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Understanding vulnerability of agricultural production system to climatic stressors in North Indian Plains: a meso-analysis

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Abstract
The present study has mapped the hot spots vulnerable to changing climate and identified the underlying driving indicators in subtropical Trans and Upper Gangetic plains (TUGP) of India. The long-term trends indicate that the area between latitude 25 and 28° N has been more exposed to adverse climatic changes especially rise in maximum summer/monsoon and minimum winter temperatures. The more predominant correlates of vulnerability in the region come not from the exposure to adverse meteorological conditions but from prevailing socio-economic conditions (adaptive capacity) and the increased environmental pressure (sensitivity). Among the top 40 most vulnerable districts in the TUGP, in about two-third, the exposure was at moderate to low level, but sensitivity was high and adaptive capacity very weak. Among the sensitivity indicators, the factor loadings, obtained through modified principal component technique, were high for average size of landholdings, Temperature Humidity Index load and productivity of paddy and wheat crops. Irrigation intensity, farm mechanization, cropping intensity, livestock density, proportion of milch animals stock, rural literacy rate and veterinary institutions were the critical factors in determining the adaptive capacity of a district. The study outlines range of research and policy imperatives for enhancing resilience of crop–livestock production system.

Keywords Exposure · Sensitivity · Crop–livestock production · THI Load

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1 Introduction

With mounting scientific evidence of climate change, building the resilience of the agriculture sector has become a priority agenda of development planning, especially in the tropical countries like India where the brunt of changing climate in anticipated to be high (Mendelsohn, 2006; IPCC, 2014). Since vulnerability is the flip side of resilience, in order to design and implement climate-resilient programmatic interventions, numerous studies have been conducted at macro, meso and micro levels for vulnerability assessment of various sectors to climate change (Berry et al., 2006; Bouroncle et al., 2017; Parker et al., 2019; Sehgal et al., 2013).

There is a great deal of methodological heterogeneity in the literature with respect to the approach followed for assessing vulnerability. Its conceptualization broadly consolidates around IPCC framework as stated in its Third Assessment Report. Vulnerability is defined as a function of the degree of exposure of the system to climatic hazards, its sensitivity to changes in climate and adaptive capacity. This approach has the advantage of integrating both the biophysical and socio-economic aspects and gives a more comprehensive assessment of vulnerability. Since the mid-2000s, a large number of studies have used the integrated approach to analyse the vulnerability of the agriculture sector and communities to climate change and variability in different regions of the world (Deressa et al., 2008; Etwire et al., 2013; Heltberg & Bonch-Osmolovskiy, 2011).

Recent growth trends in Indian agriculture sector have shown its resilience to external shocks like COVID-19 pandemic. However, when it comes to susceptibility to climate shocks there is ample evidence to suggest that the agriculture sector in India is highly vulnerable (Auffhammer et al., 2012; Choudhary & Sirohi, 2020). Given that India is the habitat for 17.7% of the world's population and it has the largest cultivated area in the world, the dimensions of agricultural vulnerability in this country have far-reaching implications for the global achievement of Sustainable Development Goals. Answers to questions like what is causing this system to be vulnerable and how is vulnerability distributed within the system are of paramount importance and need to be addressed with empirical firmness.

A number of studies have conducted the vulnerability profiling of districts in India at regional (Palanisami et al., 2008; Ravindranath et al., 2011; Sehgal et al., 2013; Tripathi, 2013) and national (O'Brien et al., 2004; Ramarao et al., 2016) level. The choice of indicators and coverage of a study have bearing on the outcome of vulnerability research and its policy relevance (Crane et al., 2017). For instance, for a vast and agro-climatically diverse country like India, vulnerability assessment covering all the 500+ districts in a single study conceals the crucial regional dimensions for policy planning as vulnerability is captured in relative terms. Similarly, in areas such as in Northern plains, where ownership of dairy animals is widespread and complements the rice- and wheat-based cropping systems as the basis of rural livelihoods (Erenstein et al., 2007), the adaptive capacity and sensitivity is conditioned by correlates of livestock farming—an aspect that has not been adequately considered in the available literature .

The approach to vulnerability in this study, while explicitly encompassing this aspect, conceptualizes vulnerability as the degree to which a system is prone and unable to cope with adverse effects of climate variability and changes (IPCC, 2007). Following the IPCC definition of vulnerability, which is most authoritative in the context of climate change, the present study uses an integrated approach to assess vulnerability as an outcome/state of being. The purpose of the paper is to answer some of the key questions related to the extent (how much), causes (why) and spatial distribution (where) of vulnerability.

2 Material and methods

The Northern plains—a region well endowed in natural resources in terms of fertile soil and flow of perennial rivers, has been the seat of the Green Revolution in India. Two agro-climatic regions, viz., Trans and Upper Gangetic Plains (TUGP) from the Northern Plains (Fig. 1), comprising of 82 districts from the states of Punjab, Haryana, Uttar Pradesh and 2 districts from Rajasthan (neighbouring Punjab) cover an area of 26.6 million hectares formed the study area. Alarmed by the recent evidence on erratic precipitation and rising temperature in TUGP (Mathison et al., 2013), estimates of 6.5–10.5 per cent loss in gross margin per hectare from crop due to rise in temperature (Choudhary & Sirohi, 2020) and sensitivity of dairy animals to heat stress in the region, we have aggregated all the indicators and developed district wise vulnerability profile (since districts are the smallest administrative unit in India at which reliable agricultural data are available) across TUGP for making comparisons and effective adaptation planning.

