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Research Article

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Posted Date: August 20th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10519589/v1

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Additional Declarations: No competing interests reported.

Drought Exposure and Gender Disparities in School Dropout Among Children in India

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Abstract

Among the most widespread climate threats for India, drought impacts have not been quantitatively examined with respect to their implications for children's schooling in a national context. The present study brings together over twenty years of satellite Earth observations and nationally representative household survey data to explore the impact of meteorological and agricultural drought on child school dropout rate in the age range of 6-17 years old in India. The SPEI metric was used to characterize meteorological drought conditions by calculating Standardized Precipitation Evapotranspiration Index (SPEI) based on CHIRPS rainfall dataset and GLEAM evaporation. Agricultural drought was evaluated by Scaled Drought Combined Indicator (SDCI), which combines three condition indices – Vegetation, Temperature and Precipitation indices obtained from MODIS data for 2001-2021. The satellite drought metrics were combined with the fifth National Family Health Survey data to calculate child-specific drought exposure ratio over the whole lifetime. Using multivariate logistic regression, Kaplan-Meier survival analysis, and spatial error models the link between drought exposure and school dropout was estimated controlling for socioeconomic and demographic factors. Both types of droughts increase dropout risk; however, the association is significantly stronger for agricultural drought and is more robust. The older children and females experience increased risks of dropout under both meteorological and especially agricultural drought conditions. Satellite-derived surfaces reveal significant clusters of drought dropouts mainly across central, eastern and northern India, including states of Uttar Pradesh, Bihar, Jharkhand, Rajasthan and Gujarat. Dropout results mostly from financial hardships, lack of drinking water and increased domestic and labor demands on children. This study is, to our knowledge, the first satellite-based evaluation of the relationship between drought and school dropout rate for India. It is directly related to the fulfillment of SDG 4 and SDG 13.

Keywords: School dropout; Drought exposure; Satellite remote sensing; Agricultural drought; Gender inequality; India

1. Introduction

Climate change has become a matter of grave concern globally. Climate change can create various hazards, which include floods, heat stress, and droughts, while the consequences of such hazardous events are far more devastating in vulnerable areas of developing nations [1-3]. Drought is a natural phenomenon of dry weather prevailing for a long duration during the natural cycle of climate and occurs across the world; however, it is common to tropical or equatorial zones, including India [4]. There is great geographical variation in India, where the climatic variations happen each year. In recent decades, due to extreme climate events, especially droughts, the lives of many people in India have been affected [5,6]. Also, the frequency and intensity of droughts in various parts of India have increased [7,8].

Meteorological drought can be described as a situation characterized by a consistent shortage of precipitation as compared to climatic norms for long periods of time, while an agricultural drought represents the condition in which there is insufficient soil moisture for crops even without large rainfall shortages [9]. Both types of drought limit the availability of water resources, diminish agricultural productivity, and impact the well-being of rural communities negatively, especially in developing countries because of the high dependence on climate-sensitive industries [10-12]. In India, due to the fact that a considerable number of people earn their living through rain-fed agriculture, frequent droughts cause instability of income, increased vulnerability of families, and decreased resilience [11,13]. Economic shocks may have social repercussions, such as reductions in spending on food, healthcare, and education, or removal of children from schools to earn more money [14,15].

India falls in the third phase of the demographic transition where it has a demographic dividend because of its young population that represents a vital chance for the demographic transition from the developmental stage of an economy to the development one [16]. The role of education in this situation is pivotal as it equips people with important knowledge and skills needed for getting the advantage from the demographic transition and producing skilled workforce. In accordance with the 2011 Census, the rate of literacy in India is 74 percent with great gender disparity [17]. Additionally, about 17 percent of the students drop out of schools in India [18].

Although children in India begin attending schools when they are young, many children end up dropping out after not completing their basic education. Studies about schooling attainments in India have indicated that there are various reasons why children drop out from schools, including economic issues, parents' educational attainments, gender-related expectations and perceptions, among others. Economic hardship, lack of interest, distance to schools, and unequal gender expectations have been some of the factors found to be associated with increased dropout risks [18-20]. Additionally, climatic shocks affect dropout via effects of socio-economic and institutional constraints such as economic hardship, distance to school, difficulties in learning, lack of support from parents, and involvement in agricultural labor. For instance, meteorological drought causes increased variability of income, reduced food security, water shortage, and other factors that affect household capacity to afford the cost of schooling, thus increasing chances of dropout [21,22]. This type of drought may also increase domestic chores that prevent school attendance [23]. Agricultural drought, on the other hand, increases opportunity costs of schooling and causes children to engage in farming labor [21,24,25]. In both cases, climatic shocks are involved in the interaction between various socio-economic and institutional constraints, which are identified to be the proximate causes of dropout [3,22,26].

In the Indian scenario, many studies have been carried out on different dimensions of education, such as the factors of school dropouts and their determinants. But none of them has considered the effect of climatic variability, specifically the drought situation and its effect on education or school dropouts. In India, all existing studies were mainly either literature review or sample-size and geographical area-specific studies (Supplementary Table S.1). However, in the current study, a bibliometric analysis is being carried out to find out the literature available on climate change and school dropout. Co-occurrence network of keywords indicates that terms related to school dropout and education are mostly associated with rainfall, climate variability, climate change, weather, floods, and natural disaster (Supplementary Figure S.1). Though it indicates considerable attention to climate and education association, there are very few studies which have specifically focused on the effect of drought and its effect on school dropouts in the Indian scenario. Co-authorship network further confirms that the majority of the study on the effect of climate on education was done by African countries and Western countries. Very few contributions are found from India and

other Asian countries (Supplementary Figure S.2). There is a clear evidence of empirical and geographical gap which will be bridged by the current study. This study attempts to analyze the effect of meteorological and agricultural drought on school dropouts of children in the age group of 6 to below 18 years with the help of satellite indices and national survey data, relevant to the achievement of SDGs, specifically SDG 4 (Quality Education), SDG 5 (Gender Equality), SDG 1 (Poverty Eradication) and SDG 13 (Climate Change Action).

2. Theoretical Background

This paper uses global risk models associated with climate change and social theories to assess how drought influences educational attainment of children in India. IPCC Climate Risk Framework views drought as a slow onset hazard where educational consequences arise in situations where high exposure, like reliance on rain fed farming, is combined with socio-economic vulnerability and poor institutional capacity (Figure 1a; [27]. In addition, there is UNICEF's cumulative climate shock and child resilience framework where recurring interruptions to the schooling process result in reduced learning capability and increased vulnerability of children especially those who are socially excluded and economically poor (Figure 1b; [28]. Finally, the World Bank's learning disruption pathway illustrates how climate shocks impact education via direct factors, for example school closure, water shortage and indirect factors, like income loss, child labor and early marriage, causing learning losses in the short run and increasing dropout probability and human capital destruction in the long run (Figure 1c; [29]. Thus, these frameworks show how climate shocks influence education through immediate and cumulative channels.

There are three social theories applied in order to understand the models in the Indian context. First of all, there is the Feminist Political Ecology approach, according to which girls experience greater domestic and care burden in situations of drought owing to gender norms and inequality in the distribution of resources, and therefore have a high rate of absenteeism and dropout [30]. Second, there is the Sustainable Livelihoods Framework, which explains how drought causes loss of livelihood and forces households to make trade-offs in which children's schooling becomes an opportunity cost [31]. Finally, there is Human Capital Theory that identifies why liquidity constraints lead to lower priority of educational expenditure, especially of girls [32].

3. Conceptual framework

The theory synthesis results in the perception of the phenomenon of school dropouts as socially-mediated phenomena that are outcomes of the risk of climate, where drought acts as a driver of livelihood stresses that interact with gender inequality and household dynamics in education. Thus, according to the above-discussed theory, mitigation of the risks of education due to drought should mean not only climate mitigation but overcoming the social and economic inequalities. Conceptual framework (see Figure 2 below) demonstrates how droughts from the meteorological and agricultural perspectives may cause school dropout in India through the interlink between gender, livelihood, and socio-economic factors. According to the above conceptual framework, one could reasonably hypothesize that the risk of drought increases the probability of school dropout in India and its impact on children is more substantial in the case of girls than that of boys due to gender vulnerabilities. Furthermore, the risk of drought is expected to influence poor households with lower levels of livelihood assets, especially those households where women collect water and take care of children. It is noteworthy that the above-discussed hypotheses are developed on the basis of the insights provided by the IPCC Climate Risk Framework, Feminist Political Ecology, Sustainable Livelihoods Framework, and Human Capital Theory.

4. Study area and Methods

4.1. Study area

Figure 3 illustrates the study area analysed in this research. It displays the land-use and land-cover areas, along with SDCI-DHS clusters. The most common land use identified is cropped land, followed by forest land. However, the sample of DHS clusters-SDCI analysis reveals that most extreme and severe drought clusters are concentrated in the northern, central, western, and eastern parts of India. In the same way, the sample SPEI DHS clusters were plotted on the elevation map of India. It shows that clusters with higher drought values are mostly concentrated in the Northeastern region of India; keeping in mind the elevation map, it can be observed that drought-prone clusters are concentrated in the plain areas.

4.2. Meteorological drought data

In this study, a high-resolution drought index dataset containing SPEI values for India was prepared for one-month time scales using the method proposed by [33]. The input data used was the CHIRPS precipitation dataset, which has a monthly temporal resolution and a 5 km spatial resolution, and the GLEAM evaporation data, which was downscaled from 25 km resolution to 5 km, using bilinear interpolation and has a monthly temporal resolution. To calculate the SPEI, obtaining the water deficit values (D) is necessary. These values are derived by subtracting the potential evapotranspiration (Ep) from the precipitation (P) values, as per the following equation:

$$D_i = P_i - Ep_i \quad \text{..... (1)}$$

Enhancing the regional drought assessment requires addressing these impacts through additional studies, which can be validated when regional data becomes accessible. The water deficit values are aggregated depending on the time scale before being standardized using the log-logistic distribution with the following probability density function:

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)\left[1 + \left(\frac{x-\gamma}{\alpha}\right)\right]^{-2} \quad \text{..... (2)}$$

The parameters are β, γ and α representing shape, origin and scale. The probability distribution function for log-logistic distribution is given by,

$$F\,(x) = \left[1 + \left(\frac{\alpha}{x-y}\right)^{\beta}\right]^{-1} \quad \text{..... (3)}$$

Then, the SPEI values can be estimated by standardizing the $F\,(x)$ Values using the following equation:

$$SPEI = W - \frac{C_0 + C_1 W + C_2\, W^2}{1 + d_1 W + d_2\, W^2 + D_3\, W^3} \quad \text{..... (4)}$$

where C0=2.515517, C1=0.802853, C3=0.010328, d1=1.432788, d2=0.189269, d3=0.001308. The value of *W* depends on the probability of exceedance *P,* as shown below:

$$W = \sqrt{-2\ln(P)} \quad \text{..... (5)}$$

where *P* = - 1 (F *x*) when *P* ≤. 0 5, but in case *P* >. 0 5, then the *P* is replaced by1 - *P* and the sign of SPEI is reversed. The datasets exhibit a wide range of drought index values, spanning from extremely wet to arid conditions. The thresholds have been identified, as presented in Table 1.

The results were evaluated by comparing high-resolution SPEI results with CRU SPEI results for 1 month. To ensure data consistency for comparison, the high-resolution results were upscaled to 50 km. This upscaling process allowed us to assess the correlation between the high-resolution SPEI and CRU-SPEI datasets both in temporal and spatial dimensions.

4.3. Agricultural drought data

In this research, three remotely sensed derived indices (VCI, TCI, and PCI) were used to assess drought conditions in India from 2001 to 2021. These indicators were computed using the Google Earth Engine platform, a service allowing the retrieval of satellite imagery as well as remote sensing-derived products, such as NDVI, LST, and CHIRPS, and to process them in the cloud. A flowchart of the whole process for map and chart production is represented in **Figure 4**.

