Development of Climate Vulnerability Index for Bundelkhand Region, India

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Abstract

The present study aims to develop a climate vulnerability index for different districts in the Bundelkhand region of India. The indicator approach and the IPCC's AR4 methodology were used to develop potential vulnerability and climate vulnerability indices. According to the calculated vulnerability index, Lalitpur districts is highly vulnerable due to their greater exposure to changing climate. On the contrary, Chitrakoot district is the least vulnerable to climate change. Hence, the current study suggests the following policy recommendations. First, most of the districts are facing a water crisis even in the rainy season due to the continuous decline in monsoon rainfall distribution, while water is the most critical factor for farming. Therefore, water conservation through rainwater harvesting and the construction of new ponds and check dams would be a possible solution for the current crisis. Second, wheat, rice, and sugarcane are highly water-consuming crops and are not suitable for the Bundelkhand region. Hence, shifting from high water-intensive cropping patterns like wheat, rice, and sugarcane to less water-intensive crops such as kharif pulses and minor cereals would be a better adaptation strategy to increase net farm returns.

Keywords: *Exposure Index, Sensitivity Index, Indicator Approach, IPCC, Water Conservation, Climate Vulnerability*

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1. Introduction

Global, regional, and national economies are all being affected by climate change. Impacts threaten the viability of traditional farming, cattle, and forestry businesses, as well as pre-existing community infrastructure (Singh, 2020a). Inadequate precipitation, high temperatures, and the introduction of harmful pests and diseases are just a few of the ways in which climate change has been shown to damage agricultural production across the world (IPCC, 2018). Crop failure and sterile soil are all direct consequences of climate change, as are the declines in water-holding capacity, economic development, income distribution, and agricultural demand (FAO, 2008). Prices of agricultural goods and services will rise because of the global economic crisis, having a ripple effect on the agricultural sector. Because of agricultural productivity declines, it increased food prices, and reduced purchasing capacity, climate changes will have a significant effect on crop production stability and food availability (Singh and Sanatan, 2014; Singh, 2019; Singh, 2020a & b; Singh and Sanatan, 2020; Jatav et al., 2021a & b; Jatav, 2022).

The concept of climate vulnerability has been defined in many different ways and several conceptual frameworks have been developed to categorise vulnerability factors and describe the various vulnerabilities (McCarthy et al., 2001; Fussel, 2006; Kumar et al., 2016; Singh, 2020a & b; Balaganesh et al., 2020; Datta et al., 2022). (Singh, 2020b). McCarthy et al (2001) and Fussel (2006) defines vulnerability as the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes. Climate vulnerability is a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity (Fig. 1). The exposure of a system to climate stimuli depends on the level of global climate change and, due to the spatial heterogeneity of anthropogenic climate change, on the system's location. The sensitivity of a system denotes the (generally multi-factorial and dynamic) complex and dynamic link between its exposure to climatic stimuli and the resulting impacts. Adaptation refers to adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities. Further, Singh, (2020a & b) presents a conceptual framework of vulnerability that combines a nomenclature for describing any vulnerable situation in terms of the vulnerable system, the hazard(s) of concern, the attributes(s) of concern, and a temporal reference; a classification scheme for vulnerability factors according to their sphere and knowledge domain; and a terminology for vulnerability concepts that is based on the vulnerability factors included. The conceptual framework allows to concisely describe any vulnerability in the literature as well as the differences between alternative concepts (Kumar et al., 2016; Balaganesh et al., 2020; Datta et al., 2022).

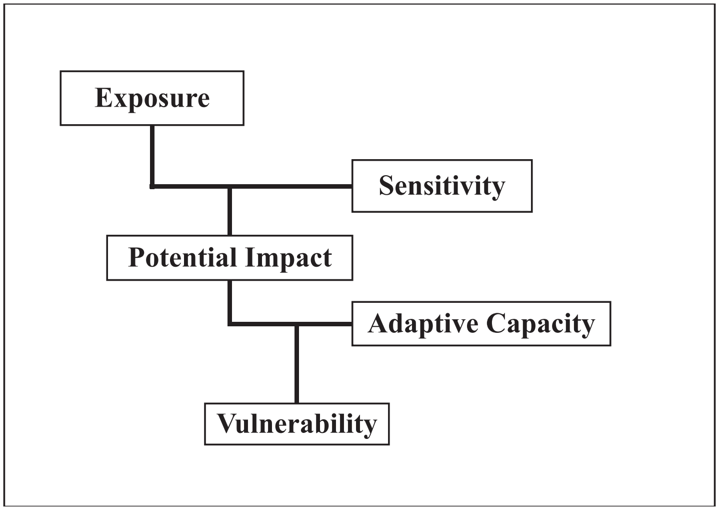

Figure 1 : Conceptual Framework of Climate Vulnerability

Source: IPCC, 2001

The "capacity or inability to be adversely impacted by climatic variability and severe climate events and support them" is a straightforward definition of vulnerability in the context of climate change. Vulnerability assessment is a difficult task because of the complex relationships between many parts of natural systems and human interventions. However, among the many tools necessary for the adaptation of social and biological systems, vulnerability assessment is often regarded as the most crucial.