2.1 Selection of indicators

The distinction between the indicators of exposure, sensitivity and adaptive capacity can sometimes be blur (Smit et al. 2006). Since sensitivity and adaptive capacity of a system are internal to it, selecting indicators for these two dimensions become relatively difficult and largely based on personal judgement (Kavi Kumar and Viswanathan, 2006). What constitutes each of these aspects of vulnerability is dependent upon the context of the question and pre-defined criteria. The indicators that determine the extent of the possible impact of

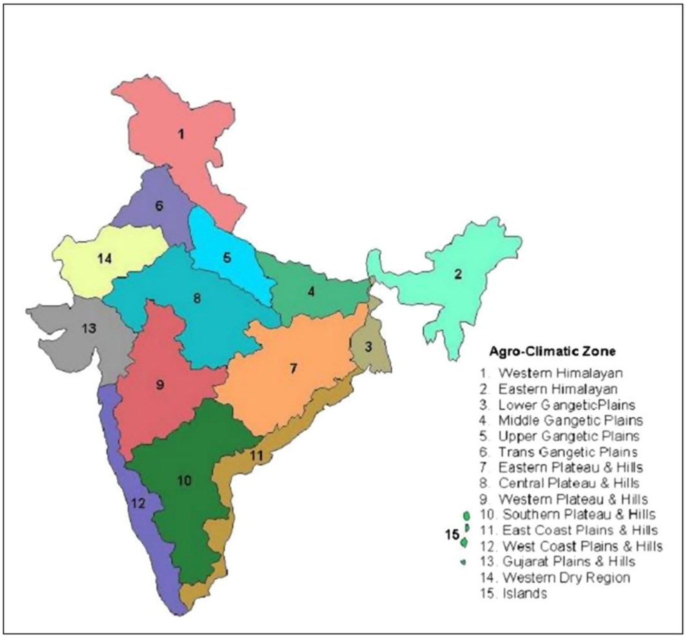

Fig. 1 Agro-climatic zones of India.
Map Source: https://vikaspedia.in/agriculture/crop-production/weather-information/agro-climatic-zones-in-india

climate change and/or variability have been included in sensitivity. Likewise, under adaptive capacity we have selected those indicators that can be targeted to increase the resilience of the system through policy measures. Since the choice of indicators to be included in constructing an index involves some amount of subjectivity, this study relies on theoretical insights drawn from the literature reviewed in selecting indicators to minimize the subjectivity. A total of 32 indicators for the three components of vulnerability were taken (Table 1) and data for the latest year available at the time of conducting the study were used.

2.1.1 Exposure

Changes in two main climatic parameters, i.e., temperature and precipitation, over the years were taken as the indicators of exposure. Rate of change in maximum and minimum temperature, and coefficient of variation of precipitation during the two main cropping seasons in the region, viz., *kharif* (June–September) and *rabi* (October–February) over the period of 30 years (1980–2009) are observed. Further, in accordance with the definition given by the Indian Meteorological Department (IMD), the number of days having very heavy rainfall (124.5–244.5 mm) and the number of days having extremely heavy rainfall (>244.5 mm) during 1980–2009 were also selected as indicators of exposure. As increasing trends in temperature and rainfall variability can have a negative impact on agriculture production system, a positive functional relationship of these indicators with vulnerability was hypothesized.

2.1.2 Sensitivity

While all the indicators of exposure led to increase in vulnerability, in case of the sensitivity indicators, the relationship with vulnerability was both positive and negative. Indicators such as higher cultivated area and concentration of population in rural areas were hypothesized to enhance the sensitivity of agricultural production system to potential climate stress; while larger size of land holding, higher productivity of major crops in the region (rice, wheat and sugarcane) and more organic carbon content of soil were hypothesized to decrease the sensitivity and hence, vulnerability. The typical evidence of a relationship between land holding size and agricultural productivity in the region (Sehgal et al., 2013) suggests that districts with smaller land holdings will be more climate sensitive as small holders face financial constraints in adopting an improved package of agricultural practices. Soil carbon improves the physical properties of soil, contributes to its structural stability and increases the cation exchange and water-holding capacity, thereby stimulating plant growth. Low organic carbon content of soils in a region hampers crop production and productivity and hence increases sensitivity and vulnerability of agriculture.

