Farmers' Vulnerability to Climate Change in Uttar Pradesh, India: Measurement and Correlates

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Abstract

This paper 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, 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. 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

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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 (1 in 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, is likely to affect crop productivity adversely which, in turn, threatens food and livelihood security—particularly in developing counties like India, where agriculture employs 58.2 per cent of its population (Census, 2001) 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 & 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.

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

[2] Government of India

[3] According to the Central Statistical Organization (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.

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 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 (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. 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. 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. Uttar Pradesh is selected for the study because it is important to India's food and nutrition security programme and its sensitivity to climate change and variability is documented in the literature (O'Brien et al., 2004).

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, coast line 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

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

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 & Narayanan, 2005; Malone & Brenkert, 2008; Palanisami, et al. 2009; Hiremath & Shiyani, 2012). O'Brien et al. (2004) and Malone & Brenkert (2008) carried out a country-level assessment using district level information, while Patnaik & Narayanan (2005), Palanisami et al. (2009), and Hiremath & 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 discusses the methodology used to assess farmers' vulnerability to climate change and variability, explains why UP was selected as a study area and presents an overview of the state, and discusses the conceptual framework that builds on the concept of vulnerability to climate change developed by the IPCC (2001). This study calculates five indices: exposure, sensitivity, potential impact, adaptive capacity, and vulnerability. Section 3 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 4 concludes the study and suggests some policy actions to reduce farmers' vulnerability to climate change.

2. EMPIRICAL METHODOLOGY

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[6] state and its most populous,[7] is diverse in geography and culture. A study based on a large and heterogeneous region always

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

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, 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 Zonr, western plain, and mid-western plain (Table 2A, Appendix).

The western region is more developed than other regions. Its per capita income (Rs 17273) is significantly higher than the other three regions: central (Rs 13940), 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, agriculture performance 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).

2.2. Methods

2.2.1. *Conceptual Framework*

[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.

Vulnerability is a theoretical concept (Hinkel, 2011) that does not indicate an observable phenomennon (Patt et al., 2008), like inflation. The phenomennon 'inflation' can be mesured by associting a number called inflation rate (i.e. percentage change in average price at two points in time).[8] We have therefore tried to make vulnerability concept operational instead of measuring it. A number of indicating variables is used to make it operational. Thereby, we first select indicating variables and then aggregate them. 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, p. 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.

2.2.2. *Calculating the VI: Indicator Approach*

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 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.

After selecting the indicating variables, we try to aggregate them to make a composite index for farmers' vulnerability to climate change and variability. The aggregation of indicating variables can be done either assigning equal weight or unequal weight to all indicators. Applying equal weight to all indicating variables is not justifiable because all variables are not equally important. Each indicating

[8] For details, see Hinkel (2011).

variable affects climate change vulnerability differently (Hebb & Mortsch, 2007). Hence, we apply unequal weight to all variables.

The literature on vulnerability to climate change uses two approaches to decide the weight for each indicating variable: deductive and inductive. Expert judgment is used to determine the weight in the deductive approach, but experts are not always available; when they are, they rarely agree.The inductive approach uses statistical methods such as principal component analysis (PCA), 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 & Mueller, 1978a; Kim & Mueller, 1978b). Therefore, the PCA was used to develop the weight for each indicating variable.

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, 2007).

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

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.

After each was standardised, we finally aggregated them 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.

$$VI_d = \sum_{i}^{i=17} f_{id} A_{id} \quad \dots (2)$$

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.

2.2.3. *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 which 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:

$$VI_i = a_i + \sum_{ji} \beta_{ji} X_{ji} + \varepsilon_i, i = 1, 2, \dots 70; j = 1, 2, \dots j \quad \dots (3)$$

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 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.

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. Information on agroforestry in India is very meagre; therefore, the percentage of land under forest to total reported area was used as the proxy variable for agroforestry. This information at the district level were collected from the *Jila Sankhyaki Patrika*.[9]

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

[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.

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 taking the percentage of urban population to total population. The data on urban and total population were collected from the above same source.

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-Jonson, 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.

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.

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 adversary. 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.

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. The literacy rate is also considered an indicator of social development. But the literacy rate was already taken in the climate change VI; therefore, considering literacy rate as an explanatory variable was illogical in the above relational analysis since the VI was a dependent variable in this relational analysis.