4.3.1. Vegetation Condition Index (VCI)

The VCI compares the current NDVI to the range of values observed in the same period in previous years and can detect vegetation growth in a time interval. VCI was derived using Equation (6) and can provide information about the intensity and extent of drought (Supplementary **Figure S.3**).

$$VCI = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad \text{..... (6)}$$

where NDVI, NDVImax, and NDVImin are the average monthly NDVI, and the corresponding multi-year absolute maximum and minimum for the same month as NDVI, respectively.

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad \text{..... (7)}$$

Where NIR is the near-infrared light reflected by vegetation and RED is the visible red light absorbed by vegetation. This index ranges from -1 to +1, where higher values (closer to +1) indicate healthier and denser green vegetation, and lower values (closer to -1) can indicate sparse or unhealthy vegetation. NDVI is obtained using MOD13Q1, which is a product of the MODIS sensor and is generated every 16 days at 250 m resolution. Lower and higher values of VCI indicate bad and good vegetation state conditions, respectively. Since VCI does not apply to water bodies, areas where at least 60% is covered by permanent water bodies are masked from the map. The water bodies were detected considering the MCD12Q1 product, Version 6.1, that was derived using supervised classifications of MODIS Terra and Aqua reflectance data.

4.3.2. Temperature Condition Index (TCI)

TCI was used to determine temperature-related vegetation stress and stress due to excessive moistness. This indicator has a similar formula with respect to VCI. To calculate TCI, the MOD11A2 products of the MODIS sensor are used, which provide land surface temperature (LST) every 8 days with 1000 m spatial resolution (Supplementary **Figure S.4**).

$$TCI = \frac{T_{\max - T}}{T_{max} - T_{min}} \quad \text{..... (8)}$$

where T, Tmax, and Tmin are the average monthly temperature coming from LST, and its multi-year maximum and minimum for the same month, respectively. TCI varies from 0, for extremely unfavourable temperature conditions, to 1, for optimal temperature conditions.

4.3.3. Precipitation Condition Index (PCI)

Since one of the main causes of aridity in any region is lack of rainfall, in addition to the defined indicators, the amount of rainfall should be explicitly defined. In this research, the precipitation condition index (PCI) was calculated using Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) and was used to detect the precipitation deficits from climate signals. PCI has the following expression:

$$PCI = \frac{CHIRPS - CHIRPS_{min}}{CHIRPS_{max} - CHIRPS_{min}} \quad \text{..... (9)}$$

where CHIRPS is the monthly average rainfall, and CHIRPSmax and CHIRPSmin are its multi-year maximum and minimum for the same month, respectively. This index ranges from 0 to 1, corresponding to changes in precipitation from extremely unfavourable to optimal rainfall conditions. In case of a meteorological drought, which has extremely low precipitation, PCI is close to or equal to 0, and in flooding conditions, PCI is close to 1 (Supplementary **Figure S.5**).

4.3.4. Scaled Drought Combined Indicator (SDCI)

Since the climate classes obtained from the De Martonne aridity index are based on long-term precipitation and temperature data, we assume that the precipitation pattern and temperature are similar within each class. Therefore, instead of a temporal climatic zone, we assumed that all the parts of India come under the semi-humid, humid, and very humid climatic zones. The SDCI is a composite index that represents agricultural drought, formed by integrating TCI, PCI, and VCI. The computation formula adopted is:

$$SDCI=0.25\times TCI+0.5\times PCI+0.25\times VCI \quad \text{(10)}$$

This weighted formula ensures the index is sensitive to precipitation variations, crucial for drought assessments in monsoon-dependent agricultural regions like India. Each index component was normalised and scaled from 0 to 1, facilitating comparative analysis across different regions and times.

4.4. Population data

Population data were extracted from the National Family Health Survey (2019-2021) data [34] of India, conducted across 36 states and union territories at the national level. A stratified two-stage sampling procedure was employed in the survey design. Primary Sampling Units (PSUs) were villages in rural areas and census enumeration blocks (CEBs) in urban areas. Survey questionnaires were prepared to collect detailed information on maternal and child health, as well as socioeconomic data. Additionally, the NFHS data incorporated the collection of biomarker data [34]. The protocol for the NFHS (2019-2021) survey, including the content of all the survey questionnaires, received approval from the Institutional Ethical Review Board of the International Institute for Population Sciences (IIPS-IRB), Mumbai, India, and the ICF International Institutional Review Board (ICF IRB), Rockville, USA. Furthermore, it underwent

review protocol by the U.S. Centres for Disease Control and Prevention (CDC). All methods involved in the NFHS-5 survey and in the present secondary data analysis were carried out in accordance with the relevant guidelines and regulations, namely the Declaration of Helsinki and the Indian Council of Medical Research (ICMR) National Ethical Guidelines for Biomedical and Health Research Involving Human Participants (2017). Further details on the sampling design can be obtained in the Indian National Report (https://dhsprogram.com/pubs/).

4.4.1. Outcome variable

The survey collected information about all household members regarding their school attendance status. School dropouts were defined as respondents aged 5 to under 18 who did not attend school during the current year.

4.4.2. Confounding factors

Age, gender, place of residence, marital status, caste, religion, wealth index, sex of the household head, disability, household size, agricultural land ownership, source and distance of drinking water, and the sex composition of younger children in the household are considered confounding factors in the analysis. However, other important factors, such as the education and occupation of parents, could not be included due to their unavailability in the survey data, which is a limitation of the present study.

The confounding variables used in the spatial analysis were compiled from standard national data sources. Socio-demographic indicators, including the percentage of urban population, poverty rate, the share of Scheduled Caste and Scheduled Tribe population and female literacy, were obtained from the most recent round of the Census of India. School-level characteristics, such as the pupil-teacher ratio, school density and midday meal coverage, were taken from the Unified District Information System for Education Plus (UDISE+). Indicators related to child nutrition, including district-level stunting prevalence, were sourced from NFHS. Seasonal migration estimates and the percentage of agricultural land were derived from the Census and agricultural statistics. These datasets were harmonised at the district level and linked to the drought and dropout data to allow adjusted spatial modelling.

4.5. Drought exposure analysis

Each survey participant was assigned an "Exposure-Age" ratio to measure their lifetime drought exposure based on the child's date of birth and the survey date recorded in the NFHS survey data. For instance, if a child was born in January 2010 and the survey was conducted in March 2019, the age of that child would be 110 months. Using the cluster points from the survey, drought values (i.e., SDCI and SPEI) were extracted from the raster images generated in the study using satellite data. The total number of drought events was calculated for each cluster point, and the "Exposure-Age" was then determined. For example, if the child in question was exposed to drought for 50 months, the "Exposure-Age" ratio would be 0.45. A value of 1 indicates that the child was exposed to drought throughout their entire life. To ensure participant privacy, cluster points in the dataset were randomly displaced by 2 km in urban areas and 5 km in rural areas. A 3 km buffer was created around each cluster point for the extraction of pollutant data. It is important to note that the study assumes participants did not migrate throughout their lifetime, which is a limitation of the analysis.

4.6. Statistical analysis

The weighted prevalence of school dropout was estimated using the exposed sample, and the Chi-square test ($\chi 2$) was performed to evaluate the association between dependent and independent variables. Geospatial analysis has been conducted using Google Earth Engine (GEE) and ArcGIS (version 10.8) to prepare the prevalence maps. Further, multivariate logistic regression was employed to examine the association between exposure to drought and school dropouts after controlling all the possible confounding factors. The logistic regression model is defined as,

$$\text{logit}(p)=\log(p/(1-p)) =\beta_0+\beta_1 x_1 \ldots\ldots. +\beta_k x_k +\varepsilon \ldots\ldots\ldots\ldots (11)$$

Where, β_0 is intercept and β_1 to β_k are regression coefficients indicating the relative effect of a particular explanatory variable on the outcome, while ε is an error term. Further, a Kaplan-Meier survival plot was employed to examine the probability of school attendance based on exposure to drought. The Kaplan-Meier estimator is commonly used to estimate the survival function from lifetime data, and in this case, it provides a way to assess the likelihood of school attendance as a function of extreme drought exposure. The survival function is given by the following equation:

$$S(t) = \prod_{i:t_i \le t}\left(1 - \frac{d_i}{n_i}\right) \quad \text{..... (12)}$$

where S(t) represents the probability of school attendance (survival) at time t, t_i denotes the observed times, d_i is the number of dropouts at time t_i, and n_i is the number of children at risk just before time t_i. This method allows for the estimation of the probability of remaining in school given varying levels of drought exposure, providing a clear view of how extreme drought conditions impact school attendance over time. The Kaplan-Meier survival curves were plotted for both Agricultural Drought and Meteorological Drought exposures to highlight differences in school attendance probability across different levels of exposure. SPEI and SDCI were not included in the same model because the two variables are strongly correlated (Supplementary **Figure S.6**).

4.7. Spatial analysis

A preliminary bivariate spatial association between SPEI and SDCI episodes during the study period from 2001 to 2021 and district level dropout was examined to describe the unadjusted pattern. The main analysis was then carried out using a spatial error model to account for residual spatial autocorrelation [35]. Dropout percentages were transformed to the logit scale, and both drought indicators were standardized along with all confounding variables, which included the percentage of urban population, pupil teacher ratio, school density, poverty rate, female literacy, childhood stunting, midday meal coverage, seasonal migration, agricultural land share and the share of Scheduled Caste and Scheduled Tribe population. A queen contiguity matrix was used to define spatial neighbours, and the model was estimated by maximum likelihood. Because the objective was to quantify the impact of drought on dropout, only marginal effects were reported, calculated by predicting dropout at the observed drought level and again after increasing the drought indicator by one standard deviation, with the difference expressed in percentage points, and the associated uncertainty shown in Supplementary **Figure S.7-8**.

5. Results

5.1. Spatial distribution of school dropout

The choropleth map was created to highlight (Figure 5) the prevalence of school dropouts among children aged 6-17 years old in different districts of India. The analysis revealed the presence of considerable variations in the patterns of school dropouts among children in the spatial sense. It was found that the prevalence of school dropout children is higher (21 percent-40 percent) to moderate (10 percent -20 percent) in the districts in Central India that include Madhya Pradesh and Chhattisgarh; in the East, that includes the states of Bihar, Jharkhand, West Bengal; in the North-East that includes the state of Assam; in the Eastern coast, that includes the state of Odisha; in the North, that includes the states of Uttar Pradesh, Jammu and Punjab and; in the West, that includes the states of Gujarat, Rajasthan and parts of Maharashtra. On the other hand, the prevalence of school dropout was low (less than 9 percent) in the Southern part of India except some districts of Tamil Nadu, northern districts of Karnataka and Telangana (10-20 percent), most of the north-eastern districts except Assam and districts in the northern region that includes Uttarakhand, Himachal Pradesh, Jammu & Kashmir and NCT of Delhi.

5.2. Meteorological drought

Figure 6 represents the SPEI, depicting the monthly meteorological drought pattern in India during the year 2020. As per the results, it can be noted that as per the retreating monsoon pattern, October experienced moderate to extremely dry conditions across India; more specifically in coastal areas of Odisha, southern parts of Tamil Nadu, western Ghats, and interior southern parts. On the other hand, November experienced a deviation, with northern India experiencing almost normal conditions due to cyclonic rainfall and western India facing extremely wet to wet conditions due to Western disturbance pattern. By the end of December, southern India, including Coromandel and eastern coast, experienced very wet to extremely wet conditions due to retreating monsoon rainfall. During the period from January to April, with the development of low-pressure conditions, very dry or high temperature conditions were witnessed in western India, some part of northern India, northeastern India, and the whole eastern and western coast, as well as southern inland areas. After the onset of monsoon during the month of June, the situation changed, as most of the India faced wet to extremely wet conditions. Overall during the year, the major drought prone hot spots have

been observed in western India (particularly Rajasthan and Gujarat), central India, and interior southern India.

