *d* district at time *t*, while $H\_AvgTemp_{dt}$ and $H\_AvgRain_{dt}$ represents the long-run average temperature and rainfall for *d* district in *t* year. Lastly, Y_{idt} and ϵ_{idt} are the other household-specific factors and the error term.

Results and discussions

Temperature trends in India

Using IMD data, we first established the broader context of rising temperatures over recent decades, a critical factor in understanding the impacts of climate change on household water poverty. To empirically assess this trend, we apply the non-parametric Mann–Kendall test and Sen's slope estimator on district-level temperature data from 1970 to 2011. The results, presented in Fig. 1 and Tables 1 and 2, indicate a significant increasing trend in average, maximum, and minimum temperature over time. Specifically, the Mann–Kendall test yields *p*-values well below 0.05 for average, maximum and minimum temperature, confirming the presence of a monotonic upward trend. The Sen's slope estimates further quantify this change, showing that average annual temperatures increased at a rate of approximately 0.0124 °C per year, with maximum and minimum temperatures increasing at 0.0150 °C and 0.0100 °C per year, respectively. These findings are consistent with existing literature on long-term warming in India[44,45]. Hence, these trends provide essential background for examining how such temperature fluctuations have exacerbated household water poverty across different regions of India.

Spatial distribution of temperature and water poverty

We further examine the spatial distribution of temperature shocks to understand regional disparities in climate exposure. For this purpose, temperature shocks for any given district *d* at a specific time *t*, defined as the deviation of the actual temperature at time *t* from the district's long-term average temperature, normalized by the district's long-term temperature variability ($TS_{dt} = (\chi_{dt} - \overline{\chi}_d)/\sigma_d$)[15,46]. For IHDS-I and II, the long-term mean and standard deviation are based on 1970–2003 and 1977–2010, respectively. Figure 2 maps the intensity of these shocks across 379 Indian districts for the years 2004 and 2011. Between 2004 and 2011, there was a noticeable increase in temperature stress across all regions of India, with districts showing varying levels of intensity. Southern states such as Kerala and Tamil Nadu, along with parts of Eastern and North-Eastern India, shifted from low to high shock exposure. The persistence of high shocks in Northern and Central regions, coupled with no observed decline elsewhere, signals a nationwide intensification of climate stress. Complementing the analysis of temperature shocks, Fig. 3 presents the spatial distribution of the Multidimensional Water Poverty Index (MWPI) for the years 2004–05 and 2011–12, constructed using the Alkire-Foster approach[37]. The MWPI maps illustrate varying degrees of household water poverty across 379 Indian districts, with temporal comparisons revealing significant shifts. Some districts have seen worsening water poverty over time, while others have shown improvement. These changes are intricately linked to the broader impacts of climate change, particularly temperature shocks, which have heightened water scarcity in many regions. The spatial alignment between rising temperature shocks and persistently high-water poverty suggests a climate-induced constraint on