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 and also not statistically justifiable to impose all these variables in relational analysis, because of strong multicolinearity among these variables and loss of degree of freedom. So, the consumption of fertiliser in kilogram per hectare was used, and three and eight dummy variables were concurrently used to control regional variations in farmers' vulnerability to climate change. 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 2.2). This variation is also reflected in the climate change vulnerability indices, as is evident from the results of the vulnerability indices (Sub-section 3.5).

2.2.4. *Data and Data Transformation*

The present study is based on cross-section data of 70 districts[10] of UP. Districts are observation in this study. 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 *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 2009-10) and converted into the form of the above three years average; its estimate was used for detailed analysis.

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

Table 1: List of Indicators, their relationship with vulnerability and data source

Determinants		Indicators	Variables	Unit of Measurement	Hypothetical Relationship	Data Source
1.	Exposure	Extreme climate events in last 40 years (from 1970 to 2010)	1. Frequency of drought and flood	Number	The higher the frequency, the higher the vulnerability level	1. India Water Portal 2. India Meteorology Department, Pune
			2. Frequency of warming years (temperature above to long term average temperature)	Number		
		Variability in climatic variables	1. Inter-annual variation in rainfall	No unit	The higher the variation, the higher the vulnerability level	
			2. Variation in diurnal temperature	No unit		
2.	Sensitivity	Irrigated Land	Irrigation ratio	Percent	The higher the irrigation, the lower the vulnerability level	Jila Sankhyaki Patrika
		Small and marginal farming	Percentage of small and marginal holdings in total holdings	Percent	The higher the small and marginal, the higher the vulnerability level	Jila Sankhyaki Patrika
		Diversification	Diversification index	Percent	The higher the diversification, the lower the vulnerability	Jila Sankhyaki Patrika

				level	
	Population	Rural population density	Percent	The higher the population, the higher the vulnerability level	Census
	Agriculture Share	Percent of agriculture GDP	Percent	The higher the share, the higher the vulnerability level	Jila Sankhyaki Patrika

Continued Table 1: List of Indicators, their relationship with vulnerability and data source

Determinants	**Indicators**	**Variables**	**Unit of Measurement**	**Hypothetical Relationship**	**Data source**
3. Adaptive Capacity	Social Capital	Number of farmer members of primary cooperative societies	Number	The higher the members, the lower the vulnerability level	Jila Sankhyaki Patrika
	Human Capital	Literacy rate	Percent	The higher the literacy, the lower the vulnerability level	Jila Sankhyaki Patrika
	Financial	1. Farm income	Rs	The higher the farm income, the lower the	Jila Sankhyaki

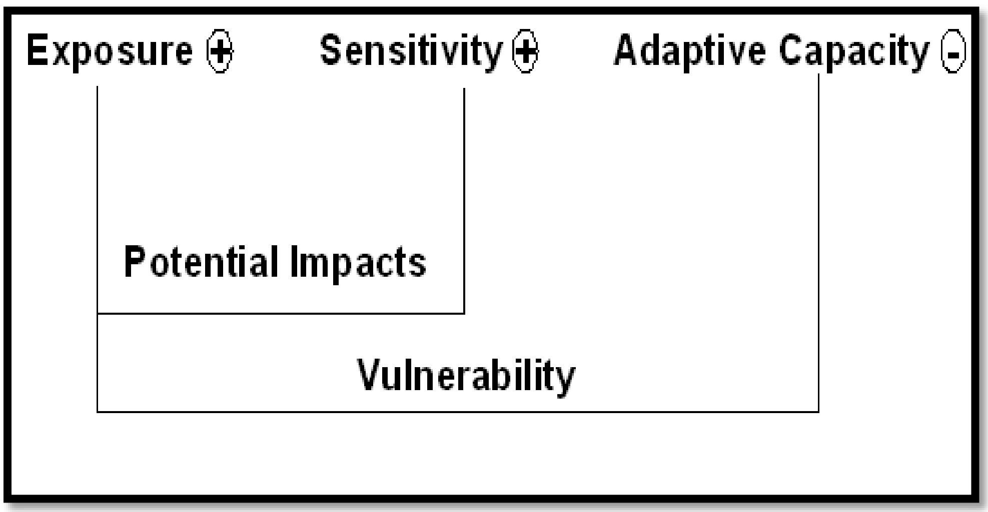
	Capital			vulnerability level	Patrika
		2. Percent of people below poverty	Percent	The higher the poverty, the higher the vulnerability level	Jila Sankhyaki Patrika
		3. Average farm holding	Hectare	The higher the farm size, the lower the vulnerability level	Jila Sankhyaki Patrika
		4. Access to credit	Rs	The higher the access to credit, the lower the vulnerability	Jila Sankhyaki Patrika
	Physical Capital	Infrastructure index[11]	No unit	The higher the infrastructure index, the lower the vulnerability	Jila Sankhyaki Patrika
		Cropping intensity	Percent	The higher the cropping intensity, the lower the vulnerability level	Jila Sankhyaki Patrika