5.3. Agricultural drought

The SDCI of different months in the year 2020 is shown in figure 7 below. As can be seen from the analysis, in April and May, when the weather is too dry with no rain, high to extreme drought prevails in most parts of the country except for Kerala, parts of Eastern Ghats and North-Eastern region that receives plenty of rain. The primary hotspots of extreme drought in all months of the year include western Rajasthan, Gujarat, central India and the snowy regions of Jammu and Kashmir. The dry periods from March to May and winter months from November to December witness severe drought in regions of central India, Uttar Pradesh, eastern regions of Bihar and West Bengal and southern regions of Maharashtra, Telangana, and Tamil Nadu. However, in the monsoon period i.e. July to September, the drought conditions prevail everywhere except the western Rajasthan, Gujarat, Jammu and Kashmir and eastern regions of Tamil Nadu.

5.4. School dropout by socioeconomic characteristics

Table 3 shows the prevalence of school dropout rates across various demographic and socio-economic variables. The results highlighted prevalence of school dropout rates across various socio-economic and household characteristics. Age was found to be a significant factor, with dropout rates increasing significantly from 6.76% in children aged 5-14 to 23.73% in the 15-17 age group. A slightly higher dropout rates was found among females (11.59%) compared to males (10.37%). The dropout rates were found to be high in the rural areas (12.07%) compared to the urban areas (8.16%). Economic factors played a crucial role in determining school dropout as it increased as the wealth quintile decreased, with the poorest quintile having a dropout rate of highest of 19.66% compared to just 3.37% among the richest. Household characteristics such as the sex of the household head and household size also had a significant impact in the dropout rates, with higher prevalence in female-headed households (12.35%) and larger households of 7 or more household members (13.69%). Among religion and social groups, dropout rates were highest among Muslims at 16.61% and with Scheduled Tribes (16.33%). Regional disparities are evident, with the central region having the highest

dropout rate (15.55%) and the southern region the lowest (5.25%). Other factors such as disability, water access, and household structure also correlate with dropout rates. Households fetching water from outside had higher dropout rates (12.84%), and when females fetch water, dropout rates increase to as high as 17.27%. Households with both male and female children experienced the highest dropout rates (15.76%), while those with no children have the lowest (10.28%).

A binary logistic regression analysis was conducted to examine the socioeconomic determinants of school dropout across sex and place of residence, including males, females, urban, rural, and the total sample (**Table 4**). In the total sample, adolescents aged 15–17 years had substantially higher odds of school dropout compared to children aged 5–14 years (OR: 5.06; 95% CI: 4.97–5.15), while females exhibited marginally higher odds than males (OR: 1.04; 95% CI: 1.02–1.05). Children from poorer wealth quintiles faced significantly higher odds of dropout relative to those from the richest households, and those residing in female-headed households also showed elevated odds (OR: 1.11; 95% CI: 1.08–1.14). Pronounced disparities were observed across social and religious groups, with Muslim children having more than twice the odds of dropout compared to Hindu children (OR: 2.31; 95% CI: 2.26–2.37) and Scheduled Tribe children exhibiting higher odds relative to Scheduled Castes (OR: 1.12; 95% CI: 1.09–1.15). Regional differences were evident, particularly in the Central region, where the odds of dropout were significantly higher than in the Northern region (OR: 1.74; 95% CI: 1.69–1.79). Health and household characteristics were also associated with dropout, including higher odds among children with disabilities (OR: 1.82; 95% CI: 1.76–1.88), those living in households with seven or more members (OR: 1.28; 95% CI: 1.25–1.31), households owning agricultural land (OR: 1.33; 95% CI: 1.30–1.35), households where females were responsible for fetching drinking water (OR: 1.08; 95% CI: 1.03–1.14), and households with both male and female children (OR: 1.25; 95% CI: 1.20–1.30). The magnitude of these associations varied by sex and place of residence, indicating differential vulnerability to school dropout across demographic and spatial subgroups.

5.5. Association between drought and school dropouts

Multiple binary logistic regression analysis showed a significant association between drought and school dropout across demographic groups (**Figure 8**). Exposure to agricultural drought

was associated with a higher probability of school dropout among male children (AOR: 4.28; 95% CI: 4.17–4.39) and higher chances of dropout among female children (AOR: 4.73; 95% CI: 4.61–4.86), compared with their respective unexposed counterparts. The odds of school dropout were higher among urban children (AOR: 4.57; 95% CI: 4.37–4.78) than rural children (AOR: 4.49; 95% CI: 4.40–4.58). In the analysis, urban male children and rural female children were identified as the most vulnerable groups, exhibiting the higher odds of school dropout (urban males: AOR: 4.82; 95% CI: 4.54–5.12; rural females: AOR: 4.81; 95% CI: 4.67–4.94).

For meteorological drought, a greater likelihood of school dropout was observed among both boys (AOR: 2.13; 95% CI: 2.07–2.20) and girls (AOR: 1.87; 95% CI: 1.81–1.93) relative to their non-exposed counterparts. Differences by residence were also evident, as rural children experienced higher odds of dropout (AOR: 2.05; 95% CI: 2.01–2.10) compared to the urban children (AOR: 1.73; 95% CI: 1.63–1.82). Rural male children represented the most vulnerable group to meteorological drought exposure in the analysis, exhibiting the highest odds of school dropout (AOR: 2.17; 95% CI: 2.09–2.24). It worth noting that agricultural drought was associated with substantially higher odds of school dropout than meteorological drought across all subgroups.

Figure 9 illustrates the relationship between extreme drought exposure and the probability of school attendance, with separate graphs for agricultural and meteorological drought. In both cases, the probability of school attendance decreased as the extreme drought exposure-age ratio increased. The graph for agricultural drought (left panel) showed a steep decline in school attendance, particularly as the exposure ratio approached 1, indicating a stronger negative impact of agricultural drought on school attendance. The meteorological drought graph (right panel) also showed a decline, but the decrease was more gradual, suggesting that while meteorological drought did affect school attendance, its impact was less immediate compared to agricultural drought. Overall, these results highlighted the significant influence of drought exposure on school attendance, with agricultural drought having a more pronounced effect.

5.6. Spatial association between drought event and school dropout rate

A clear spatial association was seen between dropout rates and drought exposure. For meteorological drought based on SPEI, higher dropout rates were observed in districts that

experienced recurrent precipitation deficits across Rajasthan, Gujarat, Madhya Pradesh, Maharashtra and Uttar Pradesh, with additional pockets identified in Haryana and Bihar (**Figure 10**). For agricultural drought captured through SDCI, the strongest concentrations appeared in Uttar Pradesh, Bihar, Madhya Pradesh and parts of Rajasthan, and these areas aligned with elevated dropout levels. In contrast, districts in Kerala, Tamil Nadu and Karnataka, as well as most northeastern states, showed low drought incidence and generally lower dropout rates.

Figure 11 built on these patterns by examining how drought exposure related to dropout after adjustment for key socioeconomic and school related factors. Strong spatial signals remained under both SPEI and SDCI, indicating that drought continued to influence dropout risk independently of structural conditions. Districts in Rajasthan, Gujarat, Madhya Pradesh, Uttar Pradesh and Bihar showed the largest adjusted marginal effects, suggesting that recurrent climatic and soil moisture stress contributed to higher dropout rates in these regions. In contrast, districts across the southern peninsula and the northeast displayed little evidence of drought related impacts, consistent with their comparatively lower exposure.

6. Discussion

This research is the first study that attempts to provide a combined effect of both agricultural and meteorological droughts on school dropout in India using over 20 years of satellite Earth observation data. Cloud processing of MODIS, CHIRPS, and GLEAM products enabled a quantification of drought to a consistent and high-resolution spatial level of each Indian district, which was not possible for station based or single region drought studies suffering from either coverage problems or scale mismatch and making a simultaneous treatment of several types of environmental shocks hard to manage. Hence, linking these satellite-derived indicators to national household survey allows to carry out a drought exposure assessment of individual-level data with spatial completeness. Spatially, increased rates of school dropout are seen in central, eastern and northern districts of India, particularly, in districts of Madhya Pradesh, Chhattisgarh, Bihar, Jharkhand and parts of Uttar Pradesh and Rajasthan. On the contrary, school dropout is lower in districts of southern and northeastern parts of India except some districts of Tamil Nadu and Karnataka. Socioeconomic factors such as household poverty, living in rural area and female headship are strongly associated with dropout.

Additionally, the age of the child plays a significant role since there is much higher dropout risk among 15 to under 18 year old children. Dropout risk increases among children with disability and larger families. Regression results show that the age, gender, household wealth and region variables significantly determine dropout rates; rural girls are especially vulnerable to dropout. Both droughts are found to be related with the dropout rates in Uttar Pradesh, Bihar, and Jharkhand. Meteorological drought also has stronger impact in parts of Rajasthan and Gujarat. Generally, agricultural drought shows much larger association with school dropout than meteorological one throughout the entire regions, especially in rural children.

6.1. Effects of agricultural drought on school dropout

The rural population in India faces greater disruptions in education in the context of droughts because they tend to allocate their children to household and agricultural labour owing to the crop loss and income shocks experienced [4,20,36,37]. The agricultural dependency of households makes children a part of the labour force, and education tends to be put off if there are fewer resources available for consumption [38]. The drought conditions in agricultural production reduce efficiency, household incomes, and food security, leading to increased dependency on the labour force of children and greater school dropouts [39-41]. Drought also encourages seasonal and distress migrations, causing greater disruption to schooling and increasing the risk of long-term school dropout of children, especially in the case of land-poor households [21,42,43]. Limited access to credit makes it harder for households to manage consumption smoothing and investing in children's education, especially due to limited availability of formal insurance and safety nets [15,42]. The mentioned factors lead to the spatial clustering of drought-related school dropout rates in certain states, including Uttar Pradesh, Bihar, and Jharkhand characterized by high dependency on rainfed agriculture and exposure to climate shocks [7,11,44]. It is in line with the IPCC framework that states the importance of high exposure and low adaptation capacity in the context of social impact [27] as well as with the UNICEF framework (2021).

6.2. Effects of meteorological drought on school dropout

Meteorological drought changes the rainfall distribution system and creates additional problems for people in terms of water scarcity and food insecurity, which increases stress on

families and negatively impacts children's ability to attend classes [21,45]. For families living in drought-affected areas, there is an increased cost of schooling since children are asked to contribute to family welfare in terms of gathering water in places with underdeveloped infrastructure [3,13,46]. This problem is especially relevant in rural areas, where children's labour becomes essential for overcoming the challenges associated with resource scarcity.

Additionally, there are some geographical characteristics that make school dropout rates increase in some states more than in others. Meteorological droughts have negative impacts on education primarily in states like Uttar Pradesh, Bihar, Jharkhand, and some parts of Rajasthan, Madhya Pradesh, and Gujarat, where the population experiences significant levels of poverty, lack of resources and assets in households, low social protection, and high numbers of rural residents, which increase the impact of climatic shocks on education [14,47-49]. Also, droughts disrupt some basic services, such as water supply and sanitation, which leads to a decreased number of students attending schools. This problem affects mostly girls since they need to do more domestic work [28,50]. This finding is consistent with the climate education framework developed by the World Bank [29].

