Socioeconomic Backwardness Increases Vulnerability to Climate Change: Evidence from Uttar Pradesh

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ABSTRACT

This study tries to assess the vulnerability to climate change of farmers in Uttar Pradesh (UP), a state in India. The study chose UP for its importance in India's food and nutrition security programme and its high sensitivity to climate change. It uses 17 environmental and socioeconomic factors to see which districts of UP are the most vulnerable to climate change, and attempts to identify the factors on a set of explanatory variables. The study finds that infrastructurally and economically developed districts are less vulnerable to climate change; in other words, vulnerability to climate change and variability is linked with social and economic development. This observation is corroborated by the findings of relational analysis. In relational analysis, livestock, forestry, consumption of fertiliser, per capita income, and infant mortality rate are observed to be important correlates of farmers' vulnerability to climate change; these should be focussed on to reduce farmers' climate change vulneraiblity. Also, farmers' awareness and adaptive capacity to climate change needs to be strengthened, for which policy options such as crop insurance and early warning systems would help.

Keywords: Climate change, vulnerability, farmer, Uttar Pradesh

1 INTRODUCTION

> The global average surface temperature over the past 50 years has increased at nearly double the rate of the past 100 years. Although warming is greatest at the higher northern latitudes, it has been widespread worldwide over the past 30 years. The precipitation pattern has also changed spatially; significantly increased precipitation has been observed in the eastern parts of North and South America, northern Europe, and northern and central Asia. Drying has been observed in the Sahel, the Mediterranean, southern Africa, and parts of southern Asia. Heavy precipitation events (above the 95th percentile) have increased in many land regions since about 1950, even where the total precipitation amount has dropped. Increases have also been reported for rarer precipitation events (1in 50 year return period) in a few regions (IPCC, FAR 2007).[1]

The increasing concentration of anthropogenic gases in the atmosphere is mainly responsible for these rapid changes in the climate (IPCC 2007). Climate change, now considered a major obstacle to development (Stern 2007), is likely to affect crop productivity adversely which, in turn, threatens food and livelihood security—particularly in developing countries like India, where agriculture employs 55 per cent of its total working population (Registrar General 2013) and accounts for about 14.1 per cent of its GDP (GoI[2] 2013). Both productivity and production have improved in agriculture since Independence (Tripathi 2010; Tripathi and Prasad 2009), but food and nutrition security is still one of the greatest challenges for India. Around 46 per cent of three-to-six-year-olds are malnourished (Srivastava 2012). It underlines the need for further growth in agricultural production, which will strengthen food availability, an important dimension of food security, and revive the overall economy.[3] But agriculture in India is expected to be highly vulnerable to climate change and variability mostly because

1. it depends largely on monsoon rainfall (around 60 per cent of the net cultivated area in India is rainfed); and
2. most farmers are poor, being small and marginal farmers, because they do not have enough income and have low adaptive capacity.

These problems are aggravated by the lack of knowledge and awareness among Indian farmers (GoI 2005) and poor rural infrastructure facilities.

The IPCC (2007) and several organisations predict that global climate change will speed up. To reduce the vulnerability of systems to climate change, some policy actions are required urgently. The climate policy literature suggests two policy options to deal with the inevitable

[1] Intergovernmental Panel on Climate Change, Fourth Assessment Report 2007

[2] Government of India

[3] According to the Central Statistical Organisation (CSO), the Indian economy grew at 6.2 per cent in 2011–12, and at 5.4 per cent in the first quarter of 2012–13, 5.2 per cent in the second, 4.7 per cent in the third, and at 4.8 per cent in the fourth quarter.

impacts of climate change and variability: mitigation and adaptation. While traditionally mitigation has received higher priority, nowadays adaptation has gained worldwide interest because it responds quickly to climate change. The GoI has also started to give it importance along with mitigation, as is evident from India's National Action Plan for Climate Change (NAPCC) (GoI 2008).

An entity or system tends to adapt autonomously to climate change and variability, but not enough to offset losses from it. Therefore, policy-driven or planned adaptation is required. The success of policy-driven adaptation depends on the understanding of an entity's vulnerability because it helps to identify vulnerable regions or sectors to prioritise research allocation for adaptation, and to recommend adaptation measures for specific regions and sectors (Fussel and Klein 2006). Against this backdrop, the present paper attempts to study the vulnerability to climate change and variability of farmers in Uttar Pradesh (UP) state of India. This state is selected for the study because of its importance in India's food and nutrition security programme and its high sensitivity to climate change and variability (O'Brien et al. 2004). First, the vulnerability to climate change is measured for all districts of the state using the indicator approach; then, its correlates are identified using multivariate regression analysis. In the indicator apporach, both biophysical and socioeconomic factors are combined together to mesure climate change vulnerability. This approach have been widely used at both the global level (Gbetibouo et al. 2010) and at the national level (O'Brien et al. 2004; Das 2013).

While climate change has been increasingly becoming an interesting area of research in India, most studies[4] focus either on the change in climatic variables or on the impact of climate change; few studies assess vulnerability to climate change. Of these, most assess vulnerability to natural hazards like cyclones for coastal regions or districts. Studies on the vulnerability of Indian coastal areas to cyclones have measured vulnerability either at the district level or for the coastal regions of the state as a whole, and have considered factors such as cyclone frequency, population density, coastline length, some measures of cyclone damages witnessed, etc. (Jayanthi 1998; Patwardhan et al. 2003; Kavi Kumar 2003; Kalsi et al. 2004). These studies have been criticised because these did not consider natural systems variables and socioeconomic factors, which significantly affect entities' vulnerability to climate change and variability. Das (2012) accepted these variables' importance and included these in her assessment of coastal vulnerability; she studied coastal villages of the Kendrapada district[5] and analysed the role of multiple factors on cyclone impacts.

Some studies have also attempted to examine agriculture's vulnerability to climate change and variability (O'Brien et al. 2004; Patnaik and Narayanan 2005; Malone and Brenkert 2008; Palanisami et al. 2009; Hiremath and Shiyani 2012). O'Brien et al. (2004) and Malone and Brenkert (2008) carried out a country-level assessment using district level information, while Patnaik and Narayanan (2005), Palanisami et al. (2009), and Hiremath

[4] For a list of studies, see Jha and Tripathi (2011) and Jain and Kumar (2012).

[5] Kendrapada is a highly cyclone-prone district of peninsular India.

and Shiyani (2012) confined their study to a state or region. Like the previous studies, these studies also considered coastal states such as Tamil Nadu and Gujarat and ignored states such as UP where inland agriculture predominates, which also experience climatic problems like drought, etc., although not as much as coastal states.

The present study attempts to fulfill this gap in the literature by focusing on an inland state. Section 2 explains why UP was selected as a study area and presents an overview of the state. Section 3 discusses the methodology used to assess farmers' vulnerability to climate change and variability, and discusses the conceptual framework that builds on the concept of vulnerability to climate change developed by the IPCC (McCarthy et al. 2001, 995). This study calculates five indices: exposure, sensitivity, potential impact, adaptive capacity, and vulnerability. Section 4 discusses the spatial pattern of these indices, presents the estimated results graphically, and tries to identify the correlates of vulnerability to climate change. Finally, Section 5 concludes the study and suggests some policy actions to reduce farmers' vulnerability to climate change.

2 THE STUDY AREA

2.1 Why UP?

Although UP is poor in terms of per capita income, it is the leading state in terms of agriculture production in the country; its comparative advantage in agriculture production stems from a strong agriculture base with the most fertile land masses and a well-connected river network and enables it to play a significant role in the country's food and nutrition security programme. But climate sensitivity to agriculture is very high in the state, and the recent changes observed in climate may be an obstacle (O'Brien et al. 2004). There is therefore an urgent need to make agriculture more resistant to climate change. It will help not only the state economy but also the country.

Besides, UP, India's fifth largest state[6] and its most populous,[7] is diverse in geography and culture. A study based on a large and heterogeneous region always has a wider perspective because it provides a range of outcomes, which can also be used for other parts of the country. Uttar Pradesh was selected for the present study keeping these views in mind.

2.1.1 Uttar Pradesh: An Overview

Located in the northern part of the country, UP is surrounded by Bihar in the east; Madhya Pradesh in the south; Rajasthan, Delhi, Himachal Pradesh, and Haryana in the west; and Uttaranchal in the north. Nepal touches its northern borders. It has 83 districts,

[6] Its area of 2,94,411 sq km lies between latitude 24 deg to 31 deg and longitude 77 deg to 84 deg East. It is half the area of France, three times that of Portugal, four times that of Ireland, seven times that of Switzerland, ten times that of Belgium, and a little bigger than England.

[7] Uttar Pradesh is the most heavily populated state in India. Its population (166 million) exceeds the population of Japan and is many times the population of Norway, Ireland, Switzerland, New Zealand, Spain, and even the UK.

901 development blocks, and 112,804 inhabited villages. The state is divided into four economic regions: western, central, eastern, and Bundelkhand (Table 1A, Appendix). The state is also divided into nine agro-climatic regions: central plain, south-western semi-arid, Bundelkhand, eastern plain, north-eastern plain, Vindyan, Bhabhar and Tarai Zone, western plain, and mid-western plain (Table 2A, Appendix).

The western region is more developed than other regions. Its per capita income (Rs17273) is significantly higher than the other three regions: central (Rs13940), Bundelkhand (Rs 12737), and eastern (Rs 9859). Around 40 per cent of the state's population lives in the eastern region, but only 9.5 per cent in the Bundelkhand region, where population density is also the lowest. Despite low population pressure, the region is socially and economically backward, because of its geographical and climatic conditions.

Moreover, the performance of agriculture varies greatly across regions in the state. The western region is agriculturally the most progressive; the largest chunk of the state's agriculture output comes from this region (around 50 per cent). The eastern region contributes around 28 per cent, next to the western region, of the total value of the state's agriculture output. The Bundelkhand accounts for only 4 per cent of the state's gross value of agriculture output. Agriculture in the Bundelkhand region is vastly rain-dependent, diverse, complex, under-invested, risky, and vulnerable. The average foodgrain yield in the western region is 2,577 kg per hectare—much higher than other regions, particularly the eastern (1,997 kg per ha) and Bundelkhand regions (1,067 kg per ha).

3 EMPIRICAL METHODOLOGY

The research techniques of data collection and data analysis applied in measuring the climate change vulnerability index and assessing its correlates are discussed here in the following sub-sections.

3.1 Methods

3.1.1 Calculating Vulnerability Index

In this study, an indicator-based approach was used to measure farmers' vulnerability to climate change and variability. In this approach, a composite index called vulnerability index is calculated by combining several indicating variables. These indicating variables may be either socioeconomic factors or biophysical factors or both. Considering only socio-economic factors or biophysical factors is not an appropriate approach because it overlooks each other's contribution in variations among individuals or social groups. Two individuals or social groups having similar socioeconomic characteristics but different environmental attributes can have different levels of vulnerability and vice versa. This variation in vulnerability cannot be captured if we take into account one type of factor only. Therefore, an integrated approach considering both biophysical and socioeconomic factors together would be a better way to calculate the vulnerability index. The same approach was followed in the present study.

Four steps are generally involved in calculating a composite index : (1) selection of components and component variables, (2) scaling, (3) weighting and aggregation, and (4) validation. In this study, we follow these four steps in the same sequence.