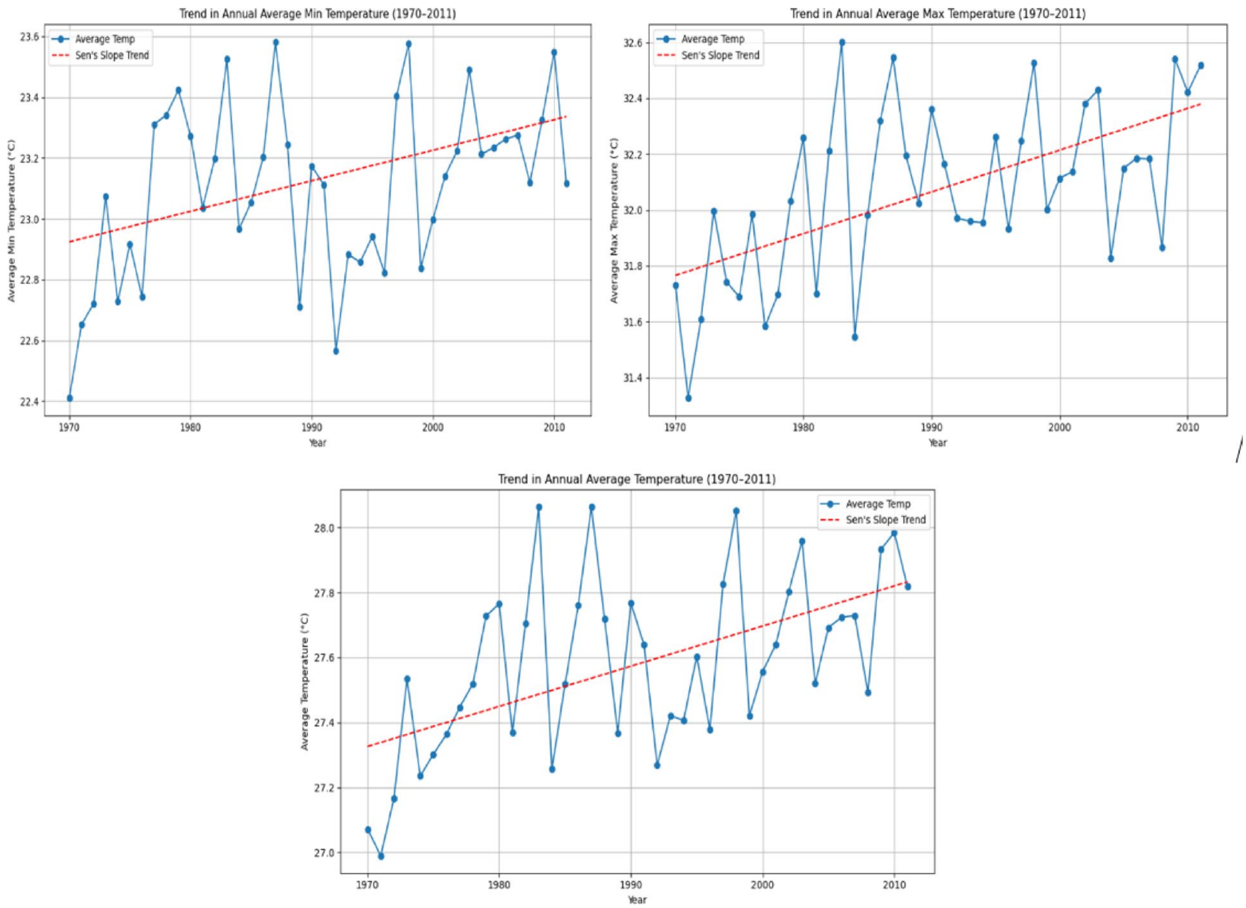

Fig. 1. Temperature trend from 1970 to 2011 in India.

	Average annual temperature	Average maximum temperature	Average minimum temperature
Trend	Increasing	Increasing	Increasing
P-value	0.000294958	0.001149122	0.016132661
Tau	0.389082462	0.349593496	0.259001161

Table 1. Mann–Kendall test statistics (1970–2011).

	Average annual temperature	Average maximum temperature	Average minimum temperature
Trend	Increasing	Increasing	Increasing
Slope	0.0124 °C/year	0.0150 °C/year	0.0100 °C/year
95% CI lower	0.0062	0.0075	0.0024
95% CI upper	0.0190	0.0213	0.0171

Table 2. Sen's slope test statistics (1970–2011).

household water security. Districts experiencing intensified temperature shock between 2004 and 2011 exhibit limited improvement in water poverty. This overlap indicates that temperature shocks may exacerbate existing water vulnerabilities, reinforcing the argument that climate shocks are a significant determinant of water poverty.

Regression analysis: Impact of temperature shocks on water poverty

The regression analysis presented in Table 3 examines the impact of climate change on water poverty, focusing on temperature shocks measured using temperature bins, a commonly utilized approach in existing literature[38,47]. Given the censored nature of our dependent variable, we employ a Tobit model for estimation. While Tobit coefficients do not directly represent marginal effects, they are still informative about the direction and significance of relationships between dependent and independent variables. In our present context, Tobit coefficients are also