6.3. Effects of meteorological drought versus agricultural drought

Agricultural drought seems to be a better predictor of school dropouts compared to meteorological drought in this study, which conforms to previous findings from India indicating that production and income shocks affect schooling more than temporary rainfall shocks [20,39,51]. While meteorological drought mainly denotes rainfall shortage, its economic effect depends on factors such as irrigation, groundwater supply, and crop pattern that can dampen the effects of short-term rainfall shortage [52,53]. Agricultural drought captures water stress during the growing season and is highly correlated with yield decline and income shortfall, especially in non-irrigated areas [37,54,55]. Income and production shocks are linked to schooling through labour supply decisions made by the household members, and several Indian studies have shown that negative income shocks increase child labour and decrease school enrolment [56,57].

6.4. Gender differences in drought impacts

The role of gender as a factor determining the impact of agricultural and meteorological drought on school dropout is very important. The data revealed that girls, especially in rural and drought-prone regions, have greater chances of dropping out of school than boys due to exposure to agricultural drought. Such findings are supported by previous evidence showing that girls were much more often removed from schools than boys during environmental emergencies because of their increased obligations within families [3,41]. It should be noted that in many rural communities, girls are mostly responsible for performing household chores, which include collecting water, cooking, taking care of young siblings, etc. [14,58]. In the drought periods, the lack of water significantly increases the time needed for household activities, which increases the cost of schooling for girls [59,60].

Moreover, in many cases, girls may be viewed as less economically valuable workers in comparison with boys because there are certain limitations in the participation of girls in the labour force. Human Capital Theory could help us understand such differences since it emphasises the fact that decisions about educational investments made by households are based on economic expectations and liquidity constraints. If there is a drought period in the community, household income decreases, which means that the economic returns associated with boys' education could be higher than those related to the education of girls. Therefore, in such situations, girls are much more likely to be withdrawn from school. In that way, girls are exposed to a double burden caused by environmental challenges and gender norms. Previous evidence confirms that during drought periods, the dropout rates among females are high [11,43].

6.5. Drought effects in Urban areas

Urban school dropout associated with drought exposure is largely driven by indirect economic and social transmission mechanisms rather than direct agricultural losses. Drought-induced shocks disrupt rural-urban supply chains, increase food prices, and reduce demand for informal and low-wage urban labour, disproportionately affecting poor and migrant households concentrated in urban settlements [61-63]. These economic pressures can force households to adopt short-term coping strategies, including reallocating children’s time away from schooling toward income-generating activities or domestic support, particularly among boys engaged in informal work and girls in economically stressed households [64,65]. In

addition, urban households often lack access to formal safety nets and rely on unstable earnings, making them vulnerable to climate-related price and employment shocks despite residing in non-agricultural settings [49,66]. These pathways help explain the persistent association between drought exposure and school dropout observed in urban populations.

6.6. Policy implications

These results suggest that efforts should be made to understand how to respond to agricultural and meteorological drought in terms of educational consequences in those districts in which this drought has the greatest effect on schooling. In addition, it is necessary to increase the strength of basic water infrastructure through the implementation of the Jal Jeevan Mission (introduced in 2019 in rural regions) and AMRUT Mission (introduced in 2015 in urban regions) in drought-affected districts as the lack of a regular water supply makes the domestic chores heavier and takes children away from studying. The expansion of the Mahatma Gandhi National Rural Employment Guarantee Scheme could stabilise income during drought periods and decrease the use of child labour in families. Investments in water points and water infrastructure at schools are especially crucial in those districts in which the female dropout rate is high because of the lack of water and domestic chores. The high correlation between drought exposure and educational interruption in low adaptive capacity regions means that these interventions could prevent the intergenerational vulnerability transfer. Nevertheless, further research using longitudinal datasets and better information about parental occupation, quality of schooling, and seasonal migration is required to get a deeper understanding of the channels of influence between drought and education and to implement more targeted policies. These results are highly important for SDG 4 and SDG 13 as drought-affected educational disruption is the result of the interaction between climate and education.

7. Limitations of the study

To be able to get a deeper understanding of how drought affects the rate of school dropouts in such a way that could not be explored by the current data sets, conducting comprehensive research is needed. It should be mentioned that our research assumes that participants did not move out of the place where they were born until the time of the survey. Our study

acknowledges that, as well as the other possible determinants – parents' occupation and education, distance to the school and quality of teaching – were excluded from the model because of the lack of data on those variables in the dataset. Additionally, the existence of bias because of self-reporting should be considered. Because of the cross-sectional nature of the research, we cannot make conclusions about causality, and other aspects, for example, seasonality effects, may be explored in longitudinal research in the future.

8. Conclusion

The results show that agricultural and meteorological droughts have a statistically significant association with school dropouts in India; however, agricultural drought has a bigger and more persistent association compared to meteorological drought, whereas rural children are more exposed to the risk of leaving school compared to urban children in both droughts. It should also be noted that there are differences in dropout rates according to gender; thus, under the agricultural drought, girls have a higher probability to be a dropout compared to boys, especially in rural areas. On the contrary, in meteorological drought, girls' probabilities of being school dropouts are lower than those of the boys. It means that drought affects schooling through its effects on agricultural production and households' economic conditions, not through short-term rainfall only. The results obtained in this study are important for improving people's livelihoods and stabilising school participation in the drought-affected areas, and they contribute to the fulfilment of SDG 4 and SDG 13.

Author Contributions

AJ did the Conceptualisation, Methodology, Data curation, Formal analysis, Visualisation, and writing the original draft. RG was involved in Conceptualisation, Data curation, Formal analysis, writing the original draft, review & editing the paper. PKP did the Conceptualisation, Methodology, Validation, and review & editing of the paper. AC did the Conceptualisation, Methodology, Supervision, and review & editing of the paper.

The authors declare that they have no conflict of interest.

Acknowledgment

The authors acknowledge the providers of the datasets used in this study, including the National Family Health Survey (NFHS-5), CHIRPS, GLEAM, and MODIS products accessed through Google Earth Engine. The authors also thank the International Institute for Population

Sciences (IIPS) and associated institutions for making nationally representative data publicly available. The use of open-access datasets and geospatial platforms greatly facilitated this research. The authors are grateful to the anonymous reviewers and the editor for their valuable comments and suggestions.

Funding

No financial assistance has been granted from any survey organization, institutional open access or any other alternative sources to carry out the research.

Data Availability

The study uses publicly available secondary datasets. Demographic and school dropout data were obtained from the National Family Health Survey (NFHS-5), 2019–21, India, hosted by the DHS Program and available at https://dhsprogram.com/data/dataset/India_Standard-DHS_2020.cfm. Meteorological drought indicators (CHIRPS rainfall) are available at https://www.chc.ucsb.edu/data/chirps, and evapotranspiration data (GLEAM) are available at https://www.gleam.eu/. Agricultural drought indicators (MODIS vegetation, temperature and precipitation condition indices) were accessed via Google Earth Engine at https://developers.google.com/earth-engine.

Ethics approval

The Indian Demographic and Health Survey (DHS) is known as National Family Health Survey (NFHS) in India. It is publicly available and free of personal identifiers. The National Family Health Survey (NFHS-5) protocol, including all survey questionnaires, was reviewed and approved by the Institutional Review Board (IRB) of the International Institute for Population Sciences (IIPS), Mumbai, and the IRB of ICF International, Rockville, Maryland, USA. The protocol was further reviewed by the U.S. Centres for Disease Control and Prevention (CDC). Written informed consent was obtained from all respondents prior to data collection by the original survey implementing agencies. As this study involved secondary analysis of anonymised, publicly available data, no additional ethical approval was required. We used published large-scale national data where every respondent was anonymised in the data set itself. As it is not based on a primary survey, we do not need to do any anonymisation in the

study as the data is already anonymised in that fashion, following all ethical protocols. Thereby, it is certified that all applicable institutional and governmental regulations concerning the ethical use of human volunteers were followed during the course of the survey.

Consent to participate

Informed consent was obtained from all adult participants prior to their participation in the NFHS-5 survey; for participants under 16 years of age, informed consent was obtained from a parent and/or legal guardian by the survey agency (IIPS) as part of the standard NFHS-5 protocol approved by the IIPS-IRB and the ICF IRB. As the present study involves secondary analysis of anonymised, publicly available data, no additional consent was required from participants for this specific analysis.

Consent to publish

The dataset is publicly available; thus consent for publication is not applicable for the study.

Declaration of Generative AI Use

The authors declare that generative artificial intelligence tools were used in a limited capacity to support language editing, proofreading, and improvement of clarity in the manuscript. These tools were not used for data analysis, interpretation of results, or generation of original scientific content. All research design, data processing, statistical analysis, interpretation of findings, and conclusions were carried out solely by the authors. The authors take full responsibility for the accuracy, integrity, and originality of the work presented in this manuscript.

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Supplementary documents

Table S1. Review matrix of existing studies on the relationship between climate change and education

Figure S1. Co-occurrence plot for keywords in the field of climate and education

Figure S2. Network visualization map of international research collaboration countries in the climate and education association

Figure S3. Spatio-temporal distribution of VCI across India for the sample year of 2021

Figure S4. Spatio-temporal distribution of TCI across India for the sample year of 2021

Figure S5. Spatio-temporal distribution of PCI across India for the sample year of 2021

Figure S6. Spatial association between agricultural (SDCI) and meteorological (SPEI) drought episodes across the Indian districts

Figure S7. Lower (left) and Upper (right) confidence bound of the estimated change in dropout rates per one standard deviation of agricultural drought (SDCI)

Figure S8. Lower (left) and Upper (right) confidence bound of the estimated change in dropout rates per one standard deviation of meteorological drought (SPEI)

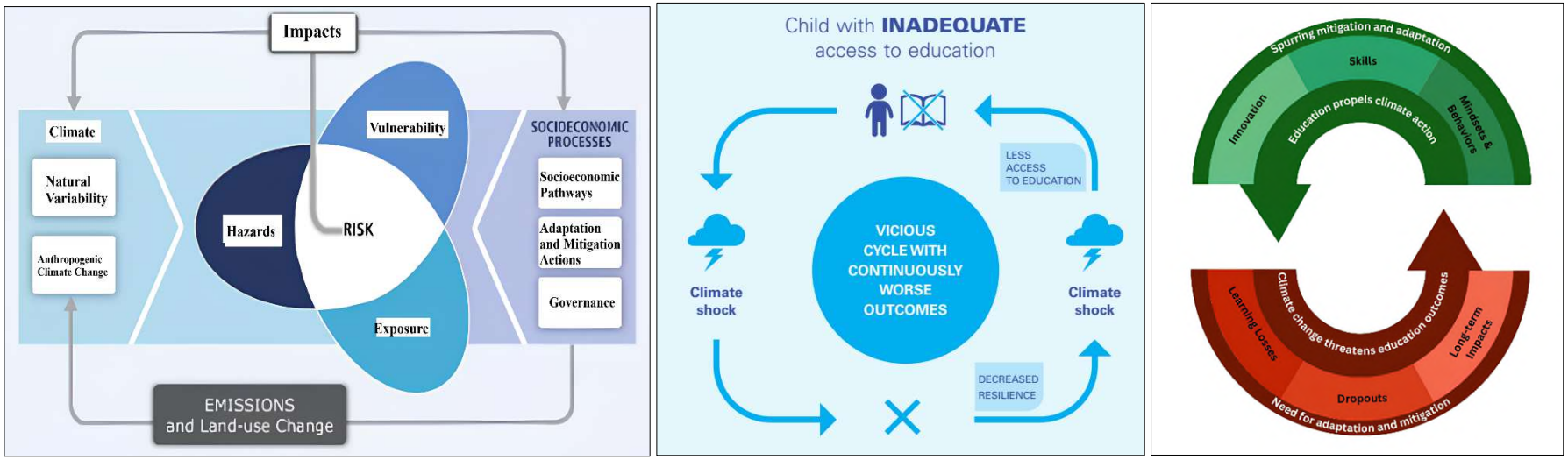


Figure 1.a Integrative concept of climate risk from the IPCC [27]; Figure 1.b UNICEF framework linking access to education with a child's capacity to cope with climate shocks [28]; Figure 1.c World Bank view that education supports climate action while climate change affects education outcomes [29].