3.1.1.1 *Selection of components and component variables*

There is no common way to select indicating variables. But most things depend on the way we define vulnerability and the system or entity, which is to be analysed. The available definitions are mostly vague; we follow the vulnerability definition developed by the Working Group II of the IPCC. This definition is the most authoritative in the context of climate change. The Third Assessment Report (TAR) of the IPCC defines 'vulnerability' as:

> the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate change and variation to which a system is exposed, its sensitivity, and its adaptive capacity (McCarthy et al. 2001,995).

Following the above definition, the vulnerability index (VI) has three major components: exposure, sensitivity, and adaptive capacity. Exposure refers to the character, magnitude, and the rate of climate change a system is or will be facing. Sensitivity refers to the degree to which a system is affected by climate change and variability. Exposure and sensitivity together show the potential impact of climate change. Adaptive capacity refers to the ability or potential of a system to respond successfully to climate change and variability to avert their impact.

Each of the above components is represented with several indicators. Finally, 17 indicators were selected (four for exposure, five for sensitivity, and eight for adaptive capacity) based on a review of literatures (Scoones 1998; Smit et al. 2001; Yohe and Tol 2002; O'Brien et al. 2004; Das 2013; and others) on each component. Table 1 presents all chosen variables, explains how each variable is quantified and their source of data, and includes the hypothetical relation of each indicating variable with vulnerability.

3.1.1.2 *Scaling: Standardisation*

Each indicating variable is measured on a different scale; therefore, it is necessary to standardise each variable as an index. We used Equation 1 for the above conversion. This equation was adopted from the equation used in the Human Development Index to calculate the life expectancy index (UNDP 2013).

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

where,

where, S_d is the original value of the variable for district d, and

S_{min} and S_{max} are the minimum and maximum values of the variable, respectively.

To ensure that high index value indicates high vulnerability in all cases, we reversed the index values by using (100-$Index_{sd}$) for indicator hypothesised to decrease vulnerability.

Table 1 Indicators and their relationship with vulnerability and data source

Determinant	Indicator	Variable	Unit	Hypothetical relationship	Data Source India Water
Exposure	Extreme climate events in last 40 years (from 1970 to 2010)	Frequency of drought and flood	Number	Higher the frequency, higher the vulnerability	Portal
		Frequency of warming years (temperature above to long term average temperature)	Number		India Meteorology Department, Pune
	Variability in climatic Variables	Inter-annual variation in rainfall	No unit	Higher the variation, higher the vulnerability	
		Variation in diurnal temperature	No unit		
Sensitivity	Irrigated land	Irrigation ratio	Percent	Higher the irrigation, lower the vulnerability	Jila Sankhyaki Patrika
	Small and marginal farming	Percentage of small and marginal holdings in total holdings	Percent	Higher the small and marginal, higher the v0ulnerability	Jila Sankhyaki Patrika
	Diversification	Diversification index	Percent	Higher the lower the diversification, vulnerability	Jila Sankhyaki Patrika
	Population	Rural population density	Percent	Higher the population, higher the vulnerability	Census
	Agriculture share	Percent of agriculture GDP	Percent	Higher the share, higher the vulnerability	Jila Sankhyaki Patrika
Adaptive capacity	Social Capital	Number of farmer members of primary cooperative societies	Number	Higher the members, lower	Jila Sankhyaki Patrika
	Human capital	Literacy rate	Percent	Higher the literacy, lower the vulnerability	Jila Sankhyaki Patrika

contd.

Table 1 Indicators and their relationship with vulnerability and data source (contd.)

Determinant	Indicator	Variable	Unit	Hypothetical relationship	Data Source India Water
	Financial capital	Farm income	Rs	The higher the farm income, the lower the vulnerability	Jila Sankhyaki Patrika
		Percent of people below poverty	Percent	The higher the poverty, the higher the vulnerability	Jila Sankhyaki Patrika
		Average farm holding	Hectare	higher the farm size,lower the vulnerability	Jila Sankhyaki Patrika
		Access to credit	Rs	Higher the access to credit, lower the vulnerability	Jila Sankhyaki Patrika
	Physical capital	Infrastructure index[8]	No unit	Higher the infrastructure index, lower the vulnerability	Jila Sankhyaki Patrika
		Cropping intensity	Percent	Higher the cropping intensity, lower the vulnerability	Jila Sankhyaki Patrika

3.1.1.3 *Weighting and Aggregation*

Prior to aggregating all standardised indicating variables, a weight is assigned to each variable following either the equal-weighting system (where each variable is equally important, and equal weights are assigned to each) or unequal-weighting system (where each variable is disproportionately important, and unequal weights are assigned to each). Applying equal weight to all indicating variables is not justifiable because all variables are not equally important. Each indicating variable affects climate change vulnerability differently (Hebb and Mortsch 2007). Hence, we apply unequal weight to all variables and determine the weight for each indicating variables using the indicative approach. In this approach, statistical methods such as principal component analysis (PCA) are used. The PCA is a kind of multivariate analysis used to form a new variable from a set of variables such that the new variable contains most of the variability of the original data (for details, see Kim and Mueller 1978). Besides the indicative approach, its alternative approach, called deductive approach, is also suggested in the literature; wherein expert judgment is used to determine the weight.

[8] Here, infrastructure is a composite index of six infrastructure-related variables—number of primary agricultural societies per lakh rural population, number of regulated markets per lakh hectare of net sown area, percentage of electrified villages, total length of pucca road per thousand square kilometre, percentage of net irrigated area by canal and government tubewells, and storage capacity in kilogram per hectare net sown area.

But, experts are not always available; when they are, they rarely agree. Therefore, only the indicative approach was followed in this paper.

After the weight of each indicating variable is decided, they are aggregated into a composite index. This aggregation follows either the additive method or the functional method. The former method is just the addition of variables, while the latter is based on the estimated functional relationship among variables. The functional method is less popular because of its complexity and empirical bias. Ideally, composite indices should remain relatively simple in terms of their construction and interpretation (Morris 1979). Therefore, the additive method of aggregation was used in the present paper. All indicating variables were finally aggregated to find VI using Equation 2. This calculation was carried out for each district of the state. The weight assigned to each variable in Equation 2 was calculated using PCA. The PCA was carried out on Stata 12.

$$VI_d = \sum_{i}^{i=17} f_{id} A_{id} \qquad \text{......................... (2)}$$

where,

VI is the vulnerability index for d^{th} district,

f_{id} is factor score of i^{th} indicating variables for d^{th} district,

A_{id} is i^{th} indicating variables for d^{th} district, and

i and d indicate indicating variables and districts, respectively.

This methodology was used to calculate the index for each component of vulnerability—exposure, sensitivity, and adaptive capacity—besides VI. Exposure and sensitivity jointly show the potential impact of climate change. Each indicator of the above two components was also aggregated to construct an index for the potential impact of climate change. Thereby, we calculated five indices to see farmers' vulnerability to climate change and variability.

3.1.1.4 *Validation*

Finally, the constructed index needs to be validated. It helps to make a consensus among stakeholders. Validation is normally performed by either using item analysis or external validation (Adelman and Morris 1972; Babble 1995; Booysen 2002). In item analysis, the correlation of components and index scores is assessed. In this analysis, we may get some indicating variables weakly correlated with index scores suggesting to eliminate such indicating variables. Thus, we may reach a contradictory situation whether we drop such variables or not. Dropping a few important variables just because of statistical underpinning, while those variables are selected following a well-recognised theory, would not be easy. And, if someone drops a few relevant variables, he would get an underestimated index score. So, how would item analysis be permissible here? In this study, therefore, the external validation method was used. In external validation, we first select some items or variables that are not included as indicating variables of the composite index and, then, assess relationship between components and index scores and select an item or variable among them as a validator. An index is considered 'good' if both the index and the component scores are found well correlated with the validator. Here, one should remember that the validator decides if the index is good or bad. Therefore, the appropriate variable or validator should be selected. This paper focusses on the vulnerability of agriculture to climate change; hence, agriculture output growth was chosen as the validator for external validation.

Apart from the above, this composite vulnerability index was validated by experts on agriculture in Uttar Pradesh, almost all of whom agree—in line with the study's findings—that Bundelkhand and Vindhyachal districts are likely to be more vulnerable to climate change.

3.1.2 Correlates

We used a regression model to examine the correlates of farmers' vulnerability to climate change and variability. Climate change vulnerability was regressed on a set of explanatory variables that may affect farmers' vulnerability to climate change and variability. A cross-section of 70 districts of UP was used in this regression analysis. The climate change vulnerability of i^{th} district is specified as:

$$VI_i = a_i + \sum \beta_{ji} X_{ji} + \varepsilon_i, i = 12,...70; j = 12,...j \qquad \text{.....................(3)}$$

where,

VI is the index value of climate change vulnerability of i^{th} district,

X denotes a set of explanatory variables,

j is the number of explanatory variables, and

ε_j is the error term.

Explanatory variables used in this study are agroforestry, urbanisation, feminisation, non-farm activities, livestock, consumption of fertiliser per hectare of cultivated land, per capita income, IMR, and three regional dummies as control variables. The selection of each explanatory variable is based on a literature review, the theory of climate change vulnerability, and data availability. Each variable is specified below.

3.1.2.1 *Agroforestry*

Agroforestry significantly mitigates the atmospheric accumulation of greenhouse gases (GHG) and helps farmers adapt to climate change (Verchot et al. 2007) and can, therefore, reduce their vulnerability to it. Despite this strong theoretical intuition, the information available on agroforestry in India is too meagre to establish a link between agroforestry and vulnerability. But information on forest cover is available, and although it cannot be used as a proxy for agroforestry—because information on forest cover in India does not incorporate information on agroforestry—the percentage of land under forest to total reported area was used as the proxy variable for agroforestry in this paper, because there was no alternative. This is an overestimation, but at least it enables us to see the impact of trees on farmers' vulnerability to climate change. Information on the percentage of land under forest to total reported area at the district level was collected from the *Jila Sankhyaki Patrika.*[9]

3.1.2.2 *Urbanisation*

The links between urbanisation and climate change vulnerability are complex. Whether urbanisation increases climate change vulnerability or not depends on the level of consumerism; notwithstanding, we assumed it does because cities generate over 90 per cent of anthropogenic carbon emissions (Svirejeva-Hopkins et al. 2004). Both historical and current clearing of land for cities and roads—and urban demand for goods and resources—are the major drivers of regional land use change, such as deforestation, which has shrunk global carbon sinks. Urbanisation was measured by calculating the percentage of the urban population to the total population. The data on urban and total population were also collected from the *Jila Sankhyaki Patrika*.

3.1.2.3 *Feminisation*

Although the literature available on gender and climate change is limited, two viewpoints are popular: (1) women are more vulnerable to the effects of climate change because of their marginal social position (Arora-Jonsson 2011); and (2) women are more sensitive to risk, more prepared for behaviour change, and more likely to support policy and measures on climate change (Aggarwal 2010). But the second proposition holds only on the conditions of gender equality and women's participation in decision-making; where their conditions are unsatisfactory, as in developing regions, women would be more vulnerable to climate change and variability. Therefore, this paper assumes feminisation affects vulnerability to climate change positively, and uses sex ratio to measure feminisation.

3.1.2.4 *Non-farm activity*

Increasing non-farm activity reduces both the burden on agriculture and provides farmers an income-generating opportunity. The increase in farmers' income further provides farmers an opportunity to adopt strategies to cope with the adverse effects of climate change. Thus, increasing farm activity will reduce farmers' vulnerability to climate change. The share of non-agriculture labour in total workforce was used to capture non-farm activity.