[11] 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, and storage capacity in kilogram per hectare net sown area.

3. 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 Districts				
	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)
Moderate	(-0.04) – (-1.18)	(-0.31) –(-1.93)	(0.02) – (-1.66)	(2.27) – (0.87)	(-0.07) – (-1.82)
Less	(-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.

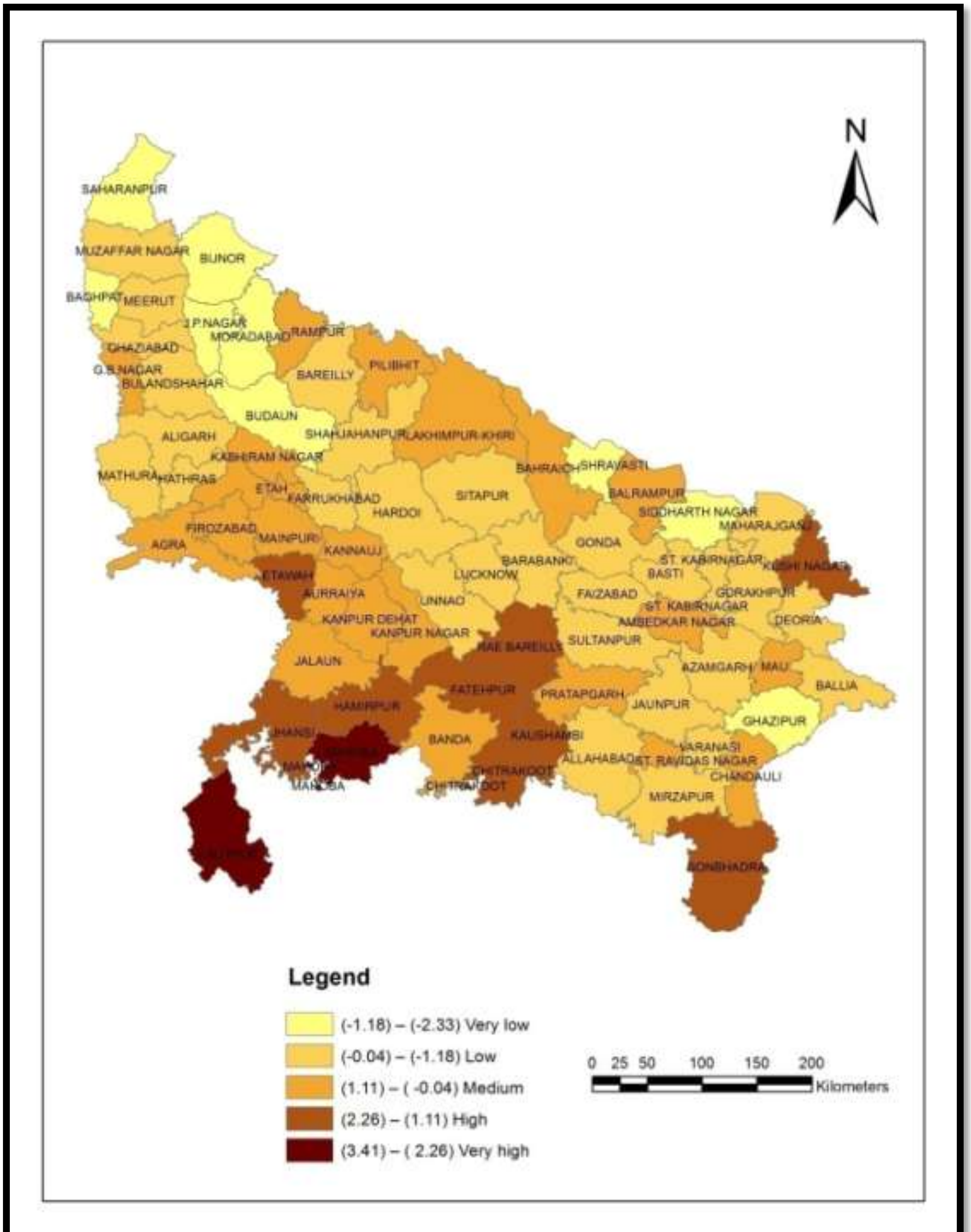
3.1. Exposure Index (EI)