The current research defines vulnerability as the extent to which climate change threatens food crop output. The idea of vulnerability has emerged as an important tool in the study of climate change in recent years. This is because of the crucial function it plays in helping us comprehend, quantify, and appraise the predicament of communities and individuals in the face of climate-induced catastrophes (Singh, 2020b). In order to better create adaptive measures and build resilience in the face of climate change, the Intergovernmental Panel on Climate Change (IPCC, 2018) stresses the need of conducting a thorough evaluation of the susceptibility of places to climate change.

1.1 Review of Literature

A growing climate vulnerability literature indicates that rural farmers in the Bundelkhand region are particularly at risk. Singh (2020b) looked at the different kinds and levels of susceptibility to economic hardship faced by farming households in the Bundelkhand region. The empirical findings reveal that farmers belonging to Scheduled Tribes (ST) groups were the most susceptible to climate change and the least prepared to respond. In a similar vein, a study by Derbile et al (2022) in Ghana, Africa, found that farmers there were vulnerable to several climatic extremes, with drought being the most often and influential adverse event that considerably impacted agricultural production. As a result, crops were damaged by the subsequent high temperatures and/or plenty of sunshine. All crops investigated, including maize, rice, millet, and soybeans, were very sensitive and susceptible to strong sunshine and temperatures, but the findings showed that rice and corn were the most sensitive and delicate to drought.

In addition, Kumar et al (2016) conducted a study in Karnataka, India, using an indicator approach and a development risk score for several districts. Losses in grain, pulse, and oilseed production were shown to be higher due to climate variability in the Gulbarga and Raichur areas. It is also estimated that over 70% of the farm land is under risk, which is important since it provides food and shelter for 60% and 67% of the state's livestock and rural inhabitants, respectively. Balaganesh et al (2020) did something similar for 30 districts in Tamil Nadu, India, and compiling agricultural and dairy data into a new composite drought vulnerability index (CDVI). The IPCC method was used to determine the index's value; this method took into account the factors of exposure, sensitivity and adaptability. The study found that 12 districts are extremely vulnerable to drought, 8 are moderately vulnerable in the eastern and southern agro-climatic zones, a few districts in Tamil Nadu's Cauvery delta and western zones are extremely vulnerable, and most districts in the north-western, and high rainfall zones are less vulnerable. Likewise, the vulnerability of three smallholder agricultural systems in Telangana, India was also studied by Kuchimanchi et al (2021), (i) crops without livestock (CWL),

(ii) crops with small ruminants (CSR), and (iii) crop with dairy (CD). They found that people's beliefs of their own vulnerability to climate change, the accessibility of resources to support themselves, and the methods they utilised in their farming all had a role in how susceptible their own families households in CWL areas were more susceptible to total precipitation decreases and higher maximum temperatures, whereas those in crop-and-cattle farming areas were more exposed to higher maximum temperatures and more erratic rainfall.

The opinions of farmers are also valuable in determining risk. Datta et al were conducted a (2022) meta-analysis and found that, consistent with meteorological data, many Indian farmers had seen an increase in temperature and an increase in the frequency and/or reduction in rainfall. It seems that Indian farmers have used a broad variety of incremental and systemic adaptation strategies. Farmers are also increasingly adopting radical adjustments such as shifting their land usage, resource and labour allocations, occupational patterns, and agricultural methods. In addition, factors like family income, farm size, gender, and resource endowment, among others, often impact the adoption of adaptation methods.

With the above evidences, the present study aims to develop a climate vulnerability index for all 13 districts of Bundelkhand region using the Assessment Report 4 methodology of Intergovernmental Panel on Climate Change. More specifically, the purpose of the paper is to answer some of the key questions to the extent (how much), causes (why) and spatial distribution (where) of vulnerability.

2. Methods and Materials

2.1 Study Area

The Bundelkhand region comprises of 13 districts in the States of Madhya Pradesh (6 districts) and Uttar Pradesh (7 districts) in central India (Fig. 2). The districts in Madhya Pradesh are Sagar, Damoh, Chhatarpur, Tikamgarh, Panna, and Datia and; the districts in Uttar Pradesh are Jhansi, Lalitpur, Jalaun, Hamirpur, Banda, Mahoba, and Chitrakoot. The Bundelkhand region lies between 23° 08 north to 26°30 north latitude and 78°11 east to 81°30 east longitude, with a total area of 71, 619 km^2. About 82% of the total population of 18.3 million depends on agriculture, the majority of which is rainfed (Census, 2011). About 33% of the territory is covered by degraded forest, grazing pasture, and degraded wasteland. In totality, of the population depends on agricultural and livestock-based industries (Gupta et al., 2014; Singh, 2020b).