3.1.2.5 *Livestock*

Like non-farm activity, livestock also helps to reduce vulnerability to climate change, as it is more resistant to climate change than crops because of its mobility and access to feed. Besides, the livestock mix crop farming system plays a role in eradicating poverty which, in turn, affects climate change vulnerability adversely. Therefore, the paper assumes that high livestock reduces farmers' vulnerability. The number of livestock per 1000 population was used to see the impact of livestock on climate change vulnerability.

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[9] There is a Department of Economics and Statistics in each district of the state governed by the state government. The department publishes these data annually for each district.

3.1.2.6 *Economic development*

The literature on vulnerability to climate change has observed that socioeconomically developed regions are less vulnerable to climate change; it shows that vulnerability to climate change and variability is positively associated with social and economic development. We employed two parameters—(1) per capita income (PCI) and (2) infant mortality rate (IMR)—to assess the level of economic development in each district. The PCI shows the wealth and economic empowerment of a district, while the IMR shows its social development. While the literacy rate is also considered an indicator of social development, it was already taken in the climate change VI; therefore, considering it an explanatory variable in the above relational analysis was illogical since the VI was a dependent variable in the analysis.

3.1.2.7 *Control variables*

Although agriculture is biological production, some non-biological factors (such as mechanisation, fertiliser consumption, etc.) affect agricultural production and should therefore be considered explanatory variables in this kind of relation analysis. It is difficult to collect information on all these variables in a developing region. Also, it is not statistically justifiable to impose all these variables in relational analysis, because of strong multicollinearity among these variables and because of the loss of degree of freedom. So, the consumption of fertiliser in kilogram per hectare was used, and three dummy variables were first used to capture the regional variation among economic regions; subsequently, eight dummy variables were used to capture the regional variation among agro-climatic regions of the state. We have already seen strong regional variation in the agriculture sector (Sub-section 2.1.1). This variation is also reflected in the climate change vulnerability indices, as is evident from the results of the vulnerability indices (Sub-section 4.5).

Some of the above explanatory variables exhibit a two-way relationship with vulnerability, for example, urbanisation, IMR, etc. This paper considers these variables causes of vulnerability; these may be effects of climate change vulnerability as well. This loop relationship between dependent and explanatory variables leads to an endogeneity problem in the regression equation. Therefore, this limitation should keep in mind when generalising the estimates of the above regression equation.

3.2 Data and Data Transformation

The present study is based on cross-section data of 70 districts[9] of UP. All data used are either on climatic variables or on non-climatic or socioeconomic variables. We collected information on climatic variables by district from the India Meteorology Department, Pune. Similarly, all non-climatic data by district were collected from the *Jila Sankhyaki Patrika.*

Climatic data were collected for the period from 1970 to 2010 to observe the frequency of extreme climate events and inter-annual variability over the past 40 years. However, non-climatic data were first pulled together for three consecutive years (2007-08 2008-09, and

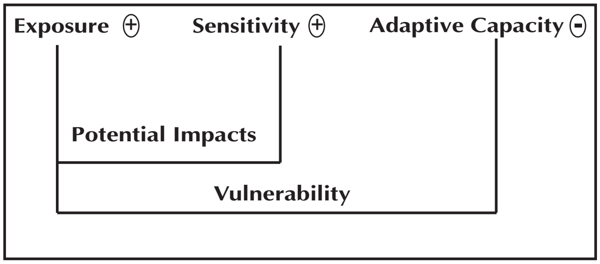
[9] Data was available—and therefore calculations made—for only 70 of UP's 83 districts.

2009-10) and converted into the form of the three-year-average above; its estimate was used for detailed analysis (see Tables A5, A6 and A7 in Appendix).

4 RESULTS AND DISCUSSIONS

We first separately constructed an index for 70 districts of UP for each component of vulnerability to climate change—exposure, sensitivity, and adaptive capacity—and subsequently calculated two indices: one for potential impact of climate change and another for vulnerability. Thus, we constructed five indices to see which districts are the most vulnerable to climate change. Figure 1 shows the relationship among five indices, and that vulnerability is positively linked with both exposure and sensitivity but negatively linked with adaptive capacity. Potential impact is the summation of exposure and sensitivity. So, vulnerability is also positively linked with potential impacts.

Figure 1 Relationship among five indices calculated in this study



Note: + and – signs show direction of relationship.

Each of the above indices is separately discussed in the following sub-sections. In view of the large number of districts in UP, we have classified districts into five groups. This classification of districts was carried out separately for each index. The classification of district is based on the index value of districts. The ranges of index value of each category of districts for each index are given in Table 2.

Table 2 Classification of districts in UP

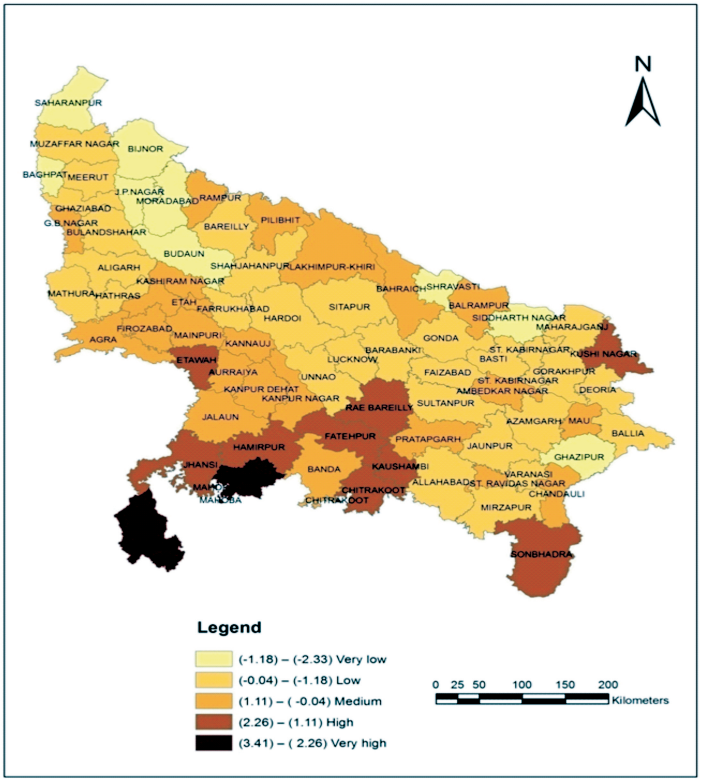
Categories	Ranges of index value of each category of district				
	Exposure	Sensitivity	Potential	Adaptive	Vulnerable
Very high	(3.41)–(2.26)	(4.58)–(2.95)	(5.07)-(3.39)	(-1.92)–(-3.32)	(5.18)–(3.43)
High	(2.26)–(1.11)	(2.95)–(1.32)	(3.39)–(1.71)	(-0.53)–(-1.92)	(3.43)–(1.68)
Medium	(1.11)–(-0.04)	(1.32)–(-0.31)	(1.71)–(0.02)	(0.87)–(-0.53)	(1.68)–(-0.07)
Low	(-0.04)–(-1.18)	(-0.31)–(-1.93)	(0.02)–(-1.66)	(2.27)-(0.87)	(-0.07)–(-1.82)
Very Low	(-1.18)–(-2.33)	(-1.93)–(-3.56)	(-1.66)–(-3.34)	(3.66)–(2.27)	(-1.82)–(-3.57)

Note: Though the number of classes was decided arbitrary, the criterion of same width for each class was followed in the above classification. The approximate class width was calculated by dividing the difference between the largest and the smallest values in the data by 5 which the number of desired classes.

4.1 Exposure Index (EI)

The frequency of extreme climate events—drought, flood, and warm year[10]—in the past 40 years (1970–2010) and variability in climatic variables—rainfall and temperature—were used to calculate the EI for each district of UP. Both these indicators are negatively related with vulnerability to climate change—higher the frequency of extreme climate events, higher the vulnerability. Spatial variation in all variables except diurnal temperature is high. The frequency of extreme temperature and rainfall events was found very high in Mahoba, Hamirpur, and Jhanshi districts of the Bundelkhand region. The annual variation in rainfall was found very high in Kaushambi, Chitrakoot, and Kushinagar districts, which belong to different agro-climatic regions. Finally, the above variables were aggregated to calculate EI and subsequently each district were divided into five categories of districts: very high, high, medium or average, low, and very low exposed to climate change and variability (Figure 2).

Figure 2 Spatial pattern of climate change exposure index in Uttar Pradesh



Note: Indicating variables are the frequency of extreme climate events drought, flood, and warm year in the past 40 years (1970–2010) and variability in climatic variables rainfall and temperature

Source: Author's own calculation

[10] Warm year is a year when average temperature exceeds the long-term (30 years) average temperature.

The exposure to climate change and variability is very high for Bundelkhand and high for Vindya district (except Mirzapur). Two districts of the central plains and one district of the north-eastern plains are highly exposed to climate change and variability. Most districts in the western and mid-western plains have little exposure to change in climatic variables.

4.2 Sensitivity Index (SI)

To estimate SI, we have chosen five indicating variables: percentage of irrigated cropped area, small and marginal land holdings, crop diversification, population density, and dependency on agriculture sector.[11] Crop diversification and the percentage of irrigated land are negatively related with vulnerability; the others are positively related. Each variable—barring crop diversification—is the ratio of two such variables which are readily available. To calculate diversification, we used Equation 4.

DI = (Percentage of sown area under x crops)/number of x crops..(4)

where, x crops are those crops that individually occupy 5 per cent or more of the sown area in a district.

The higher the index value, the lower the degree of crop diversification, and vice versa. The level of crop diversification was found from very high to high in all districts, except in Baghpat, Chandauli, Gorakhpur, Maharajganj, Muzaffarnagar, Pelephit, Bijnor, and Sidhartnagar (see Table A3 in Appendix). Barring Chandauli, most districts with low crop diversification are either in the north-eastern plain region or in the Bhabhar and Tarai zone of the state. It indicates that the pattern of crop diversification is mixed in these two regions and high in other agro-climatic regions of the state.