The frequency of extreme climate events—drought, flood, and warm year[12]— 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, moderate or average, low, and less exposed to climate change and variability (Figure 2). The exposure to climate change

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

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.

Figure 2: Spatial Pattern of Climate Change EI in UP.



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.[13] 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.

$$DI = (Percentage\ of\ sown\ area\ under\ x\ crops)/number\ of\ x\ crops \quad \dots (4)$$

where,

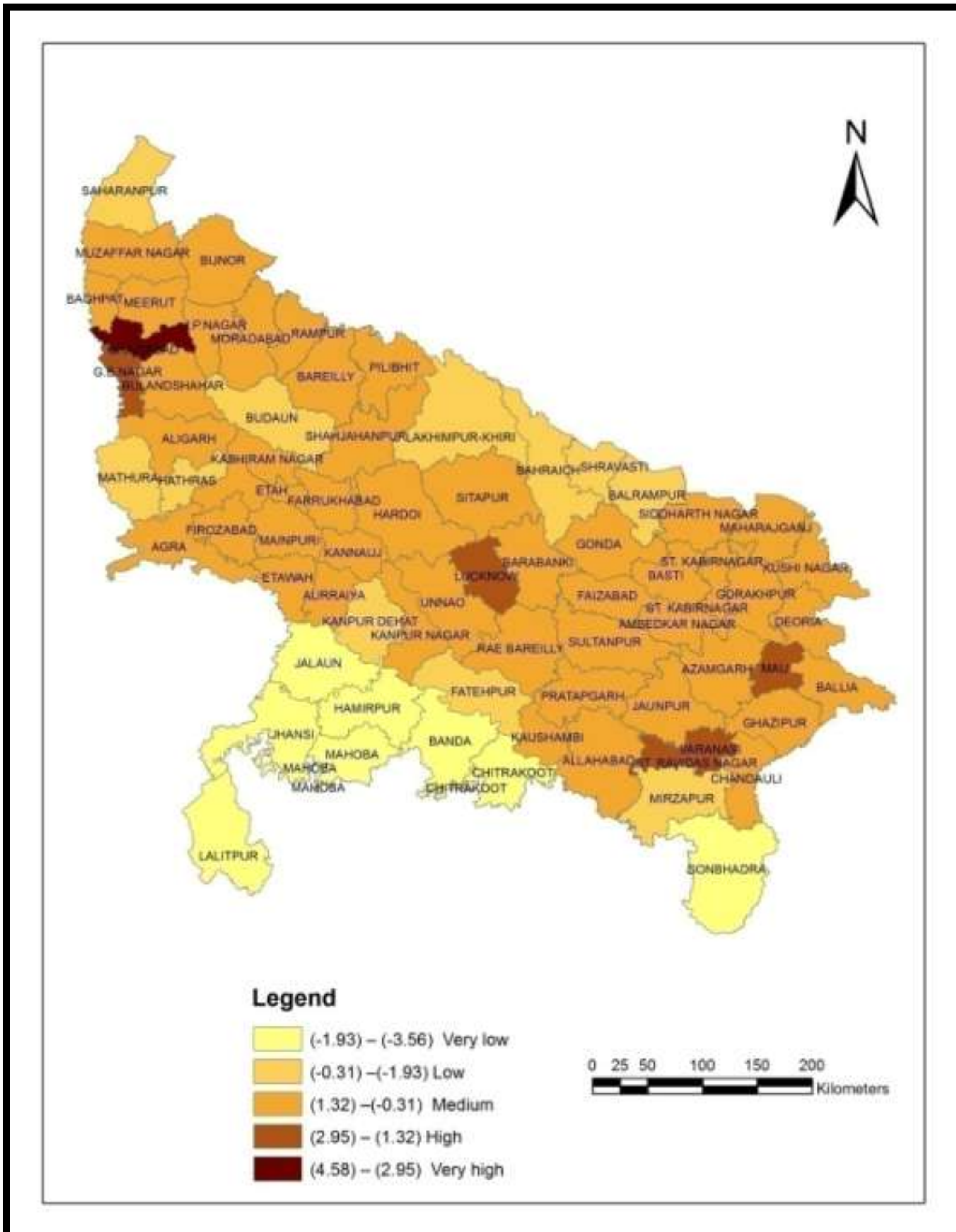
x crops are those crops that individually occupy 5 per cent or more of the sown area in a district.