The region receives a mean annual rainfall of 750 millimetres, which falls at random intervals throughout the year. More than 85% of the year's precipitation falls during the rainy season (Kharif), which runs from July to September. The remaining 15% is spread out throughout the other nine months (Singh, 2020b). The regional water balance, particularly groundwater recharge, has suffered as a result of this (Singh et al., 2014). The mean temperature is 35°C higher in the rainy season than in the dry season (rabi), which is cooler (10°C). Using long-term data (1971-1990 and 1991-2004), Rao et al. (2013) found that in the Bundelkhand region of of Uttar Pradesh, formerly semi-arid wet climates have transitioned into semi-arid dry and arid climates, affecting around 580,000 hectares.

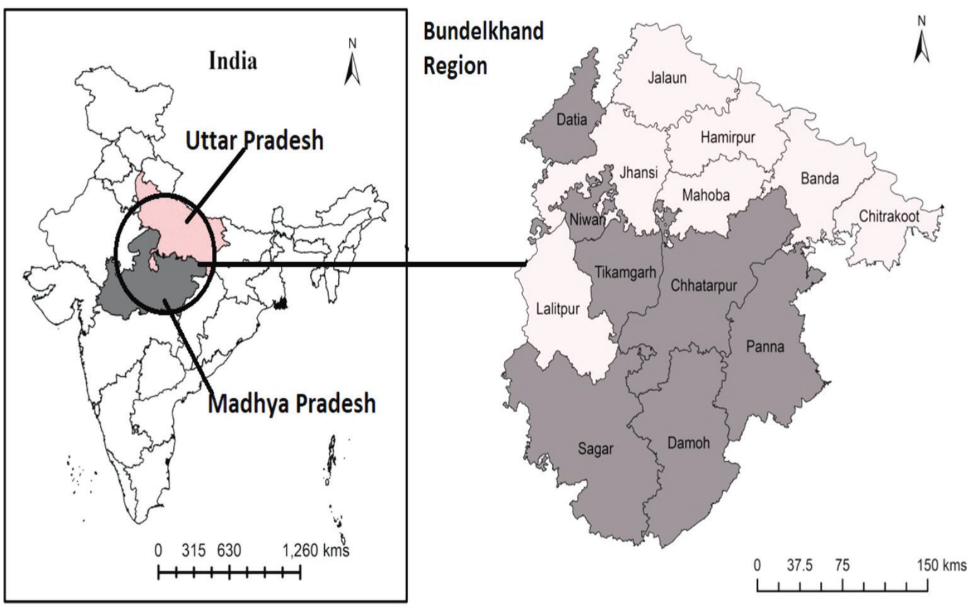

Figure 2 : Study Area Map

Source: Authors Map, 2023. Note: base map was taken from Bhuvan portal, India

2.2 Data Sources, Rationality of Indicators and Descriptive Statistics

The present study uses district-level data collected from differential sources to develop a climate vulnerability index for different districts of the Bundelkhand region. To develop an exposure index, data on temperatures and rainfall was collected from the Indian Meteorological Department, Government of India. Further, seasonal aspects of climate variability were also considered for the robust development of an exposure index. Therefore, exposure index is divided into seasonal temperatures and rainfall indices, i.e., kharif season and rabi season. Mean maximum temperature of Bundelkhand region was 32.41°C, which varies from 28.61°C in rabi season (October- March) to 34.2°C in kharif season (Table 1). Further, mean minimum temperature was 18.74°C, which varies from 12.81°C in rabi season to 25.14°C in kharif season. Mean annual rainfall was 917.36 millimetres, which varies from 78.81 millimetres in rabi season to 825.01 millimetres in kharif season during 1951-2020 (IMD, 2020).

Similarly, data for the sensitivity index were gathered from the Population Census (2011), the Ministry of Agriculture and Farmers Welfare, Government of India (2021-22), and the 76th round of the National Sample Survey organisation (2019-20). Bundelkhand region has reported 11,005 hectares of forest cover, while 3,902 hectares have been reported as not suitable for farming with 10% degraded land (Table 1). Almost half of the region's population lives in poverty, and the gender ratio is lower than in national statistics (i.e., 885). The population density of the region is 278 persons per kilometre. Access to basic amenities is also vital to lowering the climate sensitivity status of households in the region. According to the 2011 census, only half of the population has access to all-season houses, while roughly 40% has access to bathrooms and latrines. However, more than 99% of households have access to safe drinking water.