We introduce a new indicator in our analysis—THI load that has relevance for the sensitivity of livestock production. Temperature Humidity Index (THI) which incorporates combined effects of temperature and relative humidity is widely used to study climatic effects on livestock production (Choudhary & Sirohi, 2019; Gantner et al., 2015; West et al., 2003). The data on weekly normals of maximum and minimum temperature and relative humidity from 103 stations in India were used to compute the weekly average THI based on the estimation method by Ravagnolo et al. (2000). The weekly THI load was then worked out at threshold THI of 72—beyond which the physiological functions of dairy animals get adversely affected (Upadhyay et al., 2007; Zewdu et al., 2014). Assuming the

Table 1 Indicators and their functional relationship with vulnerability

Component	Indicators	Unit	Relation with vulnerability	Data source
Exposure	Rate of change in maximum and minimum temperature (*Kharif*)	°C/year	Positive	High spatial resolution daily gridded temperature ($0.5° \times 0.5°$) and rainfall ($0.25° \times 0.25$) data from India Meteorological Department (IMD), Pune
	Rate of change in maximum and minimum temperature (*Rabi*)	°C/year	Positive	
	Coefficient of variation of *Kharif* rainfall		Positive	
	Coefficient of variation of *Rabi* rainfall		Positive	
	Very heavy rainfall	Number of days	Positive	
	Extremely heavy rainfall	Number of days	Positive	
Sensitivity	Net sown area to geographical area	%	Positive	Directorate of Economics and Statistics, Government of India (GoI)
	Rural population density	No./Km^2	Positive	Census of India
	Productivity of major crops	Kg/ha	Negative	Directorate of Economics and Statistics, GoI
	Organic carbon content of soil	%	Negative	Indian Institute of Soil Science, Bhopal
	Average landholdings size	Ha	Negative	Agricultural Census, Department of Agriculture and Cooperation, GoI
	THI load	No	Positive	IMD Pune

Table 1 (continued)

Component	Indicators	Unit	Relation with vulnerability	Data source
Adaptive capacity	Cropping intensity	%	Negative	Directorate of Economics and Statistics, GoI
	Gross cropped area under fodder crops	%	Negative	
	Land area under pasture & grazing land	%	Negative	
	Irrigated area to gross cropped area	%	Negative	
	Major agriculture implements/ha of net sown area	No./ha	Negative	Interpolated from Livestock Census Vol: III Machinery and Equipments and Input Survey (various years)
	Per capita agriculture and non-agriculture Income		Negative	Directorate of Economics and Statistics of the respective state governments
	Fertilizer consumption (NPK)	Kg/ha of gross cropped area	Negative	Fertilizer Association of India
	Livestock density	No./km^2	Negative	19th livestock census Department of Animal Husbandry and Dairying, GoI
	Milch animals in livestock population	%	Negative	
	Buffalo/CB ratio	%	Negative	
	Villages with paved roads	%	Negative	Census of India
	Villages with veterinary hospitals	%	Negative	
	Villages electrified	%	Negative	
	Literacy rate	%	Negative	
	Rural literacy rate	%	Negative	

average weekly THI load to be uniform for all the seven days in the week, the total THI load in a week was computed as (Actual THI—72) * 7. The annual THI load is sum of the total weekly load over 52 weeks. At the district level, depending on the geographical coordinates of the estimates for the 103 stations, the appropriate value of the THI load was taken. Higher THI load based on climate normally implies that with increase in temperature, the heat stress in animals would aggravate, thus making the livestock production more sensitive to climate change.

2.1.3 Adaptive capacity

A total of sixteen indicators capturing physical, financial and human capital and infrastructure development of districts that help in withstanding the consequences of potential climate stresses were selected to represent adaptive capacity.

Education status of farmers has a bearing on their awareness about adverse impacts of climate change and also influences adoption of climate resilient agricultural practices. Therefore, literacy rate is hypothesized to be positively related with adaptive capacity. Higher percentage of area under assured irrigation, cropping intensity, area under fodder crops, pasture and grazing lands, livestock density and percentage of milch animal in livestock population along with ratio of buffaloes to crossbred are the resource endowment indicators of a district and therefore have positive functional relationship with adaptive capacity. Further, infrastructural facilities like veterinary hospitals, paved roads and electricity in villages strengthen the endurance capacity of a region against climate-related risks and thus are positively related with adaptive capacity. Finally, monetary strength of farm households represented by per capita income from agricultural and non-agricultural sources, and mechanization on farms in terms of agricultural implements used per hectare undoubtedly indicate good adaptive capacity.

2.2 Normalization of variables

As the indicators are measured in different units and scale, they are not additive. Therefore, they are to be converted into standard units to avoid any scale bias in final results. Various methods, viz., ranking, standardization (taking the deviation of each observation from its mean and then dividing it by its standard deviation), division by its length and division by its mean or any other ideal value, have been suggested in the literature to normalize the influence of units and scale. Though choice of any of these is not a value free decision, each has its own merits and demerits. In the present study, mean of each indicator was used for scale-free transformation of the data ($X_j^* = X_{ij}/\bar{x}_j$) as it does not affect the dispersion of indicators and satisfies the basic axioms.