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. 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.

Like EI, all indicating variables of sensitivity to climate change were aggregated to calculate SI. Figure 3 indicates its spatial pattern. 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.

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

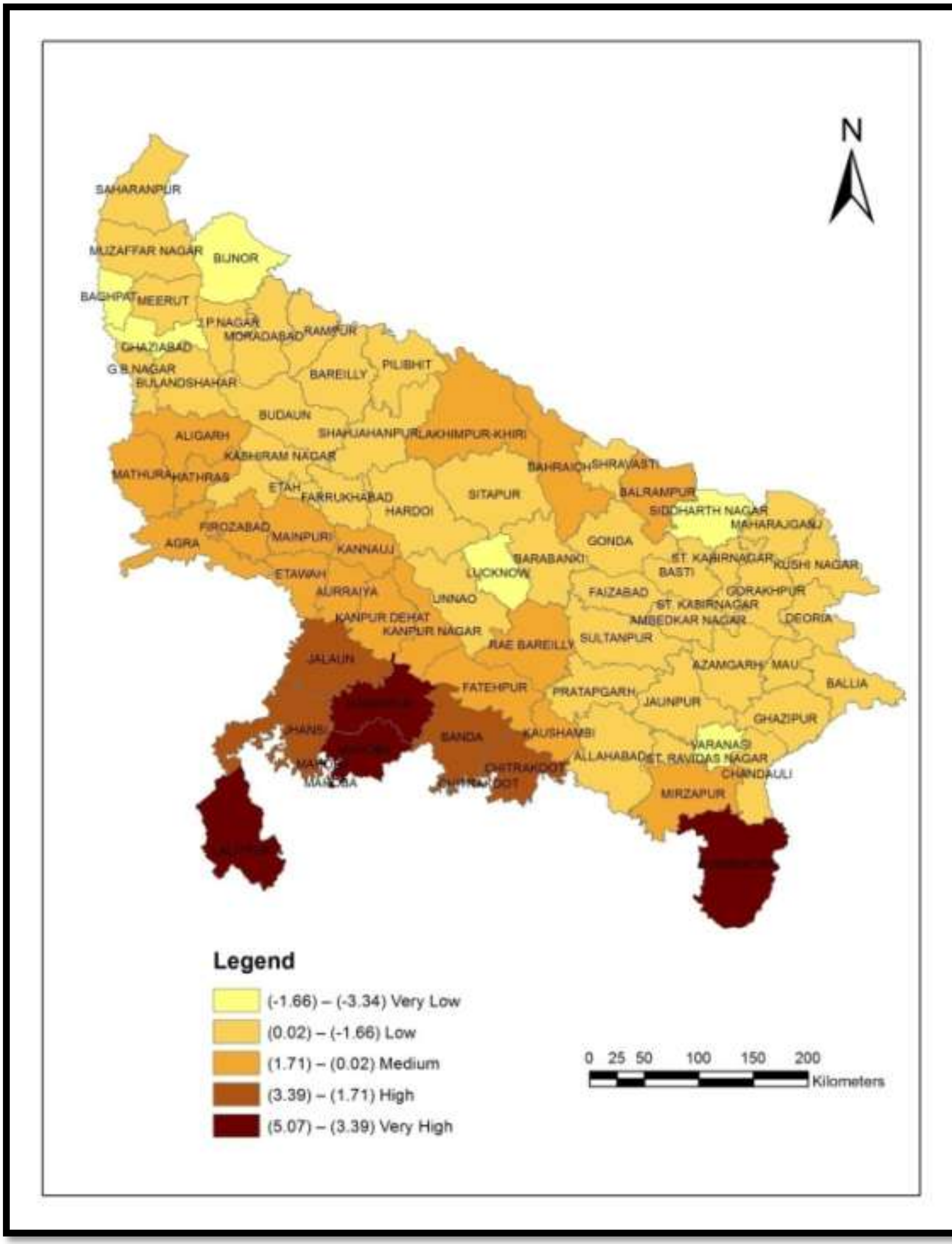
Figure 3: Spatial Pattern of Climate Change SI in UP.