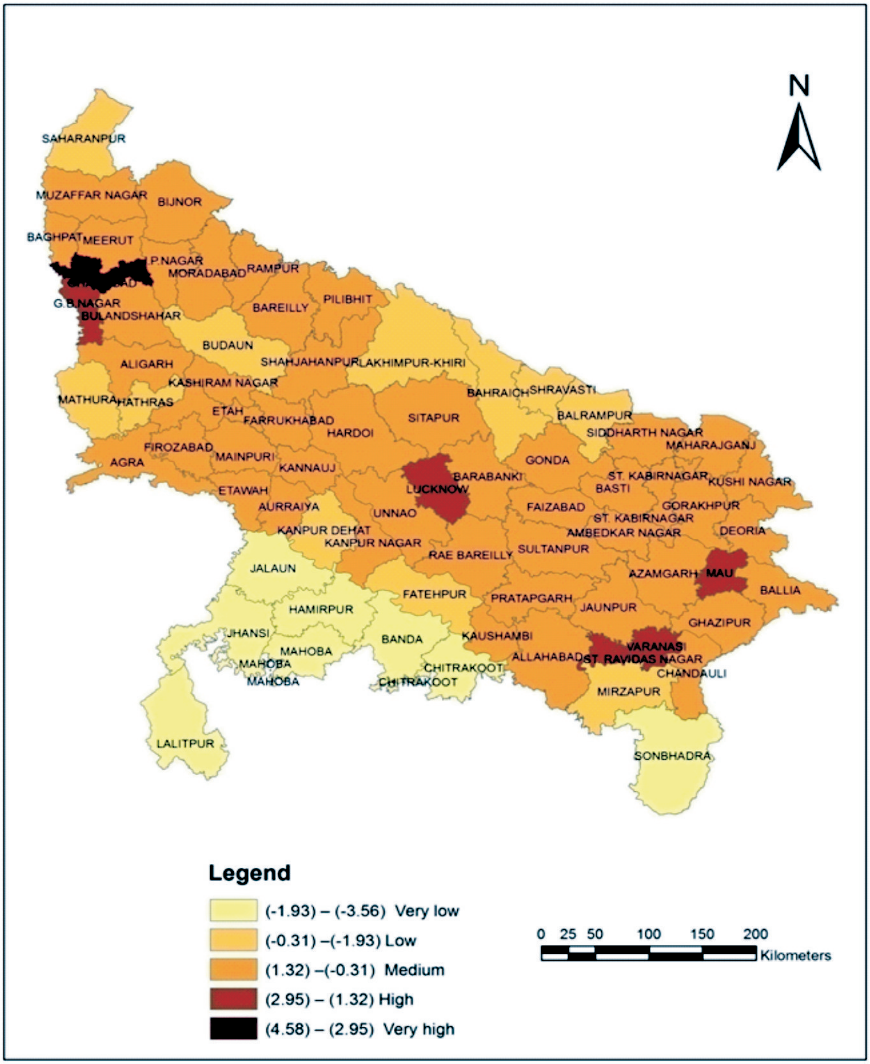
All indicating variables of sensitivity to climate change were aggregated to calculate the SI, as in calculating the EI. Figure 3 indicates spatial pattern of the SI. Farmers in Ghaziabad district are highly sensitive to climate change and variability (Figure 3), mainly because the population density in rural areas is high, as is the share of small and marginal holdings. Both variables have astronomical values for Ghaziabad. Farmers' sensitivity to climate was also found high in Varanasi, Gautam Budh Nagar, Lucknow, Mau, and Sant Ravidas Nagar. Of the above five districts, Mau and Sant Ravidas Nagar are in the north-eastern plains, indicating that the region is highly sensitive to climate change. Most districts in the Bundelkhand and Vindyachal regions are less sensitive to climate change and variability despite their high exposure to climate change and variability because of high crop diversification and low population density.

4.3 Potential Impact Index (PII)

As was mentioned at the beginning of this section, both exposure and sensitivity to climate change jointly reflect the potential impact of climate change. Hence, the PII was constructed

[11] Dependency on agriculture is measured by the percentage share of value of agriculture output in net state domestic product (NSDP).

Figure 3 Spatial pattern of climate change sensitivity index in Uttar Pradesh

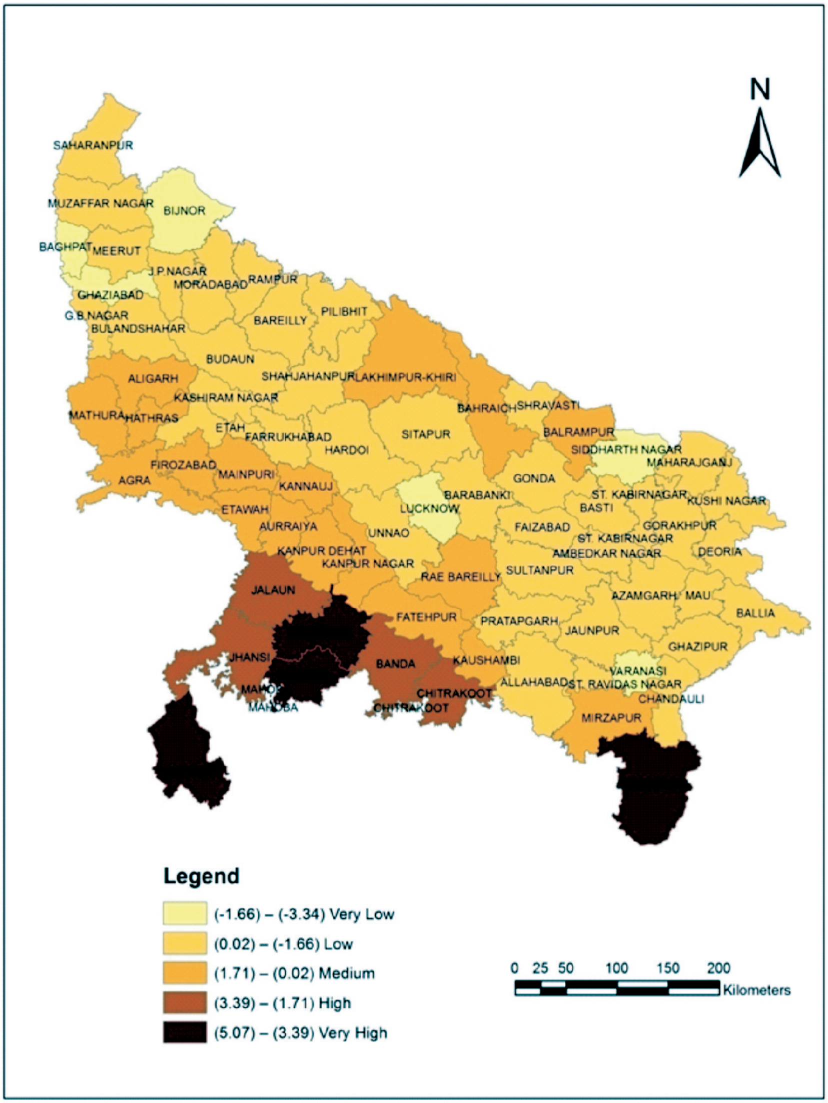


Note: Indicating variables are percentage of irrigated cropped area, small and marginal land holdings, crop diversification, population density, and dependency on agriculture sector
Source: Author's own calculation

by combining the exposure and sensitivity indicators for each district in the state. Each category of district is presented in Figure 4.

The potential impact of climate change was observed from very high to high in Bundelkhand and Vindya districts, mainly because they are highly exposed to climate change and variability. The districts with moderate or low potential impact of climate change and variability are even though spread across the rest parts of the state, most of them are located in the western plain and semi-western plain regions. It is mainly because these districts are less exposed to climate change and also less sensitive to climate change and variability.

Figure 4 Spatial pattern of index for potential impact of climate change in Uttar Pradesh



Note: Index for potential impact of climate change is calculated by aggregating indicating variables of both exposure and senstivity indices.
Source: Author's own calculation

4.4 Adaptive Capacity Index (ACI)

The potential impact of climate change is high in districts highly exposed to climate change and variability. It means that these districts have experienced greater change in climate and variability. But we do not have the option to stop or regulate changes in climatic variables. Therefore, adaptation to climate change is suggested to minimise the impact of climate change. Five types of capital assets can determine an entity's adaptive capacity: human, natural, financial, social, and physical (Scoones 1998). Several indicating variables were used to represent each of these capital assets (Table 1).

To construct the ACI, we aggregated all the indicating variables: number of farmer members of primary cooperative societies, rural literacy rate, farm income measured by the value of agriculture output at current prices, percentage of people living below poverty line, average farm holding, access to credit, rural infrastructure, and cropping intensity. Barring the variables related to rural infrastructure, all variables are easily available. To measure rural infrastructure, we used a composite index comprising six different rural infrastructure-related variables: number of primary agriculture societies per lakh rural population; number of regulated markets per lakh hecatre of net sown area; percentage of electrified villages; total length of pucca road per thousand square kilometres; percentage of net irrigated area; and storage capacity in kilogramme per hectare of net sown area. As this paper focuses on the agriculture sector, all these variables are related to it.

Rural infrastructure is highly developed in districts in the western plain, mid-western plain, central plain, and south-western semi-arid parts of the state but less developed in districts in Bundelkhand, the eastern plain, north-eastern plain, and Vindyan regions (see Table A4 in the Appendix).

As is evident from Figure 5, the adaptive capacity is found very high and high in districts mainly located in the south-western semi-arid region, western plain, mid-western plain and central plain region, but very low in districts located in Vindyan, eastern plain, north-eastern plain, and Bundelkhand regions. The figure also shows strong spatial variation in adaptive capacity within the region. In the Bundelkhand region, Jhansi and Jaluan has better adaptive capacity than other districts. Similarly, the adaptive capacity is better than moderate in all districts in the central plains except for Kaushambi, where the capacity of adaptation to climate change is very low.

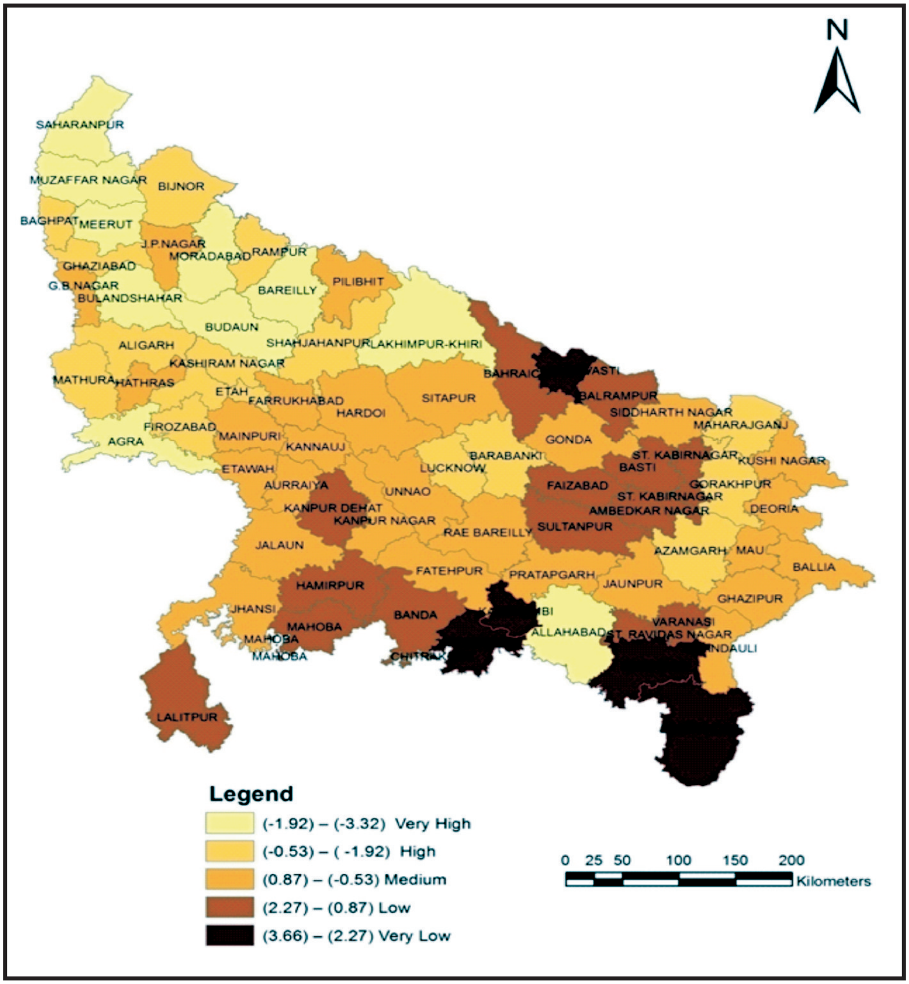
4.5Vulnerability Index (VI)

Finally, the VI was calculated by aggregating all selected indicating variables. All districts of UP were distributed into five categories according to the value of VI. These categories are very high vulnerable, high vulnerable, moderately or average (medium) vulnerable, low vulnerable, and very low vulnerable districts to climate change (Figure 6)

All the districts in the Bundelkhand and Vindya regions are highly vulnerable to climate change, as is Kaushambi from the central plains and two districts of the north-eastern plains.