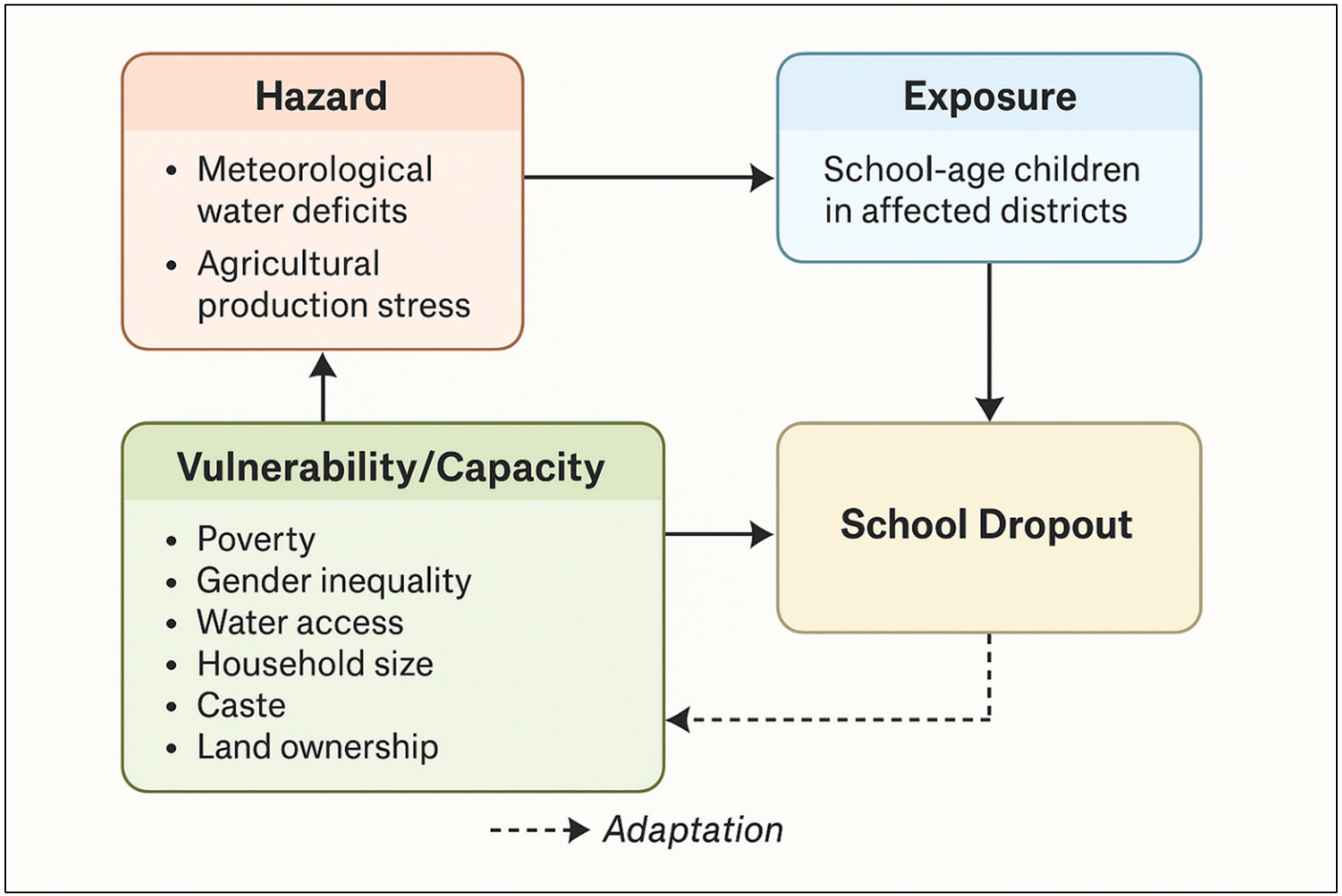


Figure 2. Conceptual framework of the study.

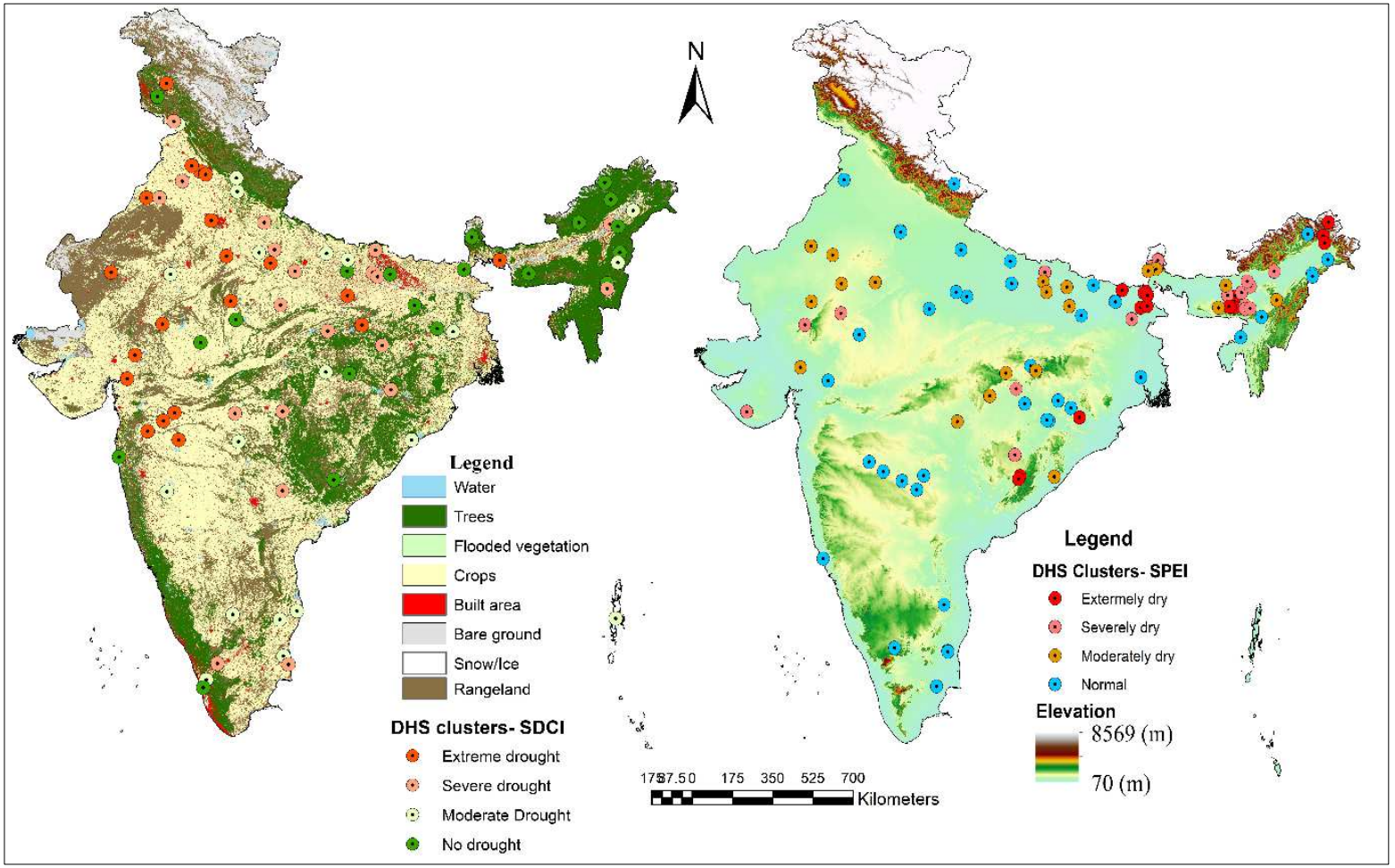


Figure 3. Study area showing elevation and land use land pattern with the sample cluster points of SPEI and SDCI.

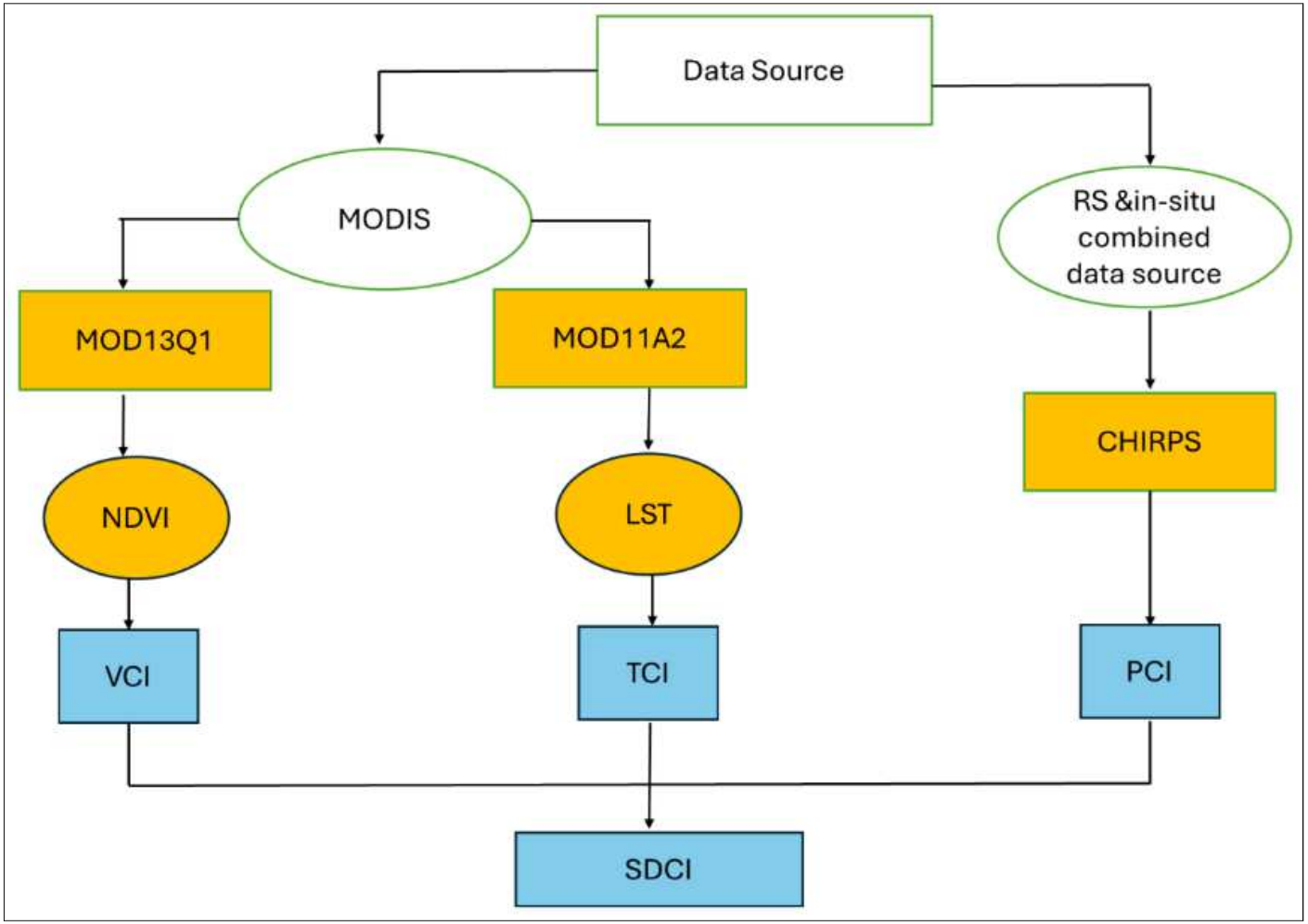


Figure 4. The processing of SDCI calculation.