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

Figure 4: Spatial Pattern of Index for Potential Impact of Climate Change in UP



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.

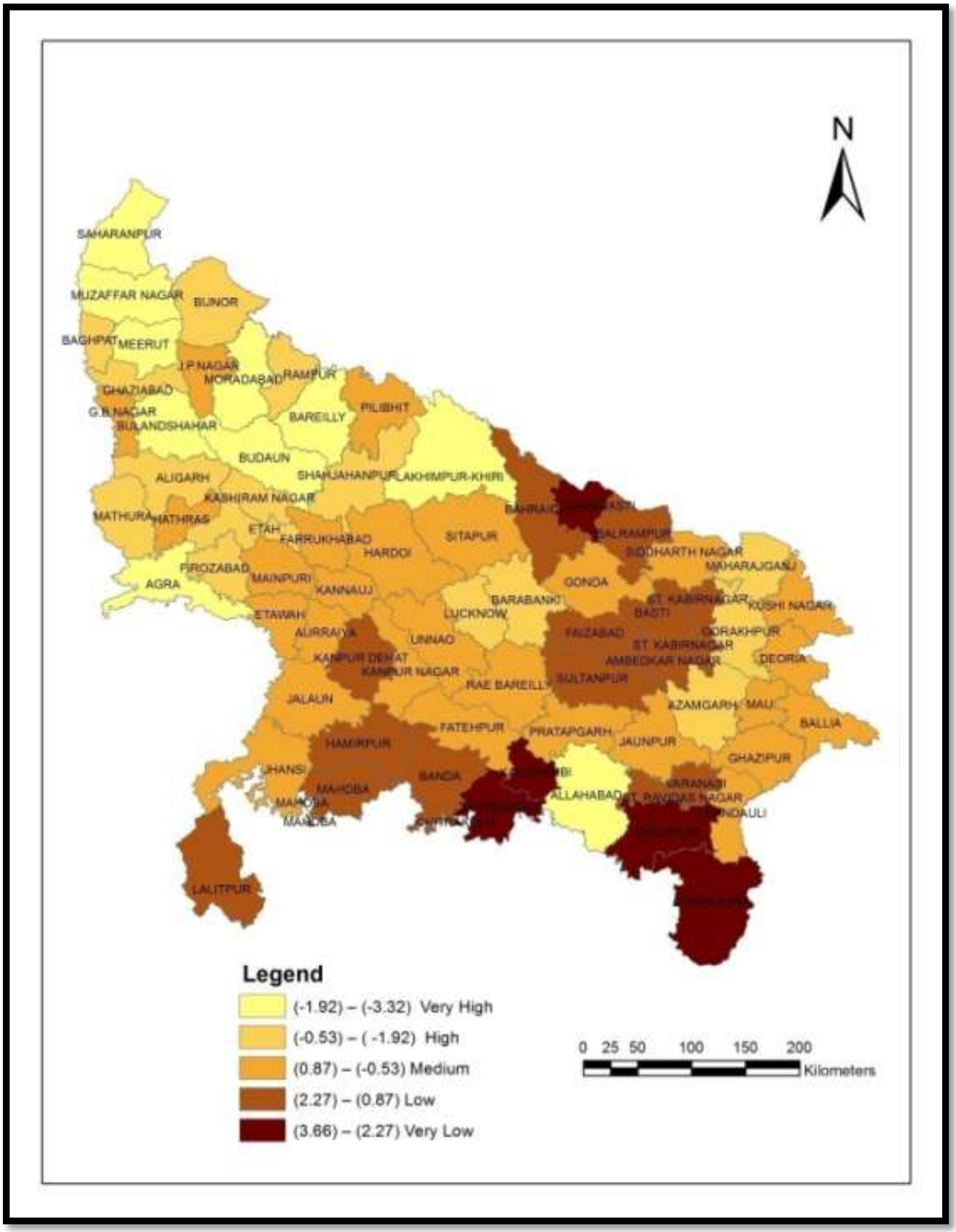
3.3. Adaptive Capacity Index (ACI)

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 variable 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.