The less or moderately vulnerable districts were observed mainly in the western plains, mid-western plains, Bhabhar and Tarai zones, and the south-western semi-arid regions. Figure 6 shows a mixed pattern in the central, eastern, and north-eastern plains. However, many districts in the above regions are moderately vulnerable to climate change and variability. The indicating variables used in the VI suggest that low adaptive capacity and high exposure to climate change and variability are mainly responsible for the high vulnerability to climate change.

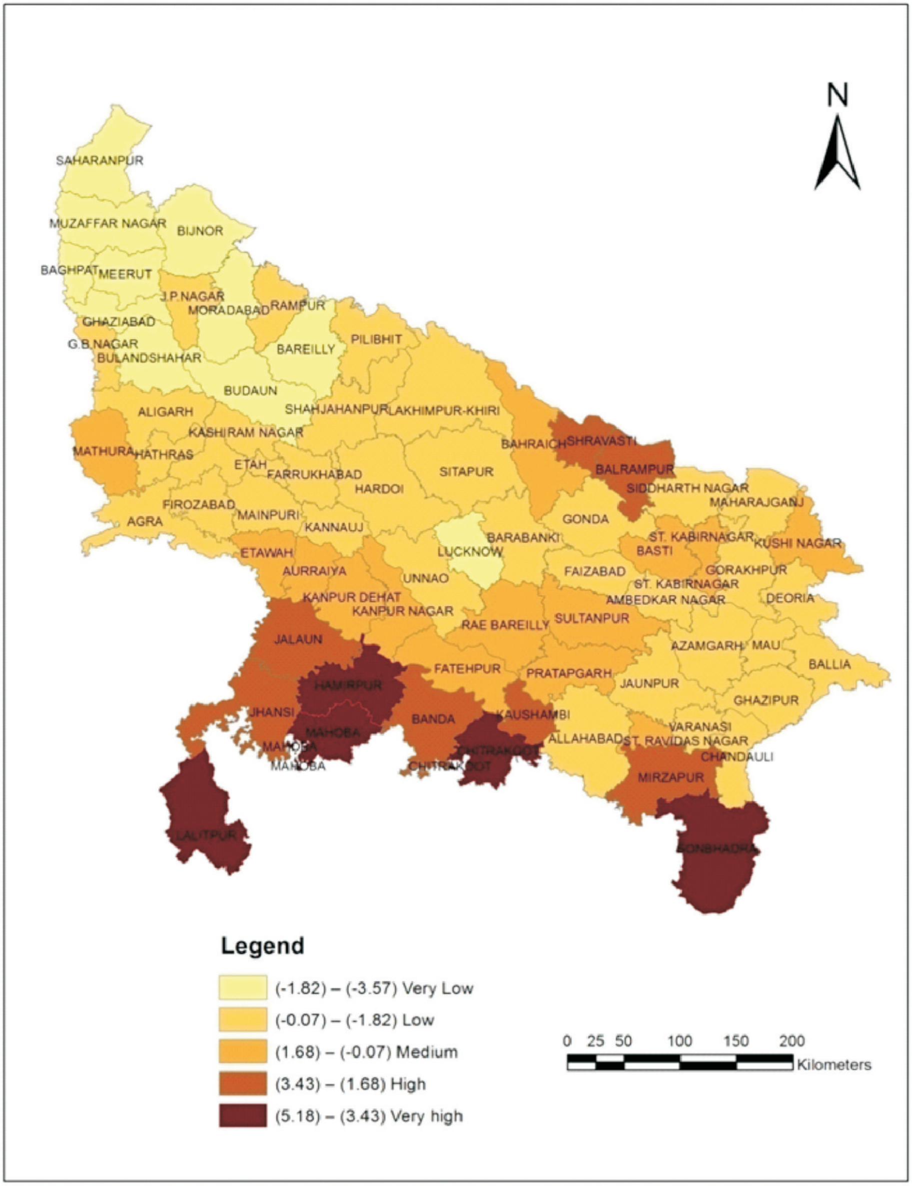
Figure 5 Spatial pattern of climate change adaptive capacity index in Uttar Pradesh



Note: (i) Vulnerability index (VI) is composite index of Exposure (EI), Senstivity (SI) and Adaptive capacity (ACI) indices.(ii)VI = EI + SI - ACI

Source: Author's own calculation

Figure 6 Spatial pattern of climate change vulnerability index in Uttar Pradesh



Note: Its indicating variables are number of farmer members of primary cooperative societies, rural literacy rate, farm income measured by the value of agriculture output at current prices, I percentage of people living below poverty line, average farm holding, access to credit, rural infrastructure, and cropping intensity.

Source: Author's own calculation.

The districts found the most vulnerable to climate change in this study were also identified as the most vulnerable in a study by the National Initiative on Climate Resilient Agriculture (NICRA) (Venkateswarlu et al. 2012).[12] It confirms that our study's findings are compatible with the findings of other studies, and as we had expected. We expected Bundelkhand and Vindya districts were highly vulnerable to climate change as they have frequently experienced natural hazards such as drought over the past decade. Thereby, the present study authenticates the data or information provided by the *Jila Sankhyaki Patrika,* although many researchers doubt the quality of its data.

4.6 Correlates

First, an attempt was made to see if VI is linked with per capita income (PCI) and economic growth (EGR). Then, a relational analysis was carreid out to ascirtain the correlates of VI. To see the link between above variables, Spearman's rank correlation coefficent was calculated. The estimated coefficents are presented in Table 3. Its value was observed -0.30 between VI and PCI and 0.01 between VI and EGR. Further, the former value is also statistically significant, while the latter one is statistically non-significant. It indicates a strong link between VI and PCI. However, there was no link between VI and EGR. The result suggests that there is negative relationship between VI and PCI. It implies that higher per capita income, lower the climate change vulnerability and vice versa. This inference supports the Environmental Kuznets Curve Hypothesis, which states that the environmental impact indicator is an inverted U-shaped function of income per capita.

Table 3 Spearman Rank Correlation Coefficents

VI and PCI	VI and EGR
-0.30*	0.01

*Note:** indicates the estimated value is statistically significant at 5% of significance level

To assess the correlates of farmers' climate change vulnerability, the VI calculated above was regressed with a set of independent variables: urbanisation (URB), sex ratio (SR), non-farm employment (NFE), livestock (LS), forestry (FOR), per capita income (PCI), infant mortality rate (IMR), consumption of fertilisers per hectare (COF), and regional dummy (RD). First, we carried out regression analysis with and without RD variables to see if the RD variables are significant. We observed that the estimate of all three RD variables are statistically non-significant, and that the coefficient of determination of regression equation with RD variables is marginally higher than the equation without RD variables (Table 4).

[12] To deal with climate change, the NICRA has planned to organise extensive farmer participatory demonstrations of location-specific, climate resilient agricultural technologies/package of practices developed by the Indian Council of Agricultural Research and the State Agriculture Universities, as well as successful indigenous technical knowledge, on farmers' fields in the most vulnerable districts of the country. For that purpose, the study identified the 100 most vulnerable districts in the country.

Table 4 Comparing coefficient of determination between two equations

Coefficient of determination	Equation without regional dummies	Equation without regional dummies
(R^2)	0.52	0.53

It shows that the negligible variation in farmers' vulnerability to climate change was together explained by these dummy variables. It was therefore decided to drop these dummy variables from the final regression equation. In the final regression equation, VI was regressed on URB, SR, NFE, LS, FOR, PCI, IMR, and COF using the ordinary least square (OLS) estimation procedure. Subsequently, the variance inflation factor (VIF) was estimated for each explanatory variable to detect multicollinearity among explanatory variables. The VIF is an index that measures how much the variance of an estimated regression coefficient is increased because of multicollinearity. There is a thumb rule: if any of the VIF values exceeds 5 or 10, the associated regression coefficients are probably poorly estimated because of multicolinearity (Montgomery et al. 2001). The calculated VIF values for each explanatory variable are presented in Table 5.

Table 5 Multicollinearity diagnostic criteria

Variable	VIF	1/VIF	R^2_xi,x
URB	2.39	0.42	0.58
SR	1.46	0.68	0.32
NFE	1.26	0.79	0.21
LS	1.64	0.61	0.39
FOR	1.27	0.79	0.21
COF	1.50	0.66	0.33
PCI	1.84	0.54	0.46
IMR	1.38	0.72	0.28

The VIF values were very low for each explanatory variable, suggesting that each variable is not linearly related to the other predictor variables.

The above diagnostic test justifies keeping all explanatory variables in the multiple regression equation. The estimates of this equation are presented in Table 6, which shows that the coefficient of URB, SR, NFE, and PCI were statistically non-significant, while the coefficient of LS, FOR, COF, and IMR were statistically significant. It shows that LS, FOR, COF, and IMR has influence on farmers' climate change vulnerability. The value of adjusted R^2 was 0.45, indicating a 45 per cent variation in VI was together explained by all the above explanatory variables. Around 65 per cent variation in VI was still unexplained. The value of intercept was found very high. It indicates that variables other than those above affect farmers' vulnerability to climate change. Except FOR, the sign of coefficient of all variables was as expected. The coefficient of FOR was expected negative but found positive. Despite it, we cannot infer that higher the area under forests, higher the farmers' vulnerability to climate change, because it is well established that trees on farms protect the soil and regulate water and microclimate, and protect crops and livestock from climate variability. Crops grown in agroforestry systems are more resilient to drought, excess precipitation, and temperature fluctuations and extremes (Verchot et al. 2007). Research in Africa shows that leguminous trees can make agriculture more drought-resilient by improving water infiltration and increasing productivity through nitrogen fixation (Garrity et al. 2010).