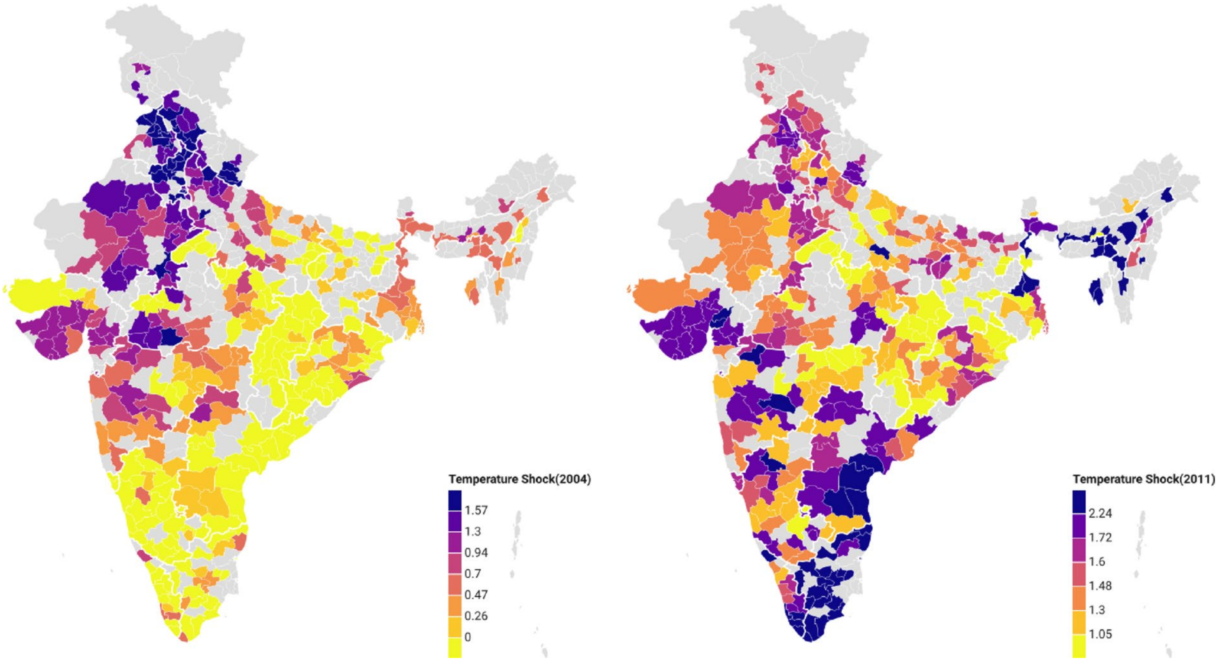

Fig. 2. The map illustrates the intensity of temperature shocks across Indian districts in 2004 and 2011.