2.3 Assigning weights to indicators

Since all the indicators cannot be of equal importance in explaining the vulnerability, they need to be attached different weights. Some researchers make an arbitrary choice of assigning equal weights (O'Brien et al., 2004), other methods base it on expert judgement (Brooks et al., 2005; Moss et al., 2001), analytic hierarchy process (Sehgal et al., 2013), etc. These methods involve a high degree of subjectivity. A more extensively used objective approach to weighted indexing is principal component analysis (PCA) (Piya et al., 2012; Tripathi, 2013). PCA is a multivariate statistical technique used to reduce dimensionality by extracting the smallest number of components that account for most of the variation in the original multivariate data and by summarizing the data with little loss of information. The PCA approach gives higher weightages to indicators having higher correlations with other selected indicators. However, this approach does not account for the presence of substantial cross-sectional disparity among development variables. Therefore, we have used modified PCA (MPCA) technique (Majumder, 2005) to assign weights to indicators of each dimension of vulnerability. MPCA calculates the eigenvalues from the covariance matrix ($X^{*'}X^{*}/n$). This approach has methodological superiority over PCA as it rejects the correlation matrix as the basis for working out weights and the weights are calculated in such a manner that besides correlation, the disparities in distribution also have a role to play. MPCA ensures that indicators with greater variability get higher weights.

2.4 Aggregation

Before the aggregation of indices in the overall vulnerability index (VI), we compute sub-indices of exposure (EI), sensitivity (SI) and adaptive capacity (ACI). Each sub-index is constructed as weighted sum indicators. Various methods for aggregation of sub-indices point towards the same idea that vulnerability is a net of exposure, sensitivity and adaptive capacity. Following Antwi-agyei et al. (2012) and others, we compute the composite vulnerability index (VI) = EI +SI—CI

2.5 Classification of districts

The districts were classified into 5 categories for each index using the Jenks optimization method in ARCGIS 10.0. Also known as Jenks natural breaks classification method, it is one of the data clustering methods designed to determine the best arrangement of values into different classes (de Smith et al., 2018). This method identifies logical break points in a data set by grouping similar values that “minimize differences between data values in the same class and maximize the differences between classes.” It is specifically advantageous for making choropleth maps because it identifies real classes within the data.

3 Results and discussion

Representation of vulnerability with the single index brings an insight about the degree of vulnerability on a regional level and identifies the most vulnerable regions. However, to avoid simplistic policy conclusions based on the composite index (Gbetibouo et al., 2010; Saisana & Tarantola, 2002) and fully assess the “big picture”, presenting the indices of sub-components is useful (Zurovec et al., 2017).

3.1 Components of vulnerability

The use of factor loading corresponding to first principal component explaining the largest amount of information from the underlying data has been widely suggested (Filmer & Pritchett, 2001; Gbetibouo et al., 2010; Poirier et al., 2020). In our data set, the first principal component explained about 64% of the total variation in exposure and adaptive capacity and about 78% in sensitivity (Appendix 1) and hence eigenvector associated with highest eigenvalue used as weights.

Rate of change in *kharif* (maximum temperature, very heavy rainfall) and rate of change in *rabi* (minimum temperature) have substantially contributed in inducing exposure across TUGP (Fig. 2a). The long-term trends substantiate a significant increase in *kharif* maximum temperature and *rabi* minimum temperature (Fig. 3). Districts located in southern parts of the TUGP (Mahamaya Nagar, Etawah, Auraiya, Mainpuri, Agra, Mathura and Firozabad) experienced comparatively higher rate of change in *kharif* maximum temperature (0.016–0.026 °C per year) and *rabi* minimum temperature (0.047–0.052 °C/year) than the regional average of 0.010 °C and 0.041 °C per annum, respectively. Additionally, these districts also had higher number of days (8–16) with very heavier rainfall than the regional average of 5 days. Hence, the southern parts of the TUGP fall in extreme and high exposure category (Fig. 4a), while in most of the districts in eastern, central and western parts, the exposure levels are moderate to low. The districts in the northern parts of Punjab and Haryana, that are closer to the Himalayan region in India, are least exposed to temperature and rainfall changes and variability in the two agricultural season.

The factor loadings for average size of landholdings, THI load and productivity of major crops (rice and wheat) were higher among the sensitivity indicators (Fig. 2b), suggesting that both crop and livestock production system have a bearing on the vulnerability of rural