Figure 5: Spatial Pattern of Climate Change ACI in UP

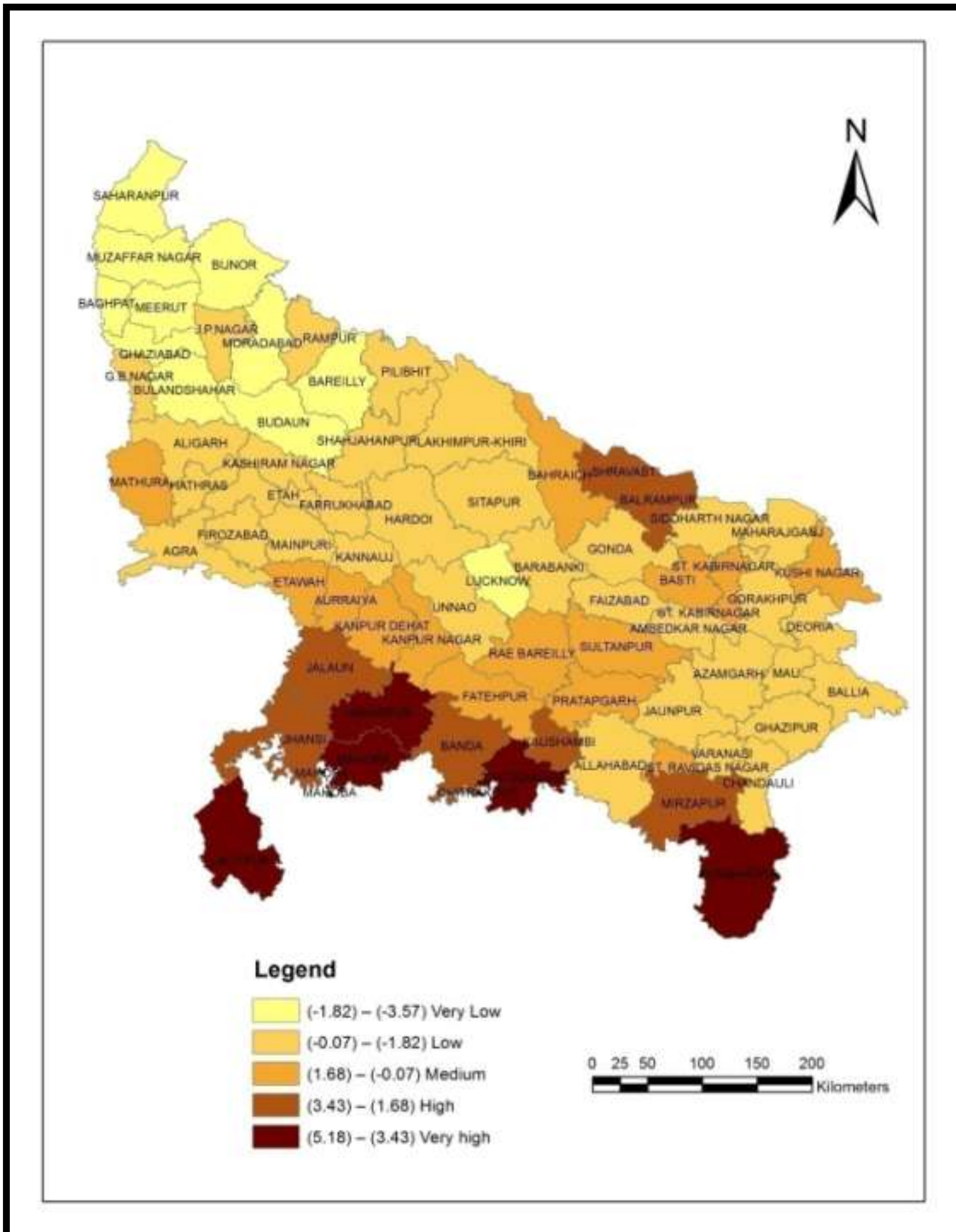


As is evident from Figure 5, the adaptive capacity is found very high and high in districts mainly located in south-western semi-arid, western plain, mid-western plain and central plain region while it is found very low in districts located in Vindyan, eastern Plain, north-eastern Plain, and Bundelkhand 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.

3.4. Vulnerability 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 vulnerable, low vulnerable, and less vulnerable districts to climate change (Figure 6).