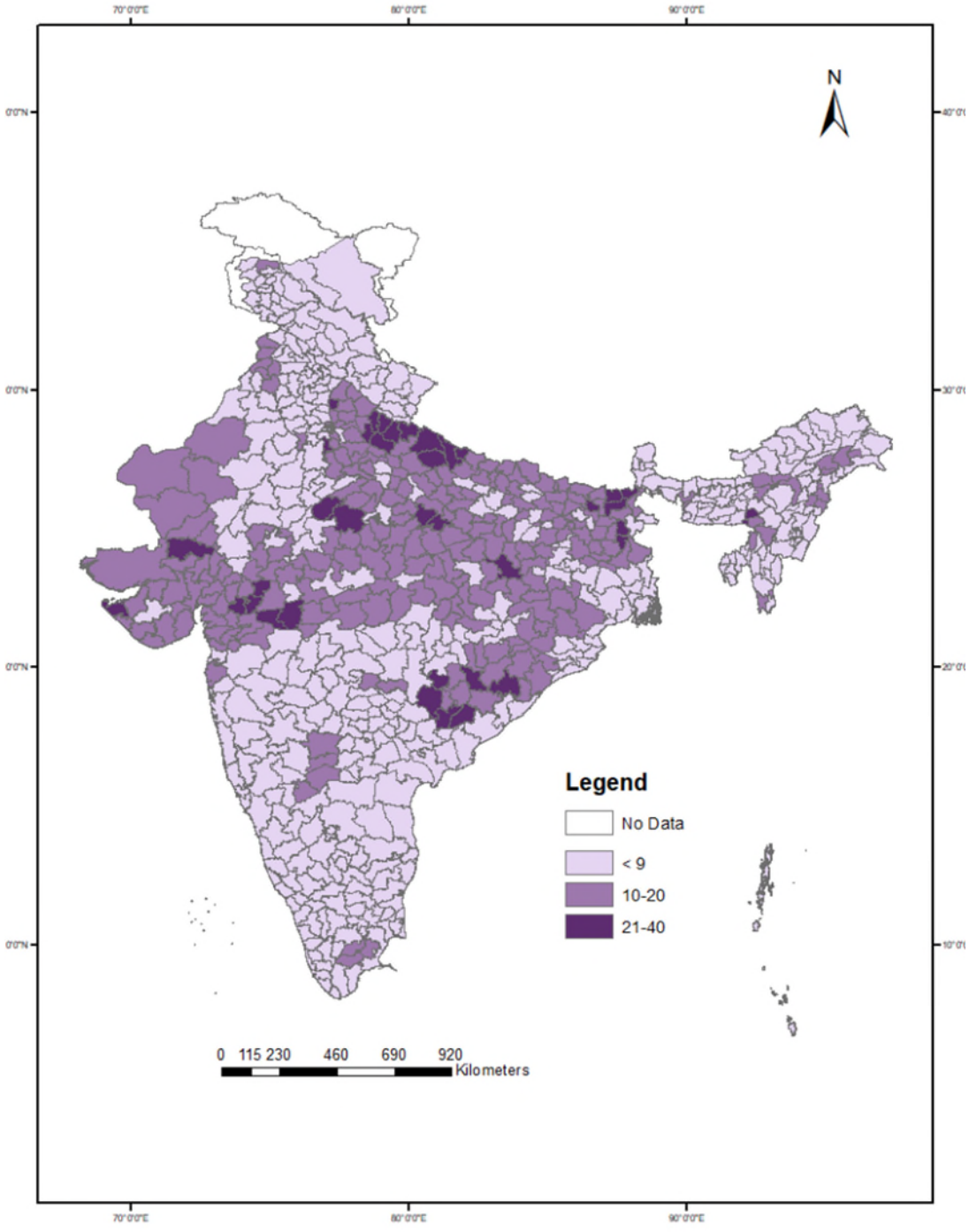


Figure 5. Spatial distribution of school dropout prevalence among Indian children aged 6 to under 18 years.

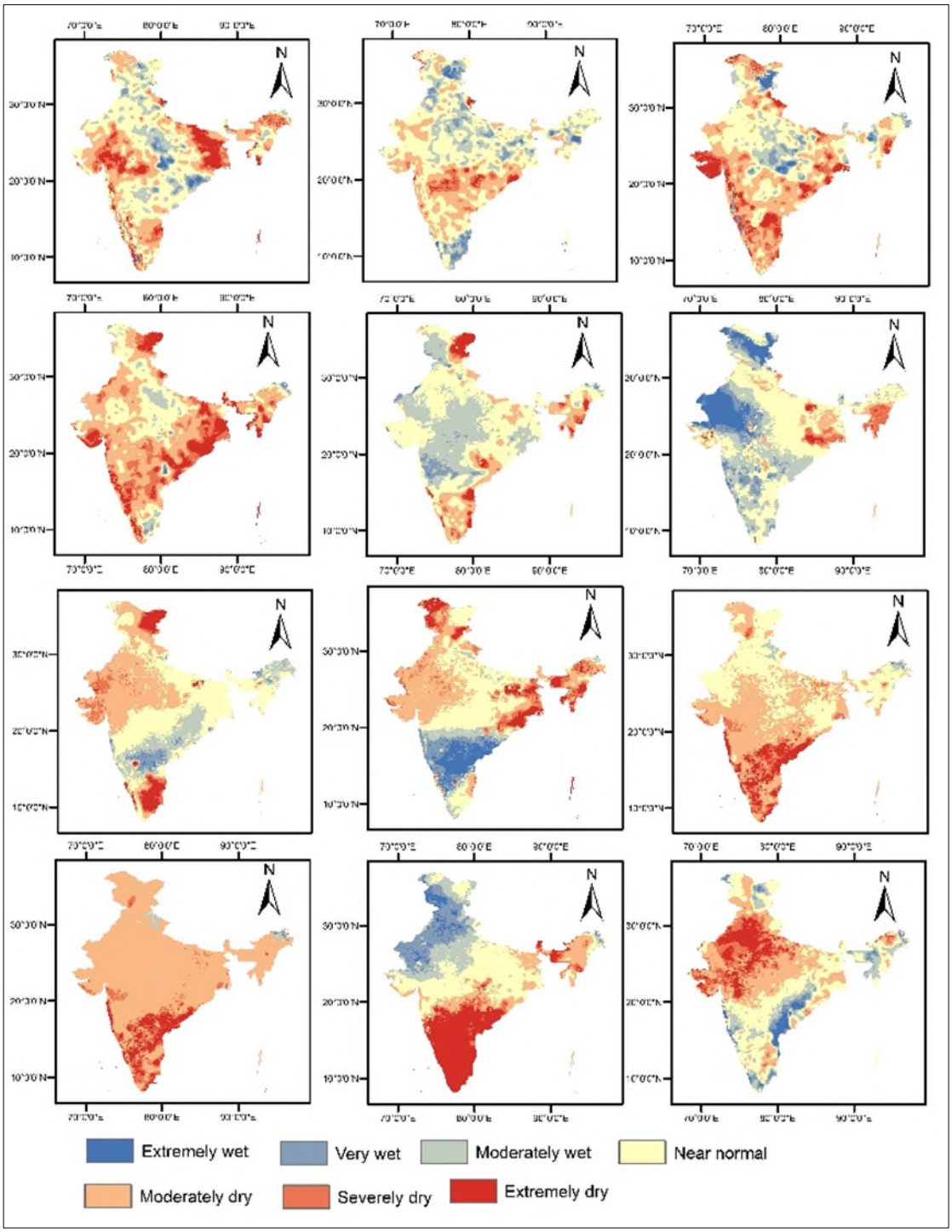


Figure 6. patio-temporal distribution of SPEI across India for the sample year of 2021

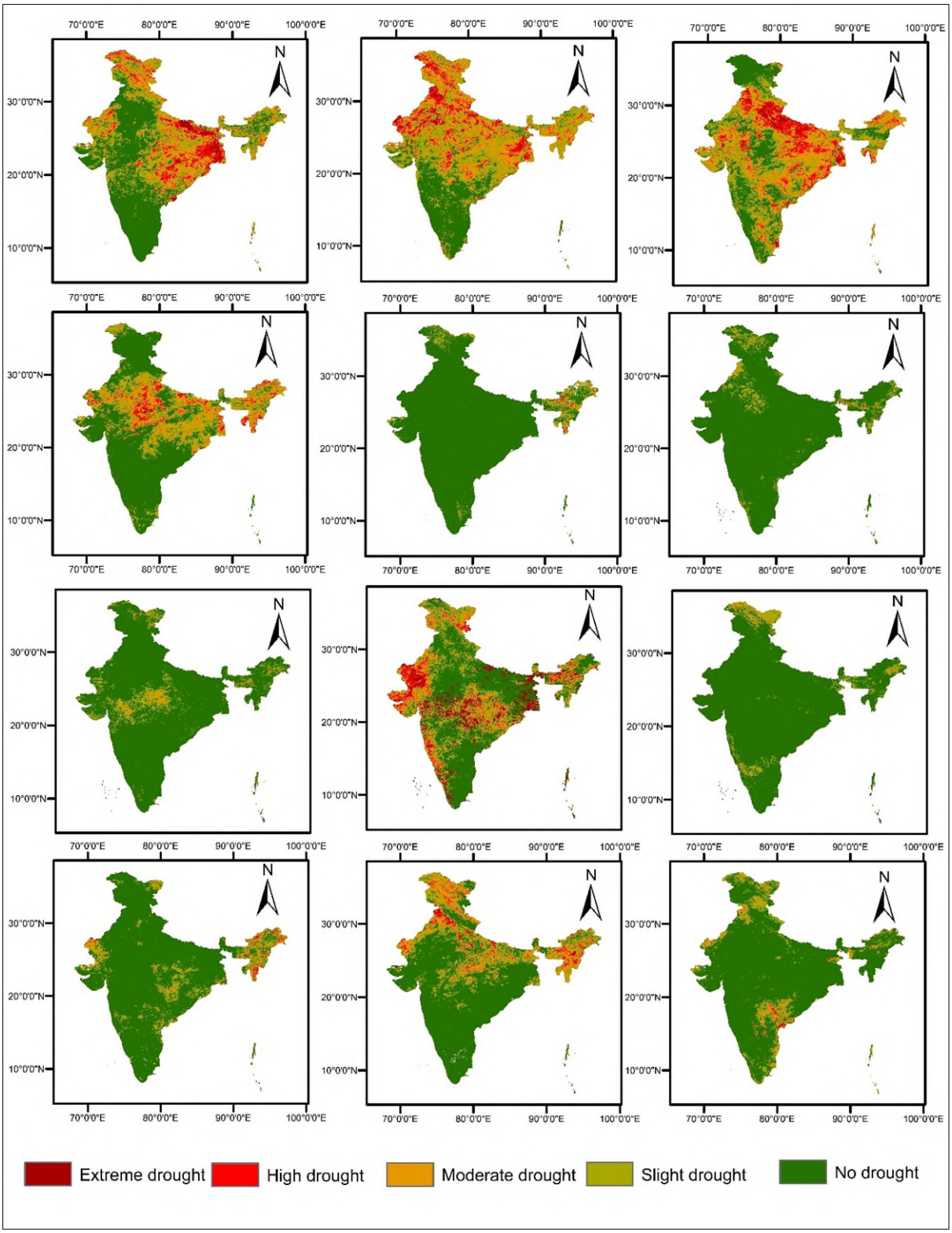


Figure 7. Spatio-temporal distribution of SDCI across India for the sample year of 2021.