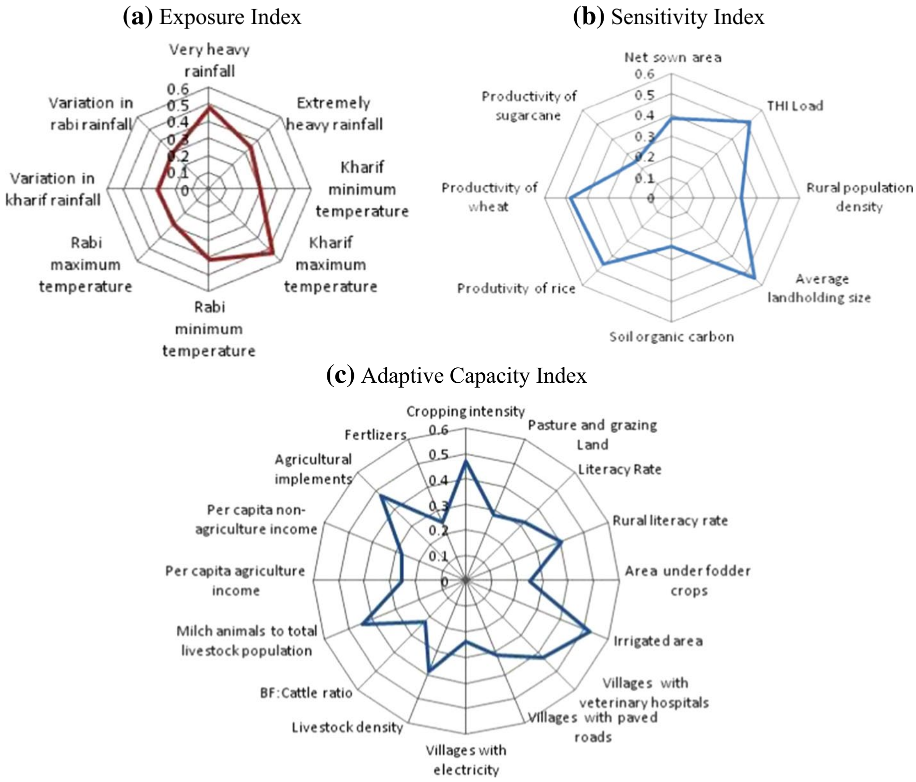

Fig. 2 Factor loadings of the vulnerability indicators

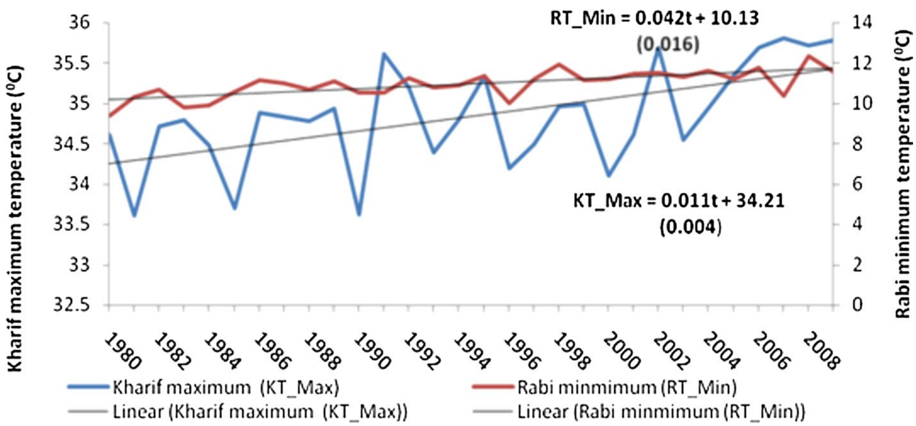

Fig. 3 Trends in *kharif* maximum and *rabi* minimum temperature in TUGP. Note: Figures in parentheses are standard errors

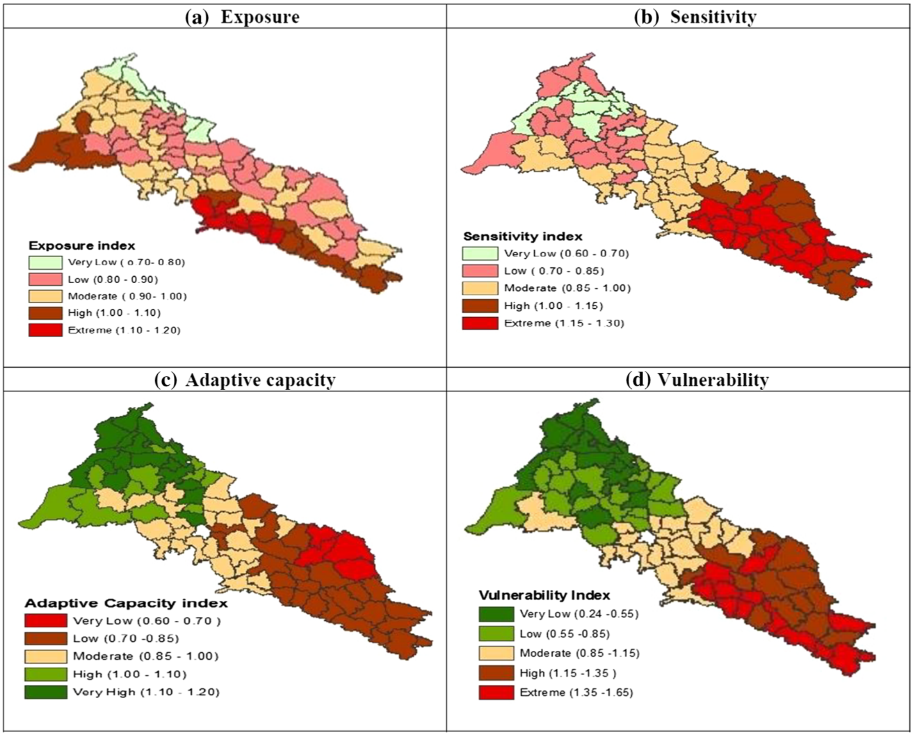

Fig. 4 Vulnerability profiling of districts across Trans and Upper Gangetic plains

livelihoods. Sensitivity index for 84 districts varied widely ranging from a very low level of 0.60 (Fatehgarh Sahib) to extreme value of 1.28 (Rae Bareli) (Appendix 2). The eastern part of the region that compares unfavourably with the regional averages in the key indicators has been categorized as extreme and highly sensitive. Here, the average fam holding size is 0.42–0.68 hectare (regional average 1.90 hectare); productivity of rice and wheat is about 1.8–1.9 tonnes/hectare and 2.1–2.7 t/ha, respectively, much lower than the average productivity of both the crops in TUGP (2.85 t/ha for rice and 3.67 t/ha for wheat). The hot humid climatic conditions cause higher THI load ranging from 1848 to 1920 units (regional average 1680), indicating that livestock, especially milk production, is very sensitive to heat stress. As we move from eastern to the central and western part of the region, a gradual decline in sensitivity is observable.