Figure 6: Spatial Pattern of Climate Change Vulnerability Index in UP.



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 average 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.

The districts found the most vulnerable to climate change in this study were also identified as the most vulnerable in a NICRA[14] study (Venkateswarlu et al., 2012)[15]. 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 *Jila Sankhyaki Patrika*, although many researchers doubt the quality of its data.

3.5. Correlates

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 3).

Table 3: Comparing coefficient of determination between two equations

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

[14] National Initiative on Climate Resilient Agriculture

[15] 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 ICAR and the SAUs, as well as successful ITKs, 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.

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 multicolinearity 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, 2001). The calculated VIF values for each explanatory variable are presented in Table 4.

Table 4: 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.

Table 5: 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		

The above diagnostic test justifies keeping all explanatory variables in the multiple regression equation. The estimates of this equation are presented in Table 5, 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).

The relationship between forestry and vulnerability to climate change is positive because forestry has been used either little or not at all in adaptation to climate change. To confirm the relationship, a tabular analysis was carried out, wherein the top ten districts were arranged in descending order of the percentage of area under forest cover (Table 6).

Table 6: Districts with the highest percent area under forest in descending order

District	Percent of area under forest	Vulnerability	Adaptive capacity	Sensitivity
Sonbhadra	47.8	Very High	Very Low	Very Low
Chandauli	30.5	Low	High	Medium
Mirzapur	24.1	High	Very Low	Low
Lakhimpur khere	21.4	Low	Very High	Low
Pelebhit	21.1	Low	Medium	Medium
Balrampur	18.2	High	Low	Low
Shrawasti	17.8	High	Very Low	Low
Chitrakoot	17.6	Very High	Very Low	Very Low
Marajganj	17.4	Low	High	Medium
Etawah	15.0	Medium	Medium	Medium

Their level of climate change vulnerability, adaptation, and sensitivity were also provided against each district. We observed that in highly forested districts, vulnerability is high but climate sensitivity is low, because adaptive capacity is low. This further confirms the limited use of forestry in adaptation to climate change.

4. 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. 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 variability in UP. 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. Therefore, vulnerability has three main components—exposure, sensitivity, and adaptive capacity. Exposure and sensitivity together show potential impact, and adaptive capacity is the extent to which these impacts can be averted.

In this study, an index for farmers' vulnerability to climate change was constructed in all districts of UP to identify the districts most vulnerable to climate change and variability. Seventeen environmental and socioeconomic indicators were identified to reflect these three components of vulnerability to climate change. These indicators were finally aggregated using PCA to estimate a VI. Bundelkhand and Vindyachal (except Mirzapur) districts, highly exposed to climate change and variability and with low adaptive capacity, were found the most vulnerable to climate change. Infrastructurally and economically developed districts are found less vulnerable to climate change. It means vulnerability to climate change and variability is linked with social and economic development.

Further, to observe its correlates, the VI is regressed on a set of explanatory variables: urbanisation, SR, NFE, livestock, forestry, consumption of fertiliser, PCI, and IMR. The findings of this relational analysis corroborate our preliminary observations discussed in the previous section. In this relational analysis, livestock, forestry, consumption of fertiliser, PCI, and IMR are observed to be important correlates of farmers' vulnerability to climate change and should be focussed on to reduce it. 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. The GoI has already taken a few steps in this direction, such as weather-based insurance scheme and agro-meteorology services.

Although this study followed all steps systematically and took all possible precaution in data collection and analysis, there are a few flaws: the vulnerability was assessed for districts; all data used for calculating vulnerability indices are averages over the districts while strong spatial variations in climate change are experienced among lower spatial units like villages of same district. Thereby, village level differences are not reflected in the above five indices.

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Appendix

Table A1: List of districts in different economic regions of UP

Regions	**Circles**	**Districts**
Bundelkhand Region	Chitrakoot	Banda, Chitrakoot, Hamirpur, and Mahoba
	Jhansi	Jalaun, Jhansi, Lalitpur
Central Region	Kanpur	Auraiya, Etawah, Farrukhabad, Kannauj, Kanpur Dehat, Kanpur Nagar
	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 Buulandshahar 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 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), Budaun (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	Balrampur (-1.96), Basti (-1.73), Chitrakoot (-1.53), Gazipur (-1.25), Kushinagar (-1.73), Mirzapur (-2.19), 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.