Although the system may be exposed to or sensitive to climatic stress and shock, it cannot considered to be fragile (Fellmann, 2012). The adaptive capability of a system impacts vulnerability by altering both exposure and sensitivity (Singh, 2020b). Three important factors determine successful and efficient adaptation (i) Timely perception and realisation of climate change and the need to adopt adaptation measures; (ii) incentives to adapt and the ability to adapt; and (iii) the need to change farming practises to maximise returns from the new climate change (Singh, 2020b).

Access to extension services is taken into account when creating an adaptation index for the Bundelkhand region. Table 1 depicts that only 62.67% of households have access to all seasonal roads, while 94.21% of households have access to an electricity connection. Limited financial inclusion is observed. Only 8.81% of rural households are members of an agricultural credit society, while 81.91% of households own livestock. Further, 34.53% of the population works as agricultural labourers. The mean annual per capita income was reported at 27,548 INR. As far as the agricultural training of farmers is concerned, only 1.08% of the population is skilled, while 48.13% of rural households are working in MGNREGA. Moreover, 65.69% of the population is literate, while the mean land size is 1.47 hectares.

Table 1 : Rational Indicators for Vulnerability Assessment

Components	Functional Relationship with targeted component	Mean	Source
Exposure			
Maximum Temperature Variability (1951-2020)			
Kharif Season (June-September)	+	34.21	Singh et al., 2019
Rabi Season (October-March)	+	28.61	Singh et al., 2019
Annual	+	32.41	Singh et al., 2019
Minimum Temperature Variability (1951-2020)			
Kharif Season (June-September)	+	25.14	Singh et al., 2019
Rabi Season (October-March)	+	12.81	Singh et al., 2019
Annual	+	18.74	Singh et al., 2019
Rainfall Variability (1951-2020)			
Kharif Season (June-September)	+	825.01	Singh et al., 2019
Rabi Season (October-March)	+	78.81	Singh et al., 2019
Annual	+	914.36	Singh et al., 2019
Sensitivity			
Forest Area (Hectares)	-	110054	Funk et al. (2019)
Area Not Available for Cultivation (Hectares)	+	39028	Shrestha et al., 2017

Components	Functional Relationship with targeted component	Mean	Source
Net Sown Area (Hectares)	-	312426	Rai et al., 2008
Degraded Land (%)	+	9.76	Rai et al., 2008
BPL Population (%)	+	42.33	Alam et al., 2017
Sex Ratio	+	885.15	Nadeem et al., 2009
Population Density (1000/Km)	+	278.15	Islam et al., 2013
Decadal Population Growth (%)	+	18.65	Islam et al., 2013
Households having all Seasonal House (%)	-	51.00	Alam et al., 2017
Households having Access of Bathroom (%)	-	39.32	Alam et al., 2017
Households having access of Latrine (%)	-	40.57	Alam et al., 2017
Households having Access of Safe Drinking Water (%)	-	99.34	Miranda et al., 2011
Adaptive Capacity			
All Seasonal Approach Road	+	62.67	Masud et al., 2017
Households having access of Power Supply (%)	+	94.21	Masud et al., 2017
Households having membership of Agricultural Credit Society (%)	+	8.81	Singh et al., 2019
Households owning Livestock (%)	+	81.91	Masud et al., 2017
Agricultural labours to total population (%)	+	34.53	Masud et al., 2017
Per Capita Income (₹)	+	27548	Hahn et al., 2009
Households taken formal Training in Agriculture (%)	+	1.08	Singh et al., 2019

Components	Functional Relationship with targeted component	Mean	Source
Households have worked in Mgnrega (%)	+	48.13	Singh et al., 2019
Literacy Rate (%)	+	65.69	Nadeem et al., 2009
Mean Land Size (Hectare)	+	1.47	Abid et al., 2015

Source: Authors estimation, 2023.

2.3 Estimation Method

Conducting a vulnerability assessment is a multistep exercise and requires setting a clear goals and objective that will determine the type of vulnerability assessment as well as the scale, sector, tier, indicators, and methods to be adopted. Because each of the sub-components is measured on a different scale, it was first necessary to standardize each as an index. Hence, equations 1 and 2 (min-max method) was used to normalized the data as follows.

$$Index_{sv} = \frac{S_v - S_{min}}{S_{max} - S_{min}} \quad \text{.......} (1)$$

$$Index_{sv} = \frac{S_{max} - S_v}{S_{max} - S_{min}} \quad \text{.......} (2)$$

Equation 1 was used if the indicator is positively associated with the targeted index, while equation 2 was used if the indicator is negatively associated. In the equations 1 & 2, sv is the original sub-component for the district d, and S_min and S_max are the minimum and maximum values, respectively, for each sub-component determined using the data from all 13 districts. For example, forest area ranged from 110054 to 120154 hectares in all 13 districts. These minimum and maximum values were used to transform this indicator into a standardized index so it could be integrated into the sensitivity component of the vulnerability index. For variables that measure frequencies such as the 'percent of household having access of safe drinking water', the minimum

$$Index_E = \frac{\text{MaxTK+MaxTR+MaxTA+MinTK+MinTR+MinTA+RK+RR+RA}}{9} \dots(3)$$

value was set at 0 and maximum value at 100. Moreover, equations 3, 4 & 5 were used to develop exposure, sensitivity, and adaptive capacity indices.