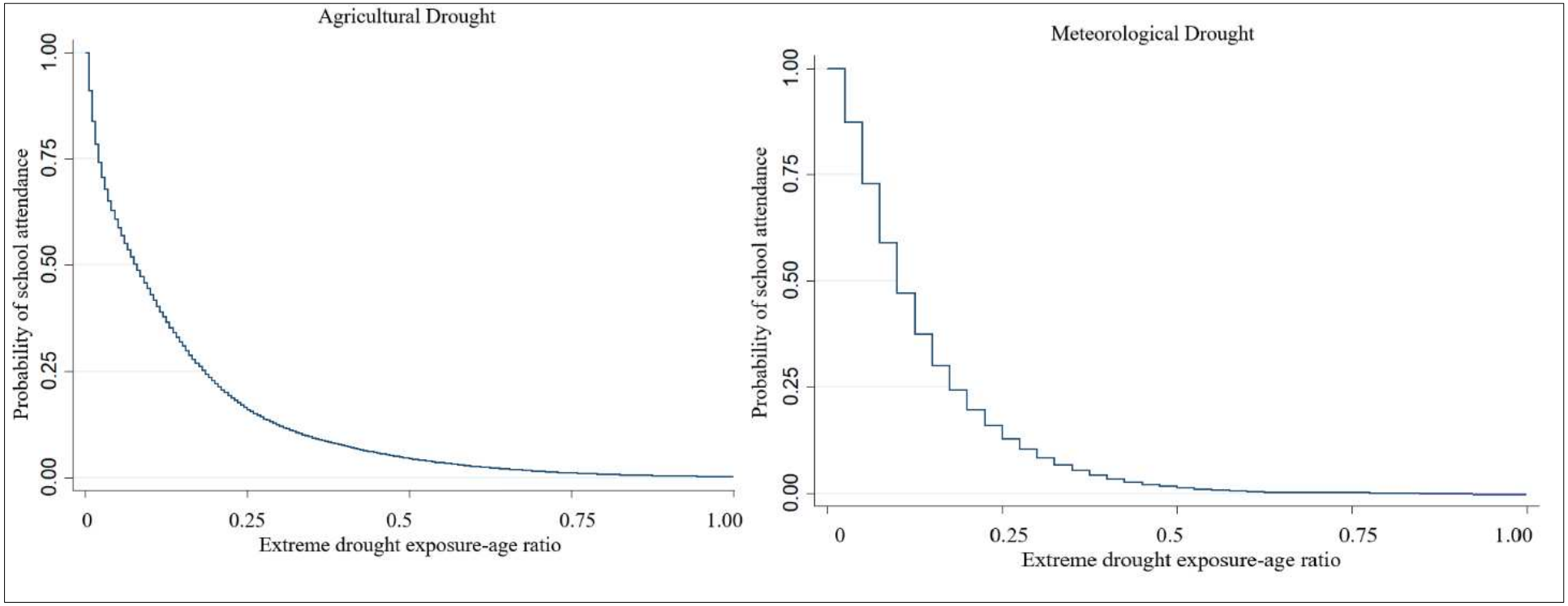
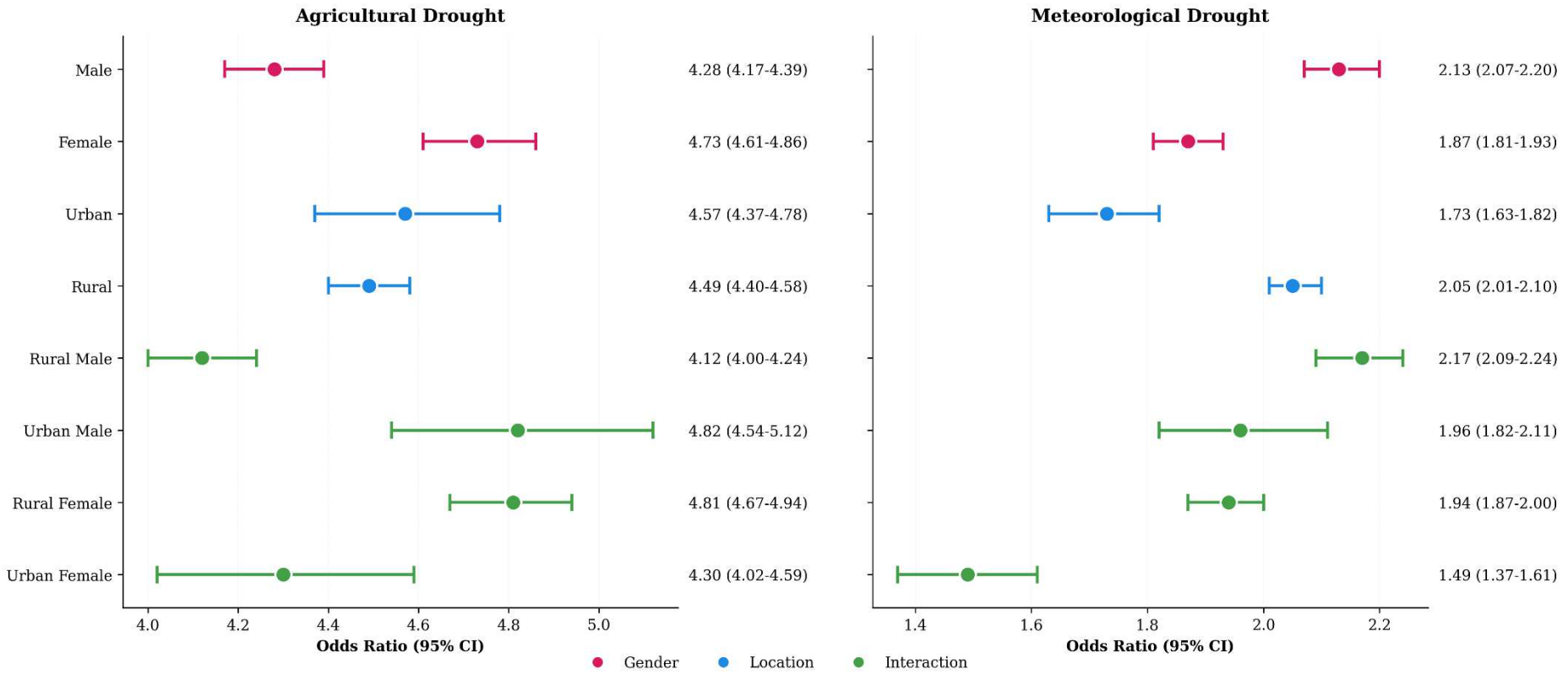


Figure 8. Probability of school attendance based on drought exposure.



Note: Dependent Variable- School dropout (0 = No, 1 = Yes); CI= Confidence *Interval # Controlled variables: marital status, caste, religion, wealth index, sex of the household head, disability, household size, agricultural land ownership, source and distance of drinking water, and the sex composition of younger children in the household.*

Figure 9. Association between drought and school dropout among Indian children by demographic groups.

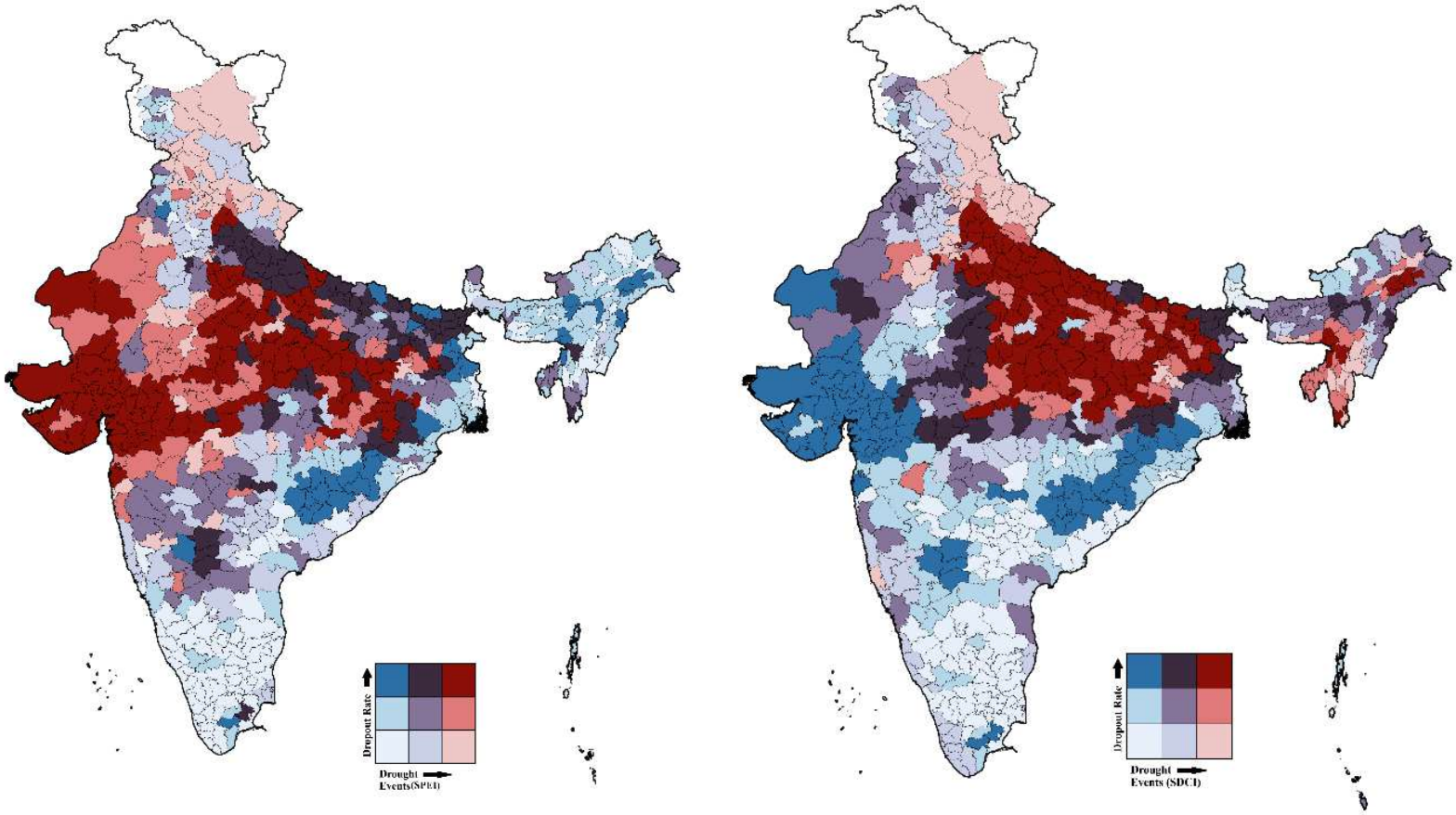


Figure 10. Spatial association between dropout rates and (left) meteorological (SPEI) and (right) agricultural (SDCI) drought episodes over the study period.