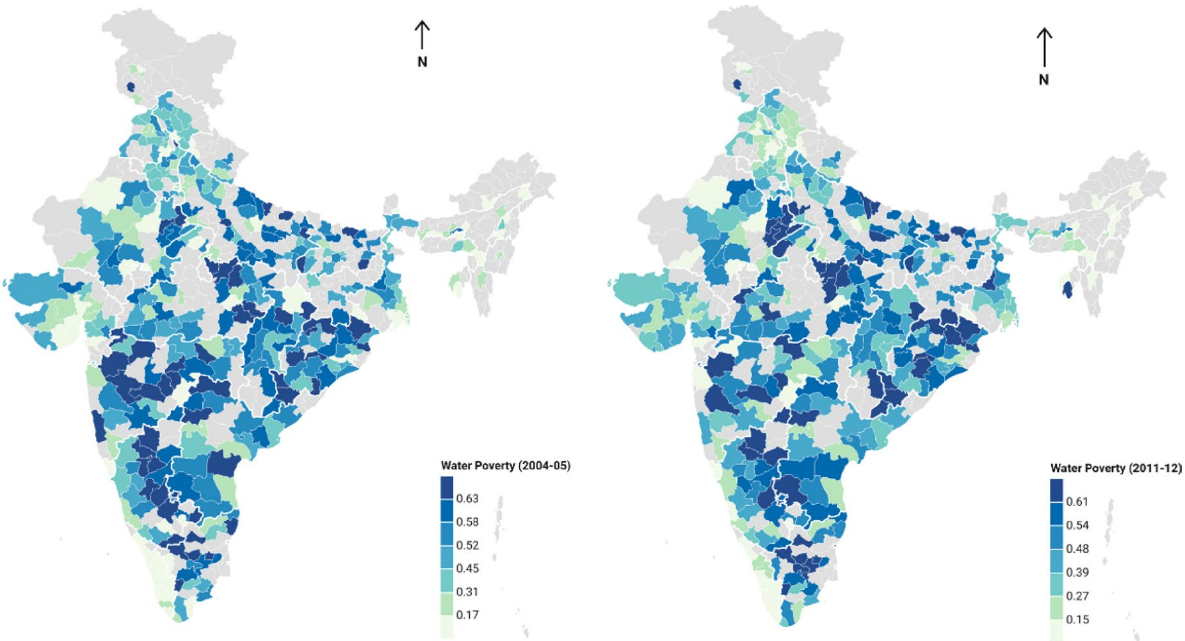

Fig. 3. The map illustrates the household water poverty in Indian districts in 2004 and 2011.

treated as marginal effects since our dependent variable (water poverty) is censored at bounds and the lower and upper censoring thresholds are rarely binding in the observed sample, causing the Tobit model to behave similarly to a linear model. Therefore, we present only the Tobit coefficients in the main text for interpretability (See supplementary materials Table S3 for the marginal effect coefficients). The finding shows that temperature shocks have a significant impact on household water poverty, with every additional day in a specific temperature range impacting water poverty. Compared to days with temperatures below 9 °C, for each additional day in the 9–12 °C and 13–15 °C ranges, household water poverty increases by 0.001 unit. As temperatures rise, this impact becomes more significant, for each additional day in the 16–18 °C and 19–21 °C ranges, household water poverty increases by 0.002 unit. Similarly, in the 22–24 °C and 25–27 °C ranges, household water poverty rises by 0.001 and 0.002, respectively. The impact remains positive across all bins, with the most significant increase occurring

Temperature (Reference: # days temperature below 9 °C)	
Dependent variable: water poverty	**Tobit coefficients**
Bin 2 (9–12)	0.00118*** (0.00004)
Bin 3 (13–15)	0.00137*** (0.00004)
Bin 4 (16–18)	0.00151*** (0.00003)
Bin 5(19–21)	0.00152*** (0.00003)
Bin 6 (22–24)	0.00122*** (0.00005)
Bin 7 (25–27)	0.00171*** (0.00007)
Bin 8 (28–30)	0.00099*** (0.0001)
Bin 9 (31–33)	0.00052** (0.00021)
Bin 10 (> 33)	0.0031*** (0.0002)
Average rainfall	− 0.00565*** (0.00054)
Log annual Income (Rupees)	0.01272*** (0.00062)
Head Age (years)	− 0.00059*** (0.00006)
Dependency ratio	0.0364*** (0.00121)
Head education	− 0.01118*** (0.0002)
Urban	− 0.15824*** (0.00213)
Wald chi2	278,497.4
Prob > chi2	0.00000
N	72,219

Table 3. Temperature shock and water poverty. The corresponding model is a double-bounded Tobit model. Standard errors in the parentheses; $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

when temperatures exceed 33 °C by 0.003 unit. While these effect coefficients on the water poverty scale may seem small, they are important when we consider their long-term impact and relevance to policy. Since the water poverty score lies between 0 and 1, even tiny changes can be meaningful, especially when they add up over time or across areas facing repeated temperature shocks. For example, a daily increase of 0.001 units means that over months or years, households could face much greater water poverty. The data also show that as temperatures rise, the negative effects get worse, especially when temperatures go above 33 °C. This highlights the growing challenges for households in hotter regions and shows why we need stronger policies to help communities adapt to climate change and protect their water resources. Additionally, the results show that average rainfall significantly reduces household water poverty, suggesting that increased rainfall improves some of the challenges associated with household water poverty. This finding aligns with the literature highlighting the advantage of adequate rainfall for improving water availability when engaging in rainwater harvesting practices[24,48–51]. Rainwater harvesting practice not only provides an additional source but also reduces the dependence on unreliable water sources[51], improving water storage and availability in areas prone to water poverty. In addition to climatic factors, socio-economic factors play a critical role in shaping the relationship between temperature and water poverty. For instance, higher annual household income significantly reduces water poverty. This suggests that economically disadvantaged households are more vulnerable to the adverse effects of temperature fluctuations, while greater economic resilience can help mitigate climate-related shocks. Similarly, the education level of the household head is positively associated with improved water access, highlighting the importance of education in building household resilience to water-related challenges. On the other hand, the dependency ratio within a household is positively significant with water poverty. A higher dependency ratio increases household water poverty because households with more dependents have greater water needs, but fewer resources and income to secure adequate supplies. Additionally, the physical effort required to collect water becomes more challenging for working members, further straining the household's ability to meet their water demands. Our findings suggest that urban households experience significantly lower poverty compared to rural households. This may be due to better access to piped water, improved sanitation, and higher investment in water supply infrastructure in urban areas. However, urban households often face issues such as ageing infrastructure, high population, inequitable resource distribution and affordability concerns, which may lead to intermittent water supply, particularly in peri-urban