Table 6 Correlates of climate change vulnerability and their estimates observed in regression analysis

Model ([a.] Dependent variable: Farmers' Vulnerability Index)	**Coefficients**	**T-stat**	**p-value**
Constant	11.229	2.453	0.01
URB	-0.0134	-0.487	0.63
SR	-0.005	-1.131	0.26
LS	-0.007	-3.186	0.00
FOR	0.045	1.945	0.05
COF	-0.006	-2.091	0.04
PCI	-0.000003	-1.374	0.17
IMR	-0.034	-2.295	0.02
NFE1	-0.003	-0.104	0.92
Model Summary			
R^2	0.52		
Adjusted R^2	0.45		
F-stat	8.12		
p-value	0.00		
Observation	69		

5 CONCLUSIONS AND POLICY IMPLICATIONS

Adaptation to climate change may reduce the vulnerability of agriculture to climate change, but a common adaptation strategy will not help because the impact of climate change is differential (Tol et al. 2004; Mendelsohn et al. 2006). Therefore, an entity's vulnerability needs to be understood better to design an efficient process of adaptation. In deciding where adaptation efforts are the most required, vulnerability mapping is instrumental. Against this backdrop, this paper attempts to assess farmers' vulnerability to climate change and

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APPENDIX

Table A1 List of districts in different economic regions of UP

Regions	Circles	Districts
Bundelkhand Regions	Chitrakoot Jhansi	Banda, Chitrakoot, Hamirpur, and Mahoba Jalaun, Jhansi, Lalitpur
Central Region	Kanpur KanpurNagar	Auraiya, Etawah, Farrukhabad, Kannauj, Kanpur Dehat,
	Lucknow	Hardoi, Kheri, Lucknow, Rae Bareli, Sitapur, Unno
Eastern Region	Allahabad	Allahabad, Fatehpur, Kaushambi, Pratapgarh
	Azamgarh	Azamgarh, Ballia, Mau
	Basti	Basti, Sant Kabir Nagar
	Devipatan	Balrampur, Bahraich, Gonda
	Faizabad	Ambedakar Nagar, Barabanki, Faizabad, Sultanpur
	Gorakhpur	Deoria, Gorakhpur, Kushinagar, Maharajganj
	Varanasi	Chandauli, Ghajipur, Jaunpur, Varanasi
	Vindhyachal	Mirzapur, Sant Ravidas Nagar, Bhadohi, Sonbhadra, Shravasti, Siddharthnagar
Western Region	Agra	Agra, Aligarh, Etah, Firozabad, Hathras, Mainpuri, Mathura
	Bareilly	Bareilly, Budaun, Pilibhit, Shahjahanpur
	Meerut	Baghpat, Bulandshahr, Gautam Buddha Nagar, Ghaziabad, Meerut
	Muradabad	Bijnor, Jyotiba Phulenagar, Moradabad, Rampur
	Saharanpur	Mujaffarnagar, Saharanpur

Table A2 List of districts in different agro-climatic zones of UP.

Zones	Zonal Research Station	Districts
Vindhyan Zone	Mirazapur	Mirazpur and parts of Allahabad and Varanasi.
Eastern Plain Zone	Kumarganj	Barabanki, Faizabad, Sultanpur, Pratapgarh, Jaunpur, Azamgarh, Ballia, Ghazipur and Varanasi.
North-eastern Plain Zone	Basuli	Gonda, Bahraich, Basti, Gorakhpur and Deoria.
Bundelkhand Zone	Bharari	Jhansi, Lalitpur, Banda, Hamirpur and Jalaun.
Central Plain Zone	Dalipnagar	Lakhimpur, Kheri, Sitapur, Hardoi, Farrukhabad, Etawah, Kanpur, Kanpur Dehat, Unnao, Lucknow, Rae Bareilly, Fatehpur and Allahabad.
South-western Semi-arid Zone	Madhuri Kund	Aligarh, Etah, Mainpuri, Mathura and Agra.
Mid-western Plain Zone	Ujhani-Badama	Bijnor, Moradabad, Rampur, Bareilly, Pilibhit and Badaun, representing mainly Rohilkhand division.
Western Plain Zone		Daurala Saharanpur, Muzaffarnagar, Meerut, Ghaziabad and Bulandshahar located between the Ganga and the Yamuna in the west are included in this zone.

Table A3 List of districts in different category of crop diversification in UP

Category	Districts
Very High Diversification	Aligarh (8.99), Allahabad (9.61), Auraiya (8.19), Balliya (10.67), Banda (10.64), Barabanki (9.73), Budaun (9.82), Bulandshahar (8.98), Chitrakoot (10.50), Etah (8.21), Etawah (9.61), Faizabad (10.61), Farrukhabad (10.14), Fatehpur (7.00), Firozabad (10.88), Gazipur (8.85), Hamirpur (8.82), Hathras (9.86), Jalaun (8.17), Jaunpur (8.84), Jhansi (9.52), Jyoti Ba Phule Nagar (10.98), Kanpur Dehat (7.48), Kanpur Nagar (7.43), Kaushambi (8.70), Lalitpur (8.78), Mahoba (7.56), Mathura (10.95), Mirzapur (8.55), Moradabad (10.97), Pratapgarh (8.85), Sant Ravidas Nagar (9.72), Sonbhadra (6.16), Sultanpur (7.52), and Varanasi (7.57)
High Diversification	Agra (13.91), Ambedkar Nagar (12.07), Azamgarh (12.13), Bahraich (15.98), Balrampur (13.88), Barreilly (13.69), Basti (12.09), Deoria (16.17), Gautam Budh nagar (12.28), Gajiabad (13.89), Gonda (12.12), Hardoi (11.40), Kannauj (13.28), Khere (15.65), Kushinagar (14.07), Lucknow (13.23), Mainpuri (12.00), Mau (16.06), Meerut (14.12), Rae Bareilly (11.31), Rampur (16.10), Saharanpur (16.18), Sant kabir Nagar (13.74), Sahjahapur (11.55), Sitapur (11.30), Srawasti (13.95), and Unnao (11.55)
Diversification	Baghpat (19.54), Chandauli (18.91), Gorakhpur (18.86), Maharaj Ganj (19.59), Muzaffarnagar (19.59), and Pelebhit (19.54)
Moderately Diversification	Bijnor (24.35)
Less Diversification	Sidharthnagar (31.40)

Note: The value given in parentheses is crop diversification index value of particular districts. Like previous, the approximate class width was calculated by dividing the difference between the largest and the smallest values in the data by 5 which the number of desire classes of agriculture diversification.

Table A4 List of districts in different category of rural infrastructure development in UP

Category	Districts
Very High development	Agra (1.84), Allahabad (1.76), Barreilly (2.31), Bulandshar (2.31), Lucknow (2.57), and Rae Bareilly (1.40)
High development	Aligarh (0.31), Auraiya (1.11), Baghpat (0.43), Balliya (1.05), Barabanki (0.25), (0.26), Etah (1.12), Etawah (0.11), Fatehpur (0.97), Firozabad (0.68), Gautam Budh Nagar (0.28), Ghajiabad (1.13), Gorakhpur (0.21), Hardoi (0.23), Hathras (0.71), Jyoti Ba Phule Nagar (0.31), Kannauj (1.16), Khere (0.47), Maharaj Ganj (0.68), Mainpuri (0.89), Mathura (0.52), Meerut (0.30), Moradabad (0.76), Muzaffarnagar (1.04), Pelebhit (0.47), Rampur (0.63), Saharanpur (0.92), and Varanasi (0.65)
Moderately development	Ambedkar Nagar (-0.41), Azamgarh (-0.86), Baharaich (-0.71), Banda (-1.09), Bijnor (-0.59), Chandauli (-0.41), Deoria (-0.79), Faizabad (-0.92), Farrukhabad (0.05), Gonda(-0.73), Hamirpur (-0.98), Jaluan (-0.48), Jaunpur (-0.98), Jhansi (-0.30), Kanpur Dehat (-0.22), Kaushambi (-0.78), Lalitpur (-1.11), Mahoba (-0.62), Mau (-0.02), Pratapgarh (-0.47), Sidharthnagar (-1.05), Sitapur (-0.30), Sonbhadra (-1.18), Sultanpur (-0.95), and Unnao (-0.38)
Less development	Balrampur (-1.96), Basti (-1.73), Chitrakoot (-1.53), Gazipur (-1.25), Kushinagar (-173), Mirzapur (-219), Sant Kabir Nagar (-2.07), and Sant Ravidas Nagar (-1.61)
Very Less development	Srawasti (-3.88)

Note: The value given in parentheses is rural infrastructure index value of particular districts. The approximate class width was calculated by dividing the difference between the largest and the smallest values in the data by 5 which the number of desire classes of rural infrastructure.

Table A5 District-wise value of each indicator used in climate change vulnerability calculation

District	E1	E2	E3	E4	S1	S2	S3	S4	S5
Agra	19	13.43	16	46240.25	16.75	66.87	84.78	13.91	1084
Aligarh	18	13.24	11	32148.96	26.38	83.48	85.03	8.99	1007
Allahabad	18	13.09	9	72297.46	10.23	77.30	93.00	9.61	1087
Ambedkar Nagar	20	13.12	10	67870.89	32.21	95.79	97.03	12.07	1021
Auraiya	18	13.85	14	53426.29	26.34	78.65	92.27	8.19	681
Azamgarh	20	13.08	7	50973.79	27.67	93.83	96.08	12.13	1139
Baghpat	18	12.96	11	28763.60	33.57	100.00	91.23	19.54	986
Bahraich	21	12.98	8	69513.56	38.62	37.15	92.00	15.98	706
Ballia	18	12.83	11	51830.20	23.02	75.49	94.14	10.67	1081
Balrampur	20	12.87	11	67213.25	33.97	39.05	92.18	13.88	642
Banda	19	13.63	11	73008.89	21.82	43.64	79.11	10.64	404
Barabanki	18	13.18	10	58483.18	33.37	89.87	95.30	9.73	740
Bareilly	16	13.41	10	54943.27	22.12	92.64	92.34	13.69	1084
Basti	19	13.06	8	56778.45	29.95	67.75	95.80	12.09	916
Bijnor	17	13.09	7	47494.90	31.74	89.76	85.57	24.35	808
Budaun	17	13.48	8	32784.73	41.62	72.51	91.71	9.82	718
Bulandshahr	20	13.11	12	33127.14	28.75	100.00	88.63	8.98	788
Chandauli	20	12.95	11	70327.64	17.92	91.53	94.41	18.91	768
Chitrakoot	20	13.23	12	111407.52	19.56	23.86	84.32	10.50	315
Deoria	20	12.86	8	42761.52	24.17	78.05	96.19	16.17	1220
Etah	18	13.58	13	40185.82	33.21	90.91	92.35	8.21	717
Etawah	20	13.78	15	53563.37	28.25	77.57	91.76	9.61	683
Faizabad	19	13.14	8	55777.77	26.43	86.23	96.75	10.61	1054
Farrukhabad	19	13.85	9	33844.19	30.69	84.26	93.19	10.14	865
Fatehpur	18	13.60	15	83249.73	26.35	67.89	92.07	7.00	634
Firozabad	18	13.56	13	38855.97	26.88	76.13	86.56	10.88	1044
Gautam Buddha Nagar	19	13.07	13	55570.11	4.59	99.99	89.29	12.28	1252
Ghaziabad	19	12.93	13	43104.70	12.93	99.99	90.46	13.89	3967
Gazipur	17	13.01	10	42075.42	24.24	85.28	94.24	8.85	1072
Gonda	19	13.04	9	53877.45	30.70	67.79	95.31	12.12	857
Gorakhpur	20	12.97	6	64375.64	15.11	63.81	95.89	18.86	1336
Hamirpur	20	13.94	13	66667.49	25.48	35.13	74.99	8.82	268
Hardoi	17	13.64	12	41723.01	32.68	81.51	93.49	11.40	683
Hathras	18	13.31	12	42693.74	34.49	84.23	86.28	9.86	851
Jalaun	20	13.82	12	54984.50	36.62	51.00	77.05	8.17	366

contd.

Table A5 District-wise value of each indicator used in climate change vulnerability calculation (contd.)