$$Index_s = \frac{\text{F+ANSA+NSA+DL+BPL+SR+PD+DPG+House+Bathroom+Latrine+Safe Water}}{12} \dots(4)$$

Where, $index_E$ is an exposure index, while MaxTK, MaxTR, MaxTA, MinTK, MinTR, MinTA, RK, RR and RA are maximum kharif season temperature, maximum temperature rabi season temperature, annual maximum temperature, minimum kharif season temperature, minimum temperature rabi season temperature, annual minimum temperature, kharif season rainfall, rabi season rainfall, and annual rainfall.

Where, *index*.is sensitivity index, while F, ANSA, NSA, DL, BPL, SR, PD, DPG, House, Bathroom, Latrine and Safe water are forest area, area not available for cultivation, net sown area, degraded land, population below poverty line, sex ratio, population density, decadal population growth, access of all seasonal house, access of bathroom, access of latrine, and access of safe drinking water.

$$Index_{aci} = \frac{\text{Road+PS+ACS+Livestock+labour+PCI+Training+MGNREGA+LR+Land}}{10} \dots(5)$$

Where, $index_{aci}$ aci is adaptive capacity index, while road, PS, ACS, Livestock, labour, PCI, Training, Mgnrega, LR and Land are all seasonal approach roads, households having access of power supply, membership of agricultural credit society, ownership of livestock, agricultural labourers, per capita income, formal agricultural training, population working in MGNREGA, literacy rate and mean land size.

Once the values of exposure, sensitivity, and adaptive capacity for the district level had been calculated, two contributing factors (exposure and sensitivity) were combined using equation (6) to obtain the district-level potential climate vulnerability index (Tripathi, 2017).

$$PCVI_d = Exposure\ Index_d + Senstivity\ Index_d \text{.........................} (6)$$

Where, $PCVI_d$ is the potential climate vulnerability index for the district d; $Exposureindex_d$ is the calculated exposure index for the district d; and $Senstivityindex_d$ is the sensitivity index for the district d. Adaptive capacity, represented byACI_d (equation 7), was taken into consideration to develop a climate vulnerability index (CVI) for the district das follows.

$$CVI_d = (Exposure\ Index_d - Adaptive\ Capacity\ Index_d) * Senstivity\ Index_d \text{......} (7)$$

PCVI and CVI were scaled so that –1 denotes the least vulnerable and +1 the most vulnerable.

3. Results and Discussion

3.1 Variability in Rainfall and Temperature (1951-2020)

Table 2 depicts the variation in rainfall and temperature from 1951 to 2020. Seasonality of rainfall and temperature was also recorded in order to connect with agriculture. Further, the study period of 1951–2020 is divided into 20–20 sub-periods to capture variability. In India, there are two main cropping seasons, namely kharif (rainy) and rabi (winter). Hence, data on rainfall and temperatures were calculated separately for the kharif, rabi, and annual seasons. The statistics of rainfall revealed that rainfall has declined while variability in temperatures has been observed. Table 2 indicated that annual rainfall during 1951-70 was 999.54 millimetres, while it was only 873.33 millimetres (about 86 millimetres less) during 2011-2020, and similar trends were also observed in the kharif and rabi seasons.

A marginal increase in maximum temperature was also observed. The annual maximum temperature was 32.35°C from 1951 to 1970, and it has risen by 0.19°C from 2011 to 2020. Furthermore, maximum temperatures have risen rapidly during the kharif season while gradually rising during the rabi season. Similar trends in minimum temperatures in the kharif and rabi seasons were also observed. Moreover, diurnal temperature is also important for farm practices. Diurnal temperature range means the variation between the lowest and highest temperatures during a given day at a certain location. It is also reported in Table 2 that the diurnal temperature in all the seasons has increased.