	Water poverty
Temperature shock	12.94322*** (0.30985)
Temperature SD	0.06228*** (0.00892)
Temperature shock* Temperature SD	− 0.64823*** (0.04148)
Temperature shock* Temperature SD*Year11	1.04758*** (0.01164)
Average rainfall	− 0.00589*** (0.00063)
Average temperature	− 0.49318*** (0.01241)
Long-run average temperature	0.52906*** (0.01262)
Long-run average rainfall	− 0.01304*** (0.00087)
Wald chi2	367,770.57
Prob > chi2	0.000
N	72,219

Table 4. Long-run impacts of climate change on water poverty. The corresponding model is a double-bounded Tobit model. Other control variables like household head age and education, household income and dependency ratio, and urban are included in the model. Standard errors in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

areas[52–54]. Temperature shocks could further intensify these challenges, contributing to water insecurity despite lower overall water poverty scores. Therefore, taken together the regression analysis, along with the spatial distributions of temperature shocks and the multidimensional water poverty index, highlight the broad impact of temperature shocks on household water poverty across India.

Robustness check

For robustness, we carry out a sensitivity analysis using two distinct approaches. *First,* we utilized alternative temperature bins, reducing the set to seven bins, and found that temperature shocks significantly increase household water poverty. Each additional day within higher temperature ranges raised water poverty, with the most notable impact observed when temperatures exceeded 33 °C, resulting in a 0.003 unit increase. In contrast, greater average rainfall reduced water poverty by 0.005 unit, highlighting the importance of sufficient rainfall in mitigating household water poverty (See supplementary text Table S4 for details). *Second,* we examined the effects of absolute mean temperature and rainfall over specified periods (1970–2004 and 1977–2011) on different thresholds of water poverty, and found that absolute mean temperature significantly increased water poverty levels at both the 1% and 30% thresholds. Conversely, increased mean rainfall was associated with a reduction in water poverty levels (see supplementary text Table S5 for details). Additionally, socioeconomic factors such as annual income, head age, dependency ratio, and head education remained significant across all models, further emphasizing their role in influencing water poverty. These robustness checks confirm the consistency of our findings and provide confidence in the validity of our results, reinforcing the relationship between climate change and household water poverty.

Heterogeneity analysis

The results of our estimated econometric model (2) are presented in Table 4. Our results in Table 4 highlight how the historical temperature variability of a region influences household water poverty in response to temperature shocks. We observed that both temperature shock and temperature variability increase households' water poverty significantly. However, the negative and significant interaction between temperature shocks and temperature variability indicates that the impact of temperature shocks on water poverty is less severe in regions with higher temperature variability compared to regions with lower temperature variability. Our empirical findings support Simpson's Paradox. This paradox means that a trend that appears in several different groups of data can reverse when the groups are combined[55]. This counterintuitive finding occurs because regions with high-temperature variability may have developed better adaptive strategies, such as improved water storage and alternative sources, which help them manage new temperature shocks more effectively. This shows that adaptive capacity plays a significant role in how regions handle temperature shocks, and this complexity highlights the importance of considering both vulnerability and adaptability in understanding household water poverty. For instance, households and communities in regions with higher temperature variability often adopt improved water storage infrastructure (e.g., rainwater harvesting systems and check dams) to buffer against water scarcity during droughts[56]. Additionally, they often go for practices such as groundwater recharge systems and diversification of water sources (e.g., reliance on communal wells, piped networks, or tanker supplies) that enhance resilience to sudden temperature shocks[57,58]. Institutional mechanisms, including community-based water management and early-warning systems for droughts, also play a critical role in fostering adaptive capacity[59]. These strategies collectively enable regions with high-temperature variability to better withstand shocks, underscoring the importance of historical exposure in shaping adaptive responses[60]. Furthermore, the contrasting signs of the coefficients for average temperature and long-run average temperature reflect distinct short-term and long-term effects of temperature changes on water poverty. In the short term, higher temperatures may reduce water poverty due to adaptive responses such as enhanced conservation efforts[56]. Additionally, short-term increases in surface run-off could alleviate immediate shortage[61,62]. However, the positive coefficient for long-run average temperature indicates that sustained warming intensifies water poverty over time. Persistent higher temperatures lead to increased evaporation, reduced groundwater recharge, declining river flows, and frequent droughts, contributing to long-term water poverty[63]. Thus, while short-term temperature increases may offer temporary relief, long-term warming intensifies structural water scarcity, highlighting the growing link between climate change and water poverty.