The critical factors (factor loading >0.4) determining the adaptive capacity of a district are irrigation intensity, farm mechanization, cropping intensity, livestock density, proportion of milch animals stock, rural literacy rate and veterinary institutions (Fig. 2c), The districts located in the north western part of the TUGP, falling in the state of Punjab, Haryana and western Uttar Pradesh, that typically have high irrigation and cropping intensity (Erenstein et al., 2007; Grover et al., 2017; Singh et al., 2012; Verma & Singh, 2006), rank higher in terms of adaptive capacity index (Fig. 4c). Further, in these regions a comparatively higher rural literacy rate, higher proportion of milch animals and livestock density accentuate its adaptive capacity. Conversely, eastern districts of TUGP have very low to low adaptive capacity, largely due to low irrigation (51–68%) and cropping (132–153%) intensity and poor infrastructural endowment.

3.2 Spatial distribution of vulnerability

Vulnerability index for more than one-fourth (29%) districts in the region was at extreme or high level, and, in one-fifth (20%) same was on the other end in very low vulnerability category (Table 2). The vulnerability of the agriculture production system gradually increased as one moves from western to eastern parts across the TUGP (Fig. 4d). All the extreme and highly vulnerable districts fall in Upper Gangetic Plains (UGP), and the less vulnerable in the Trans-Gangetic plains. The higher resilience of agriculturally and infrastructurally better endowed states of Punjab and Haryana, and adjoining areas of western Uttar Pradesh has also been substantiated by other studies (Ramarao et al., 2016; Sehgal et al., 2013; Tripathi, 2013), using other methodological approaches.

Table 2 Number of districts in different vulnerability class in Trans and Upper Gangetic plains.

Regions	Total districts	Vulnerability class				
		Extreme	High	Moderate	Low	Very low
Upper Gangetic Plains	41	13 (32)	11 (27)	14 (34)	3 (7)	0 (0)
Trans Gangetic Plains	43	0 (0)	0 (0)	9 (20)	17 (40)	17 (40)
TUGP	**84**	**13 (16)**	**11 (13)**	**23 (27)**	**20 (24)**	**17 (20)**

Figures in parentheses are percentage of districts in different vulnerability class

Table 3 Spearman's rank correlation coefficients

	Adaptive capacity index	Exposure index	Sensitivity index
Adaptive capacity index	1.000		
Exposure index	– 0.228 ** (– 2.12)	1.000	
Sensitivity index	– 0.8715 * (– 16.09)	0.3243 * (3.10)	1.000
Vulnerability index	– 0.9058 * (– 19.36)	0.5114 * (5.38)	0.9554 * (29.32)

(1) Figures in parentheses are t-ratios (2) * and ** indicate significance at 1% and 5% level, respectively

Strong negative rank correlation (– 0.91) between adaptive capacity and vulnerability index and positive correlation between sensitivity and vulnerability ranking in the study area (Table 3) highlight the importance of development and extension interventions for coping with climatic stressors. However, the rank correlation coefficient of exposure and vulnerability is of much lower magnitude, suggesting that vulnerability is not only induced

Table 4 Highly vulnerable districts: how exposed, sensitive and adaptive?

Vulnerability level	Districts	Exposure level	Sensitivity level	Adaptive capacity level
Extreme	Etawah	Extreme	Extreme	Low
	Auriya	Extreme	Extreme	Low
	Shahjahanpur	Moderate	Extreme	Very low
	Mainpuri	Extreme	Extreme	Low
	Kanpur City	High	Extreme	Low
	Fatehpur	High	Extreme	Low
	Kannauj	High	Extreme	Low
	S. R. Nagar	High	Extreme	Low
	Firozabad	Extreme	Extreme	Moderate
	Sultanpur	Moderate	Extreme	Low
	Kaushambi	High	High	Low
	Allahabad	High	High	Low
	Etah	Moderate	Extreme	Low
High	Barabanki	Low	Extreme	Low
	Kanpur Dehat	High	High	Low
	Farrukhabad	Moderate	Extreme	Low
	Pilibhit	Low	High	Very low
	Sitapur	Moderate	High	Very low
	Unnao	Moderate	Extreme	Low
	Rae Barely	Low	Extreme	Low
	Hardoi	Low	Extreme	Low
	Kheri	Low	High	Very low
	Mahamaya Nagar	Extreme	Moderate	Moderate
	Badaun	Low	High	Low

by climatic stress (as captured by exposure level) but it is a manifestation of multiple economic development factors.