Table 2 : Variability in Minimum & Maximum Temperatures and Rainfall from 1951 to 2020

Indicators	Season	1951-70	1971-90	1991-2010	2011-2020	1951-2020
Rainfall	Kharif	896.89	833.17	785.25	784.71	825.01
	Rabi	95.58	84.02	60.93	74.72	78.81
	Annual	999.54	928.76	855.82	873.33	914.36
Maximum Temperature	Kharif	34.03	33.99	34.34	34.47	34.21
	Rabi	28.65	28.45	28.76	28.59	28.61
	Annual	32.35	32.23	32.56	32.54	32.41
Minimum Temperature	Kharif	25.21	24.96	24.96	25.45	25.14
	Rabi	12.57	12.50	13.03	13.15	12.81
	Annual	18.68	18.53	18.83	19.07	18.74
Diurnal Temperature	Kharif	8.82	9.04	9.39	9.03	9.07
	Rabi	16.08	15.94	15.73	15.44	15.80
	Annual	13.73	13.67	13.69	15.37	13.94

Source: Authors estimation, 2023. Note: Kharif season (June-September) and Rabi season (October-March)

3.2 Exposure Index (EI)

Table 3 depicts exposure indices for different districts in the Bundelkhand region. The calculated exposure indices show that Lalitpur district is highly exposed to changing temperatures and rainfall, while Chitrakoot district is relatively least exposed. In general, temperatures in Lalitpur are higher than in other districts during the kharif and rabi seasons. The statistics revealed that the mean annual temperature during 1951–2020 in Lalitpur was 32.63°C while it was only 32.46°C in Chitrakoot. On the contrary, the mean minimum temperature is relatively higher in Chitrakoot than in Lalitpur. The mean minimum temperature in Lalitpur was reported at 18.40°C, while the corresponding figures for Chitrakoot were 18.81°C. It shows the variability in temperature in the Bundelkand region.

As far as rainfall variability is concerned, the mean annual rainfall in Chitrakoot was 1006 millimetres, while the corresponding figures for Lalitpur were only 971 millimetres during 1951-2020.

Table 3 : District-Wise Exposure Index

Districts	Maximum Temperature			Minimum Temperature			Rainfall			Exposure Index
	Kharif	Rabi	Annual	Kharif	Rabi	Annual	Kharif	Rabi	Annual	
Banda	0.152	0.362	0.235	0.466	0.060	0.092	0.182	0.434	0.073	0.228
Chitrakoot	0.117	0.237	0.000	0.453	0.000	0.017	0.125	0.249	0.077	0.142
Hamirpur	0.020	0.985	0.778	0.000	0.214	0.000	0.540	0.700	0.497	0.415
Jaluan	0.265	0.990	0.489	0.151	0.584	0.380	1.000	1.000	1.000	0.651
Jhansi	0.557	0.961	0.888	0.768	0.759	0.826	0.359	0.724	0.432	0.697
Lalitpur	0.830	0.701	1.000	0.704	1.000	1.000	0.193	0.667	0.249	0.705
Mahoba	0.323	0.871	0.801	0.612	0.342	0.393	0.210	0.338	0.077	0.441
Chhatarpur	0.463	0.485	0.537	0.514	0.292	0.259	0.104	0.189	0.000	0.316
Damoh	0.927	0.001	0.277	1.000	0.433	0.659	0.137	0.000	0.083	0.391
Datia	0.500	0.983	0.570	0.304	0.815	0.623	0.389	0.901	0.501	0.621
Panna	0.541	0.012	0.015	0.595	0.174	0.190	0.263	0.000	0.161	0.217
Sagar	1.000	0.017	0.370	0.607	0.495	0.513	0.000	0.223	0.017	0.360
Tikamgarh	0.632	0.639	0.750	0.626	0.619	0.632	0.234	0.597	0.265	0.555

Source: Authors estimation, 2023.

3.3 Sensitivity Index (SI)

Table 4 depicts district-wise sensitivity indexes for the Bundelkhand region. The calculated sensitivity index shows that Chitrakoot district is relatively highly climate-sensitive, while Hamirpur district is relatively less sensitive. The cross-indicator analysis revealed that the main influencing factors responsible for less higher sensitivity in Chitrakoot district than Hamirpur district are less forest area, net sown area, a higher proportion of the population living below the poverty line, higher population density, higher decadal population growth, and less access to bathrooms and latrines.

It is observed that Chitrakoot district has only 24084 hectares of forest area, while Hamirpur district has 81363 hectares. Further, Chitrakoot district has only 165019 hectares of land under cultivation, while Hamirpur district has 289212 hectares. In Chitrakoot district, approximately 36.35% of the population lives below the poverty line, while only 29.75% of the population lives below the poverty line nationally. Furthermore, only 22.22 and 47.57% of households belonging to the Chitrakoot district have access to bathrooms and latrines, while the corresponding figures for Hamirpur were relatively higher, i.e., 47.92% and 63.54%.