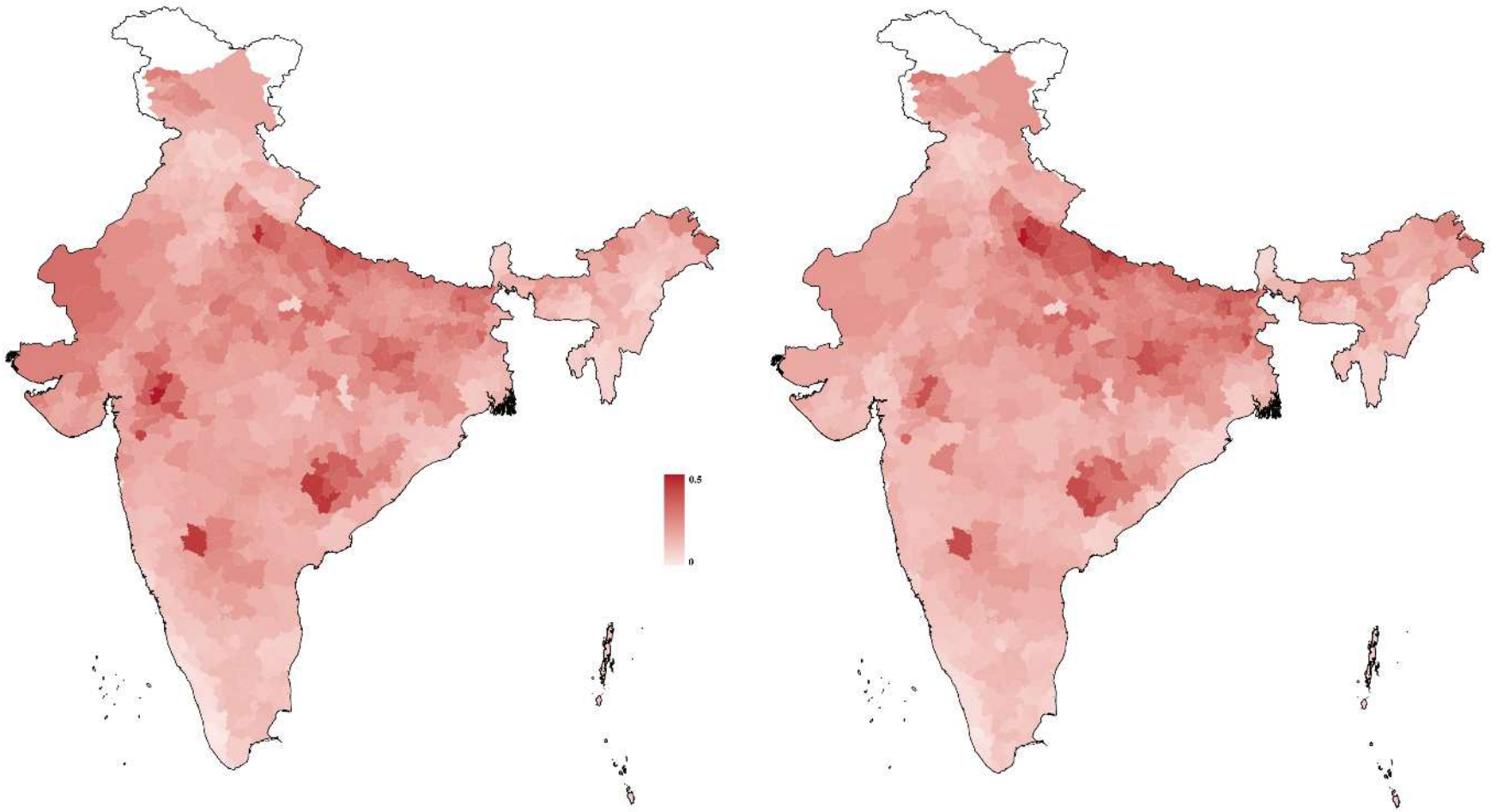


Figure 11. Marginal effects of meteorological (left) drought episodes (SPEI) and agricultural (right) drought episodes (SDCI) on dropout rates after adjusting for confounding factors.

Table 1 Classification of SPEI values based on literature (Drumond et al., 2020).

Classification	SPEI value
Extremely wet	2 & above
Very wet	1.5 to 1.99
Moderately wet	1.0 to 1.49
Near normal	-0.99 to 0.99
Moderately dry	-1.0 to -1.49
Severely dry	-1.5 to -1.99
Extremely dry	-2 & above

Table 2 Classification of SDCI values based on literature [25].

Classification	SDCI value
Extreme drought	$0 \leq SDCI < 0.1$
Severe drought	$0.1 \leq SDCI < 0.2$
Moderate drought	$0.2 \leq SDCI < 0.3$
Light drought	$0.3 \leq SDCI < 0.4$
No drought	$SDCI \geq 0.4$

Table 3 prevalence of school dropout rates by various demographic and socio-economic characteristics.

Background variables	School dropout (%)
Age group (in years)	
5-14	6.76
15-17	23.73
Sex	
Male	10.37
Female	11.59
Place of residence	
Urban	8.16
Rural	12.07
Wealth quintile	
Richest	3.37
Rich	6.35
Middle	8.75
Poor	11.94
Poorest	19.66
Sex of the household head	
Male	10.71

Female	12.35
Marital status	
Not married	55.79
Married	10.59
Religion	
Hindu	10.03
Muslim	16.61
Others	7.55
Social Groups	
Scheduled Tribe	16.33
Scheduled Caste	12.72
Other Backward Caster	10.34
Others	8.1
Region	
North	7.65
Central	15.55
West	9.84
East	12.13
Northeast	9.16
South	5.25
Disability	
Yes	10.65
No	17.74
Household size	
1-4 members	8.84
5-6 members	10.57
7 and more members	13.69
Wealth quintile	
Richest	3.37
Rich	6.35
Middle	8.75
Poor	11.94
Poorest	19.66
Having agricultural land	
Yes	11.36
No	10.41
Collect drinking water from	
Premises	10.25
Outside	12.84
Sex of the person fetching water	
Male	12.84
Female	17.27
Do not fetch	10.21
Sex of the younger* children *in the household	
Male	11.38
Female	12.12
Both	15.76
Not having any children	10.28
Total	**10.96**

Table 4 Logistic regression model to examine the socioeconomic determinants of school dropouts.

Predictors	Odds Ratio (95% CI) Males	Odds Ratio (95% CI) Females	Odds Ratio (95% CI) Urban	Odds Ratio (95% CI) Rural	Odds Ratio (95% CI) Total
Age group (in years)					
5-14®	-	-	-	-	-
15-17	4.99 (4.86-5.12) **	5.09 (4.96-5.23) **	4.71 (4.50-4.92) **	5.14 (5.04-5.24) **	5.06 (4.97-5.15) **
Sex					
Male®	-	-	-	-	-
Female	-	-	0.86 (0.82-0.89) **	1.08 (1.06-1.10) **	1.04 (1.02-1.05) **
Place of residence					
Rural ®	-	-	-	-	-
Urban	0.73 (0.70-0.76) **	0.91 (0.87-0.94) **	-	-	0.81 (0.79-0.83) **
Wealth quintile					
Richest	0.13 (0.12-0.14) **	0.12 (0.12-0.13) **	0.09 (0.09-0.10) **	0.16 (0.15-0.17) **	0.12 (0.12-0.13) **
Rich	0.23 (0.22-0.24) **	0.23 (0.22-0.24) **	0.20 (0.18-0.22) **	0.24 (0.23-0.25) **	0.23 (0.22-0.24) **
Middle	0.35 (0.34-0.36) **	0.34 (0.33-0.36) **	0.32 (0.30-0.35) **	0.35 (0.34-0.36) **	0.35 (0.34-0.36) **
Poor	0.50 (0.49-0.52) **	0.50 (0.49-0.52) **	0.50 (0.46-0.54) **	0.50 (0.49-0.52) **	0.50 (0.49-0.52) **
Poorest®	-	-	-	-	-
Sex of the household					
Male®	-	-	-	-	-
Female	1.14 (1.11-1.18) **	1.08 (1.04-1.11) **	1.27 (1.20-1.34) **	1.08 (1.05-1.11) **	1.11 (1.08-1.14) **
Marital status					
Not married	0.41 (0.36-0.48) **	0.10 (1.10-0.11) **	0.19 (0.15-0.22) **	0.15 (0.14-0.16) **	0.15(0.14-0.16) **
Married®	-	-	-	-	-
Religion					
Hindu®	-	-	-	-	-
Muslim	2.22 (2.14-2.29) **	2.43 (2.34-2.51) **	2.35 (2.23-2.47) **	2.31 (2.24-2.38) **	2.31 (2.26-2.37) **
Others	1.09 (1.04-1.15) **	1.00 (0.94-1.05)	0.99 (0.89-1.09)	1.05 (1.01-1.10) *	1.04 (1.01-1.08) *
Social Groups					
Scheduled Tribe	1.13 (1.08-1.17) **	1.12 (1.08-1.17) **	0.80 (0.73-0.88) **	1.17 (1.13-1.20) **	1.12 (1.09-1.15) **
Scheduled Caste®	-	-	-	-	-
Other Backward Caste	0.78 (0.76-0.81) **	0.82 (0.79-0.85) **	0.76 (0.72-0.81) **	0.81 (0.79-0.83) **	0.80 (0.78-0.82) **
Others	0.65 (0.62-0.68) **	0.58 (0.55-0.61) **	0.59 (0.55-0.63) **	0.62 (0.60-0.64) **	0.61 (0.60-0.63) **

Region					
North®	-	-	-	-	-
Central	1.71 (1.65-1.78) **	1.77 (1.70-1.84) **	1.47 (1.38-1.56) **	1.85 (1.80-1.91) **	1.74 (1.69-1.79) **
West	1.51 (1.43-1.59) **	1.74 (1.65-1.83) **	1.24 (1.15-1.33) **	1.76 (1.68-1.83) **	1.62 (1.56-1.68) **
East	1.19 (1.14-1.25) **	0.93 (0.89-0.97) **	0.63 (0.58-0.68) **	1.18 (1.14-1.22) **	1.06 (1.03-1.09) **
Northeast	0.77 (0.73-0.81) **	0.53 (0.50-0.56) **	0.48 (0.43-0.53) **	0.71 (0.68-0.74) **	0.65 (0.62-0.67) **
South	0.88 (0.83-0.93) **	0.74 (0.70-0.78) **	0.57 (0.53-0.62) **	0.91 (0.87-0.96) **	0.81 (0.78-0.84) **
Disability					
Yes	1.99 (1.90-2.09) **	1.65 (1.57-1.74) **	2.25 (2.07-2.44) **	1.74 (1.67-1.80) **	1.82 (1.76-1.88) **
No®	-	-	-	-	-
Household size					
1-4 members®	-	-	-	-	-
5-6 members	1.05 (1.02-1.09) **	1.02 (0.99-1.06)	1.11 (1.05-1.17) **	1.02 (1.00-1.05)	1.04 (1.02-1.06) **
7 and more members	1.32 (1.27-1.37) **	1.23 (1.18-1.27) **	1.38 (1.29-1.47) **	1.25 (1.22-1.29) **	1.28 (1.25-1.31) **
Having agricultural					
Yes	1.40 (1.37-1.44) **	1.25 (1.22-1.29) **	1.50 (1.40-1.60) **	1.31 (1.28-1.33) **	1.33 (1.30-1.35) **
No®					
Collect drinking water					
Premises®	-	-	-	-	-
Outside	0.95 (0.85-1.06)	1.17 (1.05-1.29) **	0.91 (0.78-1.06)	1.11 (1.02-1.21) *	1.05 (0.98-1.13)
Sex of the person					
Male®	-	-	-	-	-
Female	1.04 (0.96-1.13)	1.12 (1.04-1.20) **	1.23 (1.03-1.47) *	1.07 (1.01-1.13) *	1.08 (1.03-1.14) **
Do not fetch	0.89 (0.80-0.99) *	1.14 (1.03-1.27) *	0.84 (0.72-0.99) *	1.07 (0.98-1.16)	1.01 (0.93-1.09)
Sex of the children in					
Male®	-	-	-	-	-
Female	1.02 (0.97-1.07)	1.07 (1.02-1.12) *	0.95 (0.87-1.03)	1.06 (1.03-1.10) **	1.05 (1.01-1.08) *
Both	1.28 (1.21-1.36) **	1.23 (1.17-1.30) **	1.03 (0.92-1.14)	1.29 (1.24-1.34) **	1.25 (1.20-1.30) **
No children	0.79 (0.76-0.82) **	0.80 (0.78-0.83) **	0.74 (0.69-0.79) **	0.81 (0.78-0.83) **	0.80 (0.77-0.82) **

Note: ® = Reference category; Dependent Variable- School dropout (0 = No, 1 = Yes) ** p<0.01 *p<0.05; CI= Confidence Interval.

Supplementary Files

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