The cross-classification of highly vulnerable (category extreme+ high) districts according to the level of exposure, sensitivity and adaptive capacity (Table 4) brings out this point more sharply. In a number of districts (Barabanki, Pilibhit, Rae Bareilly, Hardoi, Kheri and Badaun), despite low exposure to adverse temperature and rainfall conditions, lack of adaptive capacity coupled with high sensitivity makes them vulnerable to climatic stress. Among the top 40 most vulnerable districts in the TUGP (Appendix 2), in about 25, the exposure index was below 1.0 (viz., moderate to low level). On the other hand, districts like Muktsar, Sri Ganganagar and Hanumangarh have been able to develop strong coping mechanisms and hence are not highly susceptible to extreme exposure levels experienced by them.

4 Conclusions

The meso-level vulnerability profiling in the subtropical TUGP of India brings out that eastern part of this region is most vulnerable to climatic change, while the resilience improves gradually as one moves westward. Although the level of exposure to adverse changes in temperature and rainfall is geographically heterogeneous, yet broadly, the area lying between latitude 25–28° N is more susceptible to changing climate, especially rising maximum temperature in summer/monsoon (July–September) season and minimum temperature in winters (October–February).

The development of heat-tolerant cultivar, modifications in agronomic practices, e.g., adjustment in planting date to offset the risk of climatic exposure, promoting area under climate-smart crops like pulses and nutri-cereals, development of more accurate systems for early warning of extreme climatic events such as heavy rainfall, providing weather-based crop and livestock advisory, developing low-cost precision agricultural and dairy farming techniques are some of the research and policy imperatives for coping with higher exposure levels in the subtropics. Integration of agro-forestry on farms can also go a long way in mitigating the detrimental effects of rising temperature (Dhyani et al., 2021; Inder et al., 2018).

Notwithstanding the relevance of measures to cushion against climatic exposure, the more predominant correlates of vulnerability in the TUGPs come not from the meteorological phenomenon as captured by exposure index, but from the prevailing socio-economic conditions (adaptive capacity) and the increased environmental pressure as a result of the human–environment interactions (sensitivity).

Small size of land holdings accentuates the sensitivity of the agricultural production system. The role of farm collectives can be crucial for enhancing the livelihood security of smallholders. In the past 7 years, the success of a number of Farmer Producer Organizations (FPOs) in the region provides useful learning lessons for replication of similar institutional model in other parts of the developing world. For improving sensitivity of the crop production system, enhancing the productivity of rice and wheat through dissemination of good agricultural practices is another vital area of extension focus. Augmenting resilience of dairy production to heat stress requires interventions targeted towards better housing, feeding and management of animals.

The role of agricultural infrastructure development in enhancing adaptive capacity is strikingly evident from the study. The access to assured irrigation and mechanization, two important factors that lead to exemplary agricultural growth popularly called Green Revolution in the western part of the TUGP, had limited spread in the other parts of the northern plains. Investment in irrigation holds the key in raising the cropping intensity in the central and eastern part of the region. Mechanizations of the farm operations on small-sized resource poor farm holdings do pose the challenge of economic viability requiring solutions such as agricultural implements custom hiring centres. This would also reduce the demand for draft animal power and shift the composition of bovine stock in favour of dairy animals. Supported by good health and breeding services, dairying can be an important means to build adaptive capacity of the smallholder farmers. Since rural literacy emerged to be an important component of adaptive capacity, mainstreaming practically oriented, participatory and interactive model like farmer field school (FFS) program to educate the farmers is another vital area of development planning.

Although the actual choice of interventions for reducing vulnerability would eventually depend on socio-economic factors prevailing in any region (Kumar et al., 2019), the evidence from northern Indian plains provides useful insights for setting research and policy agenda not only in the Indian context but also in other geographies in the sub-tropics where exposure to climatic change is anticipated to be similar.

Appendix 1

See Table 5.

Table 5 Factor scores from first principal component (PCA1) and associated statistics

Component	Indicators	PCA1	Eigenvalue	Proportion (%)
Exposure	Rate of change in maximum *Kharif* temperature	0.5344	8.83	63.71
	Rate of change in minimum *Kharif* temperature	0.3050		
	Rate of change in maximum *Rabi* temperature	0.2917		
	Rate of change in minimum *Rabi* temperature	0.4162		
	Coefficient of variation of *Kharif* rainfall	0.3063		
	Coefficient of variation of *Rabi* rainfall	0.3020		
	Very heavy rainfall	0.4828		
	Extremely heavy rainfall	0.3528		
Sensitivity	Net sown area to geographical area	0.3824	9.32	77.72
	Rural population density	0.3281		
	Productivity of rice	0.4512		
	Productivity of wheat	0.4758		
	Productivity of sugarcane	0.2416		
	Organic carbon content of soil	0.2337		
	Average landholdings size	0.5494		
	THI load	0.5143		
Adaptive capacity	Cropping intensity	0.4724	16.44	63.79
	Gross cropped area under fodder crops	0.2473		
	Land area under pasture & grazing land	0.2820		
	Irrigated area to gross cropped area	0.5238		
	Major agriculture implements / ha of net sown area	0.4751		
	Per capita agriculture Income	0.2514		
	Per capita non-agriculture Income	0.3709		
	Fertilizer consumption (NPK)	0.2475		
	Livestock density	0.3832		
	Milch animals in livestock population	0.4396		
	Buffalo/CB ratio	0.2302		
	Villages with paved roads	0.3140		
	Villages with veterinary hospitals	0.4283		
	Villages electrified	0.2375		
	Literacy rate	0.3238		
	Rural literacy rate	0.4042		

Appendix 2

See Table 6.