District	E1	E2	E3	E4	S1	S2	S3	S4	S5
Jaunpur	17	13.18	10	60507.41	24.33	82.65	96.97	8.84	1108
Jhansi	22	13.48	11	64818.38	15.71	42.69	78.46	9.52	398
Jyotiba Phule Nagar	17	13.06	10	46290.70	25.20	87.89	89.63	10.98	818
Kannauj	18	13.87	13	61819.34	35.43	80.60	94.96	13.28	792
Kanpur Dehat	19	13.89	11	48438.74	28.79	66.90	91.47	7.48	594
Kanpur Nagar	19	13.80	11	60245.68	5.13	67.90	90.30	7.43	1449
Kaushambi	17	13.27	14	124634.56	17.92	69.61	93.91	8.70	897
Lakhimpur Kheri	21	13.20	11	71314.26	39.17	80.75	91.21	15.65	523
Lalitpur	24	12.94	17	82703.30	38.72	52.46	77.99	8.78	242
Kushinagar	21	12.77	11	92137.20	33.55	78.31	96.75	14.07	1226
Lucknow	17	13.33	9	57006.03	9.74	88.35	95.39	13.23	1815
Maharajganj	20	12.83	8	82008.61	35.47	49.39	95.92	19.40	903
Mahoba	22	13.67	14	99728.77	20.30	27.94	72.62	7.56	288
Mainpuri	20	13.77	11	56508.72	39.92	97.15	94.78	12.00	670
Mathura	18	13.24	11	32186.76	22.00	82.55	74.35	10.95	761
Mau	20	12.99	12	66891.16	16.09	92.87	94.11	16.06	1287
Meerut	19	12.91	12	40637.11	22.25	99.98	86.39	14.12	1342
Mirzapur	17	12.91	11	63827.58	15.37	58.95	91.18	8.55	561
Moradabad	17	13.17	9	50941.38	24.33	87.30	91.47	10.97	1284
Muzaffarnagar	18	12.99	13	41202.75	31.62	99.07	86.41	19.59	1033
Pilibhit	16	13.26	16	82317.32	38.68	97.04	86.38	19.54	567
Pratapgarh	17	13.28	13	70271.13	23.28	88.36	96.69	8.85	854
Rae Bareli	19	13.43	14	77565.99	22.67	86.71	94.91	11.31	739
Rampur	17	13.20	16	73909.95	31.42	95.66	88.87	16.10	987
Saharanpur	16	13.20	7	40845.16	31.20	91.40	80.20	16.18	939
Sant Kabir Nagar	19	13.00	6	82729.49	31.57	51.86	95.73	13.74	1041
Sant Ravidas Nagar	18	13.04	14	76902.95	13.31	80.24	97.50	9.72	1531
Shahjahanpur	18	13.63	10	43346.96	30.48	90.11	90.61	11.55	673
Siddharthnagar	17	12.66	7	60404.59	32.40	49.30	94.93	31.40	882
Sitapur	19	13.25	8	62511.06	34.10	82.53	93.18	11.30	779
Sonbhadra	20	13.83	11	81853.91	5.63	20.40	83.27	6.16	274
Shravasti	19	11.89	8	57170.94	38.91	36.94	93.00	13.95	572
Sultanpur	19	13.25	9	54472.96	26.39	84.17	96.29	7.52	855
Unnao	17	13.56	10	46330.99	28.76	79.69	93.68	11.55	682
Varanasi	17	13.03	10	55101.31	9.62	85.00	98.00	7.57	2399

contd.

Table A5 District-wise value of each indicator used in climate change vulnerability calculation (contd.)

District	A1	A2	A3	A4	A5	A6	A7	A8
Agra	19.43	45.20	374.44	1814.212	69.44	1.18	147.04	1.84
Aligarh	14.64	33.14	290.68	1929.369	69.61	1.13	173.70	0.31
Allahabad	28.17	6.80	576.32	1234.849	74.41	0.75	152.83	1.76
Ambedkar Nagar	59.15	21.73	112.40	886.0144	74.37	0.59	170.14	-0.41
Auraiya	43.23	5.98	103.59	632.2296	80.25	0.82	162.72	1.11
Azamgarh	32.87	11.24	280.70	1479.804	72.69	0.6	171.20	-0.86
Baghpat	6.66	0.89	105.41	1238.53	73.54	1.01	159.68	0.43
Bahraich	72.11	14.96	186.78	1308.537	51.10	0.74	152.71	-0.71
Ballia	51.55	4.21	205.42	860.9838	73.82	0.68	154.63	1.05
Balrampur	35.69	10.69	0.00	816.0438	51.76	0.81	147.39	-1.96
Banda	40.85	11.91	97.95	592.2543	68.11	1.46	122.69	-1.09
Barabanki	46.15	29.70	223.71	1723.444	63.76	0.67	186.22	0.25
Bareilly	27.50	23.55	237.40	1955.037	60.52	0.77	164.26	2.31
Basti	47.64	12.35	166.45	835.2	69.69	0.69	139.08	-1.73
Bijnor	23.67	41.18	305.49	2883.831	70.43	1.08	130.75	-0.59
Budaun	12.24	19.56	343.02	2644.686	52.91	0.86	170.71	0.26
Bulandshahr	10.34	35.16	308.43	2520.179	70.23	1	171.27	2.31
Chandauli	43.10	6.96	135.16	603.1048	73.86	0.73	179.20	-0.41
Chitrakoot	55.13	3.10	101.68	237.1043	66.52	1.4	106.20	-1.53
Deoria	11.67	14.33	300.00	770.5935	73.53	0.56	163.39	-0.79
Etah	17.26	26.45	132.08	1396.262	73.27	0.83	160.18	1.12
Etawah	46.34	17.76	117.20	718.7177	79.99	0.86	163.94	0.11
Faizabad	48.22	25.64	133.33	905.749	70.63	0.63	161.18	-0.92
Farrukhabad	32.64	17.55	107.90	931.5655	70.57	0.75	142.28	0.05
Fatehpur	42.77	21.87	327.17	988.166	68.78	0.82	138.13	0.97
Firozabad	13.61	49.54	173.79	1142.943	74.60	1.04	160.29	0.68
Gautam Buddha Nagar	19.00	183.34	31.02	657.5515	82.20	1.27	153.63	0.28
Ghaziabad	7.12	98.08	113.69	1781.721	85.00	0.86	160.16	1.13
Gazipur	48.50	17.11	268.82	1106.096	74.27	0.69	161.19	-1.25
Gonda	36.95	18.72	192.20	1161.548	61.16	0.64	152.76	-0.73
Gorakhpur	28.24	13.31	400.26	1007.724	73.25	0.59	153.40	0.21
Hamirpur	45.32	9.01	71.76	491.137	70.16	1.78	116.80	-0.98
Hardoi	74.00	19.37	341.00	1683.796	68.89	0.78	160.22	0.23
Hathras	17.91	45.21	111.77	1217.145	73.10	0.96	157.82	0.71
Jalaun	48.34	18.50	191.19	1147.468	75.16	1.44	125.15	-0.48

contd.

Table A5 District-wise value of each indicator used in climate change vulnerability calculation (contd.)

District	A1	A2	A3	A4	A5	A6	A7	A8
Jaunpur	43.65	4.98	253.36	1173.047	73.66	0.49	166.85	-0.98
Jhansi	29.19	20.39	155.34	927.0823	76.37	1.5	146.65	-0.30
Jyotiba Phule Nagar	24.45	32.66	108.17	1105.591	65.70	1.01	151.82	0.31
Kannauj	35.85	35.32	134.13	920.7505	74.01	0.62	154.08	1.16
Kanpur Dehat	60.87	11.07	124.61	905.8149	77.52	0.88	137.99	-0.22
Kanpur nagar	49.93	22.31	122.92	748.8218	81.31	0.9	140.18	2.70
Kaushambi	74.65	13.80	89.54	457.0084	63.69	0.69	131.92	-0.78
Lakhimpur Kheri	51.01	30.89	487.63	2235.435	62.71	0.92	153.06	0.47
Lalitpur	42.66	58.14	268.35	1172.858	67.66	0.56	146.33	-1.73
Kushinagar	30.47	15.81	107.81	762.9871	64.95	1.73	153.42	-1.11
Lucknow	49.06	905.68	102.08	1483.098	79.33	0.71	152.67	2.57
Maharajganj	30.76	15.27	256.40	920.9484	64.30	0.58	177.63	0.68
Mahoba	21.33	16.98	88.70	501.9026	66.94	1.72	131.13	-0.62
Mainpuri	42.52	20.26	124.83	1163.04	78.26	0.73	186.20	0.89
Mathura	16.24	51.55	215.35	1315.054	72.65	1.66	147.50	0.52
Mau	43.34	14.14	119.49	562.1452	75.16	0.69	163.53	-0.02
Meerut	8.38	71.45	306.30	2282.081	74.80	1.11	153.97	0.30
Mirzapur	68.38	20.55	125.24	628.2919	70.38	0.92	135.20	-2.19
Moradabad	19.77	38.91	222.32	2383.602	58.67	0.78	178.00	0.76
Muzaffarnagar	11.68	46.55	325.82	3011.178	70.11	1.11	148.15	1.04
Pilibhit	45.23	29.73	175.63	1677.617	63.58	1.14	170.14	0.47
Pratapgarh	49.09	8.12	209.69	791.6862	73.10	0.57	138.07	-0.47
Rae bareli	57.78	27.62	185.46	1039.294	69.04	0.74	155.04	1.69
Rampur	31.83	30.49	211.58	1313.936	55.08	0.98	191.05	0.63
Saharanpur	24.56	53.56	395.02	2596.445	72.03	1.26	149.95	0.92
Sant Kabir Nagar	45.99	9.34	94.20	528.186	69.01	0.63	170.25	-2.07
Sant Ravidas nagar	22.74	5.59	72.09	308.4655	71.10	0.43	140.78	-1.61
Shahjahanpur	54.11	0.32	213.77	1563.342	61.61	0.98	173.84	1.40
Siddharthnagar	42.74	109.34	216.21	803.5855	61.81	0.63	151.37	-1.05
Sitapur	57.46	16.81	247.53	2240.269	63.38	0.81	149.09	-0.30
Sonbhadra	64.53	26.86	61.80	423.5533	66.18	1.39	122.25	-1.18
Shravasti	60.53	12.06	69.53	414.6144	49.13	0.77	134.45	-3.88
Sultanpur	54.62	0.23	131.92	1257.529	71.14	0.56	150.86	-0.95
Unnao	59.51	10.60	256.63	1535.358	68.29	0.76	153.80	-0.38
Varanasi	24.24	9.70	104.05	611.1788	77.05	0.6	1.61	0.65

Source: Author's own calculation

Table A6 District-wise value of each indicator related to rural infrastructure

District	I_1	I_2	I_3	I_4	I_5	I_6
Agra	5.01	6.4	98.23	986.59	14.2	564
Aligarh	5.31	2.6	95.17	741.64	13.8	605
Allahabad	5.56	5.9	100	926.49	59.2	729
Ambedkar Nagar	5.74	3.6	85.9	898.72	18.8	199
Auraiya	7.82	6.9	89.56	746.9	49.8	234
Azamgarh	6.9	1.7	87.08	883.67	23	290
Baghpat	3.85	5.4	98.62	604.09	3.8	0
Bahraich	5.13	2.4	100	49247.29	6.5	96
Ballia	6.65	4.5	92.02	575.44	21	629
Balrampur	4	1.9	76.08	424.9	13.5	16
Banda	3.74	2.3	95.6	359.87	79.9	208
Barabanki	6.31	2.7	92.42	823.72	35.9	644
Bareilly	5.85	4.6	96.46	990.05	14.2	1230
Basti	5.94	1.4	72.02	624.07	5.9	224
Bijnor	4.14	4.8	82.82	818.68	46	100
Budaun	6.45	3.4	93.83	530.63	13.7	367
Bulandshahr	6.67	4.7	96.45	671.51	28.4	1218
Chandauli	5.65	3.7	91.26	900.83	91	330
Chitrakoot	5.66	2.3	88.26	267.07	73.6	7
Deoria	7.56	3.5	78.14	1000.79	25.9	125
Etah	4.43	5.2	97.1	722.45	36.7	571
Etawah	5.82	3.4	92.57	838.17	53.5	503
Faizabad	4.37	2.3	80.12	804.78	22.2	435
Farrukhabad	5.66	4.7	88	624.48	5.9	114
Fatehpur	5.56	3.8	96.01	583.82	25.3	718
Firozabad	5.62	3.3	89.94	124.95	11.9	759
Gautam Buddha Nagar	4.51	5.1	82.4	1131.07	53	542
Ghaziabad	4.14	4.1	91.79	2954.7	22.4	924
Gazipur	6.46	4.3	63.08	1058.34	26.8	123
Gonda	6.46	1.3	92.45	534.85	6.8	281
Gorakhpur	6.27	3.2	84.54	945.2	9.9	612
Hamirpur	5.41	3	92.51	356.84	74.3	77
Hardoi	6.55	3.6	96.9	427	20.1	246
Hathras	7.68	5.4	89.33	741.85	9	197
Jalaun	6.1	3.2	92.21	476.23	88.5	337

contd.