Conclusion
Temperature shocks heighten the risk of water poverty and limit households' access to clean, reliable water. By estimating the impact of temperature shocks on household water poverty, we found that temperature shocks significantly increase water poverty. Using a double-bounded Tobit model, the results show that additional days above 9 °C sharply increase household water poverty, with the most pronounced impact of 0.003 unit increase in water poverty occurring when temperatures exceed 33 °C. Furthermore, our heterogeneity analysis shows that households in regions with higher temperature variability experience lower increment in water poverty due to temperature shocks as compared to regions with lower temperature variability. Therefore, in line with the United Nations' recognition of access to safe water as a basic human right[47,64], this study highlights the urgency of addressing the threats posed by climate change to domestic water security.

Policy implications
Based on the findings of this study, several targeted policy measures may help mitigate the impact of climate change—particularly temperature shocks—on water poverty in India. For instance, investment in climate-resilient and decentralized water infrastructure, such as rainwater harvesting and community-managed storage, is essential, especially in rural areas where water poverty is more acute. Such systems have proven effective and affordable in countries like Australia and Kenya[65]. Importantly, policies must not only focus on historically high-risk regions but also prioritize areas with low historical temperature variability, as these are less adapted and more vulnerable to emerging climate shocks. Social protection programs, including cash transfers, subsidies for water-saving technologies, and affordable credit, can support low-income households in adopting adaptive measures. For example, Water.org's partnership with AWS enabled over 210,000 people across three Indian states to access water infrastructure through microloans[66]. In addition, strengthening localized climate forecasting and data systems can further enable timely, informed responses to temperature shocks[67].

Limitations
While our findings offer important insights for policy intervention, several limitations of this study must be acknowledged. First, the analysis is based on only two rounds of IHDS data, which limits the ability to capture recent climatic trends. Second, the Water Poverty Index (WPI) focuses on household-level indicators, excluding broader hydrological factors such as groundwater availability. Third, temperature shocks are defined using state-level thresholds and a 33 °C cut-off, which may not fully reflect regional or seasonal temperature shock variations. Fourth, the study does not account for institutional and infrastructural factors, such as local water governance or service delivery, that likely moderate climate impacts. Finally, due to data constraints, we are unable to observe household adaptation strategies, limiting our understanding of resilience mechanisms. Future research may incorporate more granular, longitudinal data, hydroclimatic indicators, institutional factors, and adaptation behaviors to deepen the analysis of climate-induced water poverty.

Data availability
The study uses secondary data available in the public domain. The two data sets used in the study can be downloaded using the following links: (1) IHDS data: https://doi.org/https://doi.org/10.3886/ICPSR22626.v12, https://doi.org/https://doi.org/10.3886/ICPSR36151.v6. (2) IMD data, https://www.imdpune.ghttps://www.imdpune.gov.in/cmpg/Griddata/Rainfall_25_NetCDF.htmlov.in/cmpg/Griddata/Rainfall_25_NetCDF.html, https://www.imdpune.gov.in/cmpg/Griddata/Max_1_Bin.html, https://www.imdpune.gov.in/cmpg/Griddata/Min_1_Bin.html.

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Author contributions

R.W.N. has contributed to the conception, data cleaning, research design, analysis, interpretation of data, manuscript writing, and revision. A.S. has contributed to the conception, research design, manuscript writing and reviewed manuscript. S.K.M. has contributed to the conception, research design, supervised the work and reviewed the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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