Table 4 : District-Wise Sensitivity Index

Districts	Forest Area	Area Not Available for Cultivation	Net Sown Area	BPL Population	Sex Ratio	Population Density	Decadal Population Growth	All Seasonal House	Access of Bathroom	Access of Latrine	Safe Drinking Water	Degraded Land	Sensitivity Index
Banda	1.000	0.782	0.573	0.272	0.041	1.000	0.475	0.229	0.667	0.688	0.001	0.026	0.479
Chitrakoot	0.747	0.503	1.000	0.364	0.367	0.655	1.000	0.078	0.778	0.521	0.007	0.068	0.507
Hamirpur	0.937	0.520	0.697	0.298	0.000	0.444	0.000	0.468	0.524	0.365	0.000	0.049	0.358
Jaluan	0.924	0.741	0.566	0.494	0.082	0.874	0.441	0.281	0.417	0.569	0.005	0.076	0.456
Jhansi	0.903	0.908	0.629	0.218	0.592	0.981	0.369	0.689	0.719	0.615	0.005	0.107	0.561
Lalitpur	0.762	0.848	0.693	0.510	0.918	0.383	0.811	0.219	0.875	0.798	0.000	0.082	0.575
Mahoba	0.961	0.669	0.834	0.408	0.347	0.621	0.754	0.250	0.708	0.800	0.000	0.026	0.531
Chhatarpur	0.307	0.792	0.242	0.575	0.449	0.234	0.581	0.839	0.667	0.819	0.018	0.136	0.472
Damoh	0.131	0.422	0.616	0.596	1.000	0.119	0.458	0.594	0.719	0.750	0.008	0.131	0.462
Datia	0.920	0.000	0.860	0.394	0.245	0.575	0.538	0.786	0.692	0.708	0.010	0.104	0.486
Panna	0.000	0.743	0.773	0.489	0.898	0.000	0.547	0.625	0.218	0.197	0.010	0.185	0.390
Sagar	0.029	1.000	0.000	0.616	0.653	0.345	0.500	0.406	0.500	0.417	0.010	0.152	0.386
Tikamgarh	0.858	0.247	0.837	0.272	0.816	0.552	0.606	0.906	0.406	0.479	0.011	0.127	0.510

Source: Authors estimation, 2023.

3.4 Adaptive Capacity Index (ACI)

Table 5 depicts district-wise adaptive capacity indexes for different districts in the Bundelkhand region. The calculated adaptive capacity index results show that Hamirpur district has the highest adaptive capacity compared to other districts, while Chitrakoot district has the least adaptive capacity to cope with climate change. The cross-indicator analysis revealed that relatively higher access to electricity, higher membership in agricultural credit societies, a higher working population in agriculture, higher per capita income, a higher population working in MGNREGA, and a higher mean land size were the main contributing indicators for higher adaptive capacity in Hamirpur

It is observed that about 95.95% of households belonging to the Hamirpur districts have access to electricity, while the corresponding figure for Chitrokoot is only 92.43%. About 7.12% of farmers in Hamirpur district are members of an agricultural credit society, compared with only 6.56% of farmers nationwide. Further, more than 40% of the rural population in Hamirpur district works in agriculture, while the corresponding figure for Chitrakoot is 38.23%. There is a wide gap between the per capita income of Chitrakoot and Hamirpur districts. The per capita income of Hamirpur is 60,216 INR, while that of Chitrakoot is only 21,590 INR. MGNREGA provides employment to the unskilled population in the off-cropping season and is a major contributor to livelihood security. The statistics revealed that more than 40% of the rural population was employed in MGNREGA, while the corresponding figure for Chitrakoot was only 9.38%. Lastly, the mean land size of Chitrakoot district was only 1.03 hectares, while the mean land size of Hamirpur is 1.75 hectares.

Table 5 : District-Wise Adaptive Capacity Index

Districts	All Season approach roads	Power Supply	Agricultural Credit societies	Livestock	Agricultural labours	Per Capita Income	Agricultural Training	Mgnrega	Literacy Rate	Mean Land Size	Adaptive Capacity Index
Banda	0.519	0.988	0.061	0.896	0.233	0.348	0.020	0.229	0.559	0.417	0.427
Chitrakoot	0.796	0.924	0.066	0.813	0.382	0.124	0.010	0.094	0.773	0.000	0.398

Districts	All Season approach roads	Power Supply	Agricultural Credit societies	Livestock	Agricultural labours	Per Capita Income	Agricultural Training	Mgnrega	Literacy Rate	Mean Land Size	Adaptive Capacity Index
Hamirpur	0.789	0.960	0.071	0.851	0.409	1.000	0.000	0.426	0.668	1.000	0.617
Jaluan	0.775	0.893	0.099	0.813	0.304	0.098	0.000	0.438	0.725	0.556	0.470
Jhansi	0.755	0.893	0.099	0.867	0.304	0.836	0.004	0.200	0.702	0.611	0.527
Lalitpur	0.838	0.995	0.051	0.906	0.261	0.304	0.000	0.328	0.604	0.528	0.481
Mahoba	0.783	0.888	0.094	0.781	0.373	0.200	0.005	0.313	0.619	0.944	0.500
Chhatarpur	0.462	0.909	0.108	0.807	0.317	0.036	0.000	0.645	0.592	0.833	0.471
Damoh	0.459	0.981	0.072	0.813	0.435	0.099	0.050	0.750	0.661	0.625	0.495
Datia	0.442	0.976	0.108	0.696	0.292	0.166	0.038	0.554	0.706	0.639	0.462
Panna	0.444	0.898	0.088	0.781	0.460	0.018	0.009	0.656	0.626	0.472	0.445
Sagar	0.453	0.958	0.089	0.969	0.376	0.143	0.006	0.750	0.721	0.889	0.535
Tikamgarh	0.633	0.984	0.139	0.656	0.342	0.000	0.000	0.875	0.586	0.486	0.470

Source: Authors estimation, 2023.