Table A6 District-wise value of each indicator related to rural infrastructure

District	I_1	I_2	I_3	I_4	I_5	I_6
Jaunpur	6.27	4.3	73.25	924.72	30.4	48
Jhansi	5.73	3.7	100	376.19	95.6	182
Jyotiba Phule Nagar	3.98	3.5	97.98	718.1	0.6	355
Kannauj	4.17	7.6	92.21	690.27	16.1	112
Kanpur Dehat	6.7	4	95.16	1021.85	45.7	35
Kanpur nagar	6.59	4.8	93.4	1372.42	29.71	508
Kaushambi	5.32	2.3	96.36	746.07	21	51
Lakhimpur Kheri	4.55	3.7	96.43	350.26	6.2	427
Lalitpur	5.22	0.9	91.79	873.02	47.8	47
Kushinagar	4.91	1.9	99.86	284.78	88	145
Lucknow	7.62	5.7	100	2664.56	27.9	1005
Maharajganj	4.67	5.9	93.77	701.56	23	182
Mahoba	7.58	2.9	99.05	380.03	99.1	112
Mainpuri	4.48	4.3	98.17	865.58	26	572
Mathura	5.31	4.1	95.65	536.73	39.7	473
Mau	6.17	4	86.79	912.43	14	264
Meerut	5.36	3	98.71	1068.34	21.5	450
Mirzapur	4.7	1.5	75.95	663.79	89.5	240
Moradabad	3.87	2.5	90.7	900.75	39	1172
Muzaffarnagar	3.64	4.3	99.22	606.79	26.7	679
Pilibhit	5.63	4.7	81.33	689.63	28.2	608
Pratapgarh	6.74	3.1	89.78	1100.89	45.6	228
Rae bareli	7.12	6	100	684.31	49.9	544
Rampur	4.45	3.6	87.36	779.89	24.2	844
Saharanpur	4.94	5.1	99.92	568.18	21.2	318
Sant Kabir Nagar	6.28	1.6	73.29	605.1	28.8	27
Sant Ravidas nagar	4.41	4.3	54.79	1168.77	43.3	308
Shahjahanpur	5.64	3.5	84.93	441.31	4.7	1220
Siddharthnagar	6.47	3.8	77.07	473.92	32	18
Sitapur	6.41	2.8	85.14	598.64	12.1	394
Sonbhadra	5.39	3.1	85.84	224.81	100	205
Shravasti	3.94	0.7	42	382.42	2.2	7
Sultanpur	6.09	1.1	100	884.13	29.7	122
Unnao	7.82	2.3	96.74	529.84	26.4	148
Varanasi	5	6.2	70.67	1736.81	32.6	696

Source: Author's own calculation

Table A7 District-wise value of each correlates of climate change vulnerability

Districts	URB	SR	NFE	LS	FOR	COF	PCI	IMR
Agra	43.3	846	60.4	394.7	8.9	226.2	24744.00	51
Aligarh	28.9	862	48.9	326.5	0.7	172.85	23394.53	69
Allahabad	24.4	879	49.8	320.1	3.9	293.9	19863.62	96
Bedkar Nagar	11.4	978	30.7	263.6	0.1	228.3	13541.92	72
Auraiya	14.3	856	27.9	277.5	2.1	149.65	20566.75	63
Azamgarh	7.5	1020	33.2	329	0	110.05	11920.06	79
Baghpat	19.7	847	44.3	396.1	1.1	273.5	32667.15	56
Bahraich	8.8	868	17.9	259	14	106.2	13609.36	67
Ballia	9.8	953	36.1	220.7	0	148.5	13104.34	71
Balrampur	8.1	895	14.3	183.4	18.2	119.45	14000.69	94
Banda	16.3	860	24.9	186	1.2	5.95	17357.38	56
Barabanki	9.7	887	23.9	282.5	1.4	208.6	21683.26	72
Bareilly	32.9	871	41.8	255	0.1	199.6	22601.52	86
Basti	6.1	938	20.5	203.2	1.5	249.2	12688.04	85
Bijnor	24.30	896	43.2	204.3	11.8	179	27977.74	65
Budaun	19.6	843	22.4	327.2	1.3	137.15	22749.00	91
Bulandshahr	22.6	879	47.5	451	2.1	214.35	30121.73	62
Handauli	10.6	922	42.5	196.9	30.5	203.1	16563.53	79
Chitrakoot	9.5	872	20.6	206.8	17.6	80.25	11661.87	69
Deoria	9.9	1002	35.1	261	0.1	250.1	11020.30	74
Etah	15.1	850	26.5	496.8	0.4	267.7	20582.86	76
Etawah	23	858	35.1	271.4	15	190	19097.46	55
Faizabad	13.5	939	30.2	317	1.3	271.8	16415.59	99
Farrukhabad	21.7	848	31.3	255.8	0.2	390.75	18885.64	83
Fatehpur	11.2	893	26.2	306.8	1.8	162.3	15673.40	59
Firozabad	32.2	851	54.6	365.4	3.6	227.1	19510.37	66
Gautam Buddha Nagar	40	839	69.7	274.8	1.6	244.15	87141.75	59
Ghaziabad	68.6	855	87.4	802.3	1.25	277	32572.88	51
Gazipur	7.7	976	32.6	325.5	0	162.35	13359.97	81
Gonda	7	906	18.1	275.7	3.2	168.65	12869.40	73
Gorakhpur	19.6	960	45.9	230.9	1.7	274.9	16389.58	64
Hamirpur	17.5	852	28.3	145	6.3	50.15	19125.05	48
Hardoi	12	844	20.4	248.9	2.2	165.3	14696.08	80
Hathras	19.8	858	42.6	313.1	1	235.8	27900.70	56
Jalaun	23.4	849	30.2	178.6	6.2	104.55	23128.43	66
Jaunpur	7.4	1014	33.4	359.6	0	151.65	11858.43	80

contd.

Table A7 District-wise value of each correlates of climate change vulnerability

Districts	URB	SR	NFE	LS	FOR	COF	PCI	IMR
Jhansi	43.3	871	44.8	166.7	6.9	87.2	28210.68	50
Jyotiba Phule Nagar	24.6	885	36.9	263.6	9.8	240.9	28981.24	69
Kannauj	16.7	866	25.9	375.6	6.4	237.2	18404.44	80
Kanpur Dehat	6.9	852	25.2	259.8	1.8	229.9	17891.26	68
Kanpur Nagar	67.1	855	73.9	318.5	1.9	396.95	30166.10	56
Kaushambi	7.1	895	25.5	297.7	0.4	223.4	17454.21	81
Lakhimpur Kheri	10.8	871	20.9	167.5	21.4	160.85	18177.57	81
Lalitpur	14.5	882	24.2	169.9	14.9	54.35	20873.26	75
Kushinagar	4.6	963	22.9	257.1	0.3	192.5	11970.65	83
Lucknow	64.7	888	72.5	307.1	5.2	292	33409.51	57
Maharajganj	5.1	934	21.5	232.1	17.4	220.65	12261.60	89
Mahoba	20.4	864	26.3	179.2	5	40.8	22248.04	53
Mainpuri	14.6	857	22.4	226.3	0.7	214.8	18587.64	50
Mathura	28.3	840	47.1	311.2	0.5	171.6	28967.00	50
Mau	19.4	986	48.2	369.7	0.3	219.1	14894.02	78
Meerut	48.8	872	66.1	328.8	7.8	283.65	31535.73	57
Mirzapur	13.8	897	44.3	198.9	24.1	142.05	14026.24	83
Moradabad	32.86	881	51.1	356.5	0	220.85	23292.92	63
Muzaffarnagar	23.4	877	46.6	375.1	6.7	216.7	25925.02	59
Pilibhit	17	877	27.3	141.9	21.1	231.6	27683.60	79
Pratapgarh	5.3	1004	27.9	296.5	0.2	190.75	11536.31	88
Rae Bareli	11	949	30.6	306.8	1.4	278.05	13941.03	56
Rampur	24.95	879	33.6	313.1	2.8	138.65	22012.86	71
Saharanpur	28.8	865	48.4	214.4	9.1	165.15	27488.34	85
Sant Kabir Nagar	7.1	974	23.2	219.2	2.5	144.8	11336.53	63
Sant Ravidas Nagar	12.8	917	66.4	268.7	0.2	221.5	16444.18	80
Shahjahanpur	21.3	841	27.9	198	2.4	225.1	19519.05	92
Siddharthnagar	6.1	948	15.5	269	1.2	164.05	11873.72	91
Sitapur	12	864	32	292.1	1	173.95	18262.38	82
Sonbhadra	18.3	899	33.8	173.3	47.8	162.95	21872.24	66
Shravasti	3.9	857	12.2	217.6	17.8	84.95	9615.56	103
Sultanpur	6.1	980	31.6	322.5	0.2	254.6	14652.20	49
Unnao	15.2	898	26.4	301.6	3.7	131	17840.84	60
Varanasi	40.2	903	74.3	296.9	0	493.95	16670.94	83

Source: Author's own calculation

Table A8 List of indicators and correlates

List of Indicators	
E1	Number of years with extreme temperature event in last 40 years
E2	Diurnal Temprature
E3	Number of years with extreme rainfall event in last 40 years
E4	Variance in Rainfall
S1	Contribution of agriculture in State domestic product (in %)
S2	Irrigation Ratio (in %)
S3	Share of small and marginal holdings in total holdings (in %)
S4	Diversification index
S5	Population Density (in number)
A1	Number of poor households
A2	Access to credit
A3	Members (in number)
A4	Farm Income (in Rs.)
A5	Literacy (in %)
A6	Average land size (in hectare)
A7	Cropping Intensity (in %)
A8	Infrastructure Index
I1	No. of primary agricultural credit societies per lakh of rural population
I2	No. of regulated mandis per lakh hec. of net area sown
I3	Percentage of electrified villages
I4	Total length of pucca roads per thousand Sq. Km.
I5	Percentage of net irrigated area by Canal and Govt. Tubewells
I6	Storage Capacity in Kg per hectare net sown area
List of Correlates	
URB	Urbanisation (in %)
SR	Sex ratio (in number)
NFE	Share of non-farm employment (in %)
LS	Livestock (in number)
FOR	Forestry (in %)
COF	Consumption of fertiliser (in %)
PCI	Per capita income (in Rs.)
IMR	Infant mortality rate (in number)

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