3.5 Climate Vulnerability Index (CVI)

By using equations 6 and 7, potential vulnerability and climate vulnerability indices were calculated (Table 6). The potential vulnerability index indicates that if farmers do not adopt recommended adaptations, they will be exposed and sensitive to climate change; on the other hand, the vulnerability index increases farmers' adaptive capacity in the system. In the science of vulnerability assessment, adaptive capacity is always a determining factor. Higher adaptive capacity reduces the intensity of climate vulnerability and makes the system more resilient to climate change. Jhansi district is the most vulnerable, while Panna district is the least vulnerable, according to the calculated potential vulnerability index scores. Now if we include adaptive capacity in the system, the picture changes completely. The calculated vulnerability index shows that Chitrakoot district has the least vulnerable district, while Lalitpur district has the highest vulnerability among the districts.

Table 6 : District-Wise Vulnerability Index

Districts	Exposure Index	Sensitivity Index	Adaptive Capacity Index	Potential Vulnerability Index	Vulnerability Index
Banda	0.228	0.479	0.427	0.707	-0.095
Chitrakoot	0.142	0.507	0.398	0.649	-0.130
Hamirpur	0.415	0.358	0.617	0.773	-0.072
Jaluan	0.651	0.456	0.470	1.107	0.083
Jhansi	0.697	0.561	0.527	1.258	0.095
Lalitpur	0.705	0.575	0.481	1.280	0.129
Mahoba	0.441	0.531	0.500	0.972	-0.031
Chhatarpur	0.316	0.472	0.471	0.788	-0.073
Damoh	0.391	0.462	0.495	0.853	-0.048
Datia	0.621	0.486	0.462	1.107	0.077
Panna	0.217	0.390	0.445	0.607	-0.089
Sagar	0.360	0.386	0.535	0.746	-0.068
Tikamgarh	0.555	0.510	0.470	1.065	0.043

Source: Authors estimation, 2023.

4. Conclusion and Policy Recommendations

This study was conducted in the most backward and vulnerable region of India, i.e., the Bundelkhand region. Using the IPCC's AR4 vulnerability assessment methodology, vulnerability indices for different districts of the Bundelkhand region were calculated. The region is drought-prone, and the rural population is solely dependent on farming, which is highly susceptible to changing climates. The findings from our study can be supplemented with the vulnerability assessment of ICAR-CRIDA. The results of the study also show that livelihood options in the region are limited and primarily based on agriculture and the labour sector. Due to their high reliance on the primary sector for livelihood, the rural population is highly vulnerable to changing climatic conditions. The findings from this study are more suitable for the local rapid vulnerability assessment. Furthermore, the findings aided in the development of sector-specific as well as overall vulnerability assessments and adaptation strategies for dealing with climate change. These can be implemented by the state government and local bodies to reduce the vulnerability and enhance the adaptive capacity of all 13 drought-prone districts.

As a result, the current study suggests the following policy recommendations. First, most of the districts are facing a water crisis even in the rainy season due to the continuous decline in monsoon rainfall distribution, while water is the most critical factor for farming. Therefore, water conservation through rainwater harvesting and the construction of new ponds and check dams would be a possible solution for the current crisis. Second, wheat, rice, and sugarcane are highly water-consuming crops and are not suitable for the Bundelkhand region. Hence, shifting from high water-intensive cropping patterns like wheat, rice, and sugarcane to less water-intensive crops such as kharif pulses and minor cereals would be a better adaptation strategy to increase net farm returns.

The study's findings are critical for assessing regional vulnerability and providing direction for future research. The results of this study, however, need to be interpreted with caution because of certain limitations. First, the present study only used spatial data, while if we want to track the role of climate adaptations introduced to reduce vulnerability in the region, spatial and temporal analysis are prerequisites. Second, crop production loss due to climate change is another important factor responsible for higher vulnerability in the region. Hence, the production loss index (decomposition analysis) also needs to be calculated for robust estimation. Finally, while secondary data is useful for rapid assessment, the case study method is critical for capturing the impact of any adaptation strategy, such as how MGNREGA contributed to reduce climate vulnerability. Hence, a robust and comprehensive case study of climate vulnerability in the region is a prerequisite.

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