Table 6 District wise rank and indices of vulnerability and its components

Districts	Exposure		Sensitivity		Adaptive capacity		Vulnerability	
	index value	Rank	index value	Rank	index value	Rank	index value	Rank
Etawah	1.1478	3	1.2224	5	0.7218	80	1.6485	1
Auriya	1.1404	5	1.2220	6	0.7604	77	1.6020	2
Shahjahanpur	0.9726	25	1.2780	2	0.6952	81	1.5553	3
Mainpuri	1.1447	4	1.2217	7	0.8399	62	1.5265	4
Kanpur City	1.0803	10	1.1948	14	0.8176	70	1.4575	5
Fatehpur	1.0727	11	1.2150	9	0.8429	58	1.4448	6
Kannauj	1.0499	15	1.2102	10	0.8187	69	1.4414	7
Sant Ravidas Nagar	1.0434	16	1.2096	11	0.8200	68	1.4330	8
Nagar Firozabad	1.1020	7	1.1961	12	0.8930	51	1.4051	9
Sultanpur	0.9682	30	1.2686	3	0.8426	59	1.3942	10
Kaushambi	1.0303	18	1.1103	17	0.7570	78	1.3836	11
Allahabad	1.0878	8	1.0864	20	0.7987	72	1.3755	12
Etah	0.9193	44	1.1772	16	0.7364	79	1.3601	13
Barabanki	0.8707	57	1.2536	4	0.7926	73	1.3316	14
Kanpur Dehat	1.0668	13	1.0993	19	0.8398	63	1.3263	15
Farrukhabad	0.9017	52	1.1863	15	0.7805	74	1.3074	16
Pilibhit	0.8385	68	1.0825	21	0.6256	84	1.2954	17
Sitapur	0.9179	45	1.0499	25	0.6782	83	1.2896	18
Unnao	0.9060	51	1.2198	8	0.8414	60	1.2844	19
Rae Barely	0.8309	72	1.2887	1	0.8404	61	1.2792	20
Hardoi	0.8658	59	1.1951	13	0.8326	67	1.2284	21
Kheri	0.8360	69	1.0603	23	0.6807	82	1.2156	22
Mahamaya Nagar	1.1681	2	0.9715	30	0.9489	44	1.1907	23
Badaun	0.8620	64	1.1049	18	0.7790	75	1.1879	24
Bareilly	0.9717	27	0.9719	29	0.8096	71	1.1340	25
Agra	1.1094	6	0.9809	27	0.9580	42	1.1323	26
Aligarh	1.0677	12	0.9612	31	0.8968	50	1.1321	27
Pratapgarh	0.9095	49	1.0568	24	0.8470	55	1.1193	28
Mewat	0.9613	33	0.9821	26	0.8510	54	1.0924	29
Gurgaon	0.9710	28	0.9737	28	0.8783	52	1.0664	30
Lucknow	0.8136	76	1.0654	22	0.8394	64	1.0396	31
Mahendragarh	0.9532	36	0.9124	40	0.8445	57	1.0211	32
Gautam Budhha Nagar	0.9163	47	0.9325	35	0.8379	65	1.0109	33
Mathura	1.1792	1	0.9103	43	1.0799	24	1.0096	34
Bijnor	0.8660	58	0.9128	39	0.7761	76	1.0027	35
Gaziabad	0.8744	55	0.9570	32	0.8457	56	0.9857	36
Bulandsahar	0.9752	22	0.9511	34	0.9597	40	0.9666	37
Rewari	0.9785	19	0.9551	33	0.9849	32	0.9487	38
Moradabad	0.8208	74	0.9318	36	0.8355	66	0.9171	39
Rampur	0.8327	71	0.9308	37	0.8571	53	0.9064	40
Palwal	0.9591	34	0.8810	48	0.9410	46	0.8991	41
Bagpat	0.9270	43	0.9305	38	0.9590	41	0.8986	42
Faridabad	0.9721	26	0.8904	47	0.9718	35	0.8907	43

Table 6 (continued)

Districts	Exposure		Sensitivity		Adaptive capacity		Vulnerability	
	index value	Rank	index value	Rank	index value	Rank	index value	Rank
Meerut	0.9296	41	0.9111	42	0.9535	43	0.8872	44
Jhajjar	0.9777	20	0.8109	57	0.9190	49	0.8696	45
Rohtak	0.9278	42	0.8786	50	0.9378	47	0.8687	46
Hanumangarh	1.0569	14	0.8955	45	1.0861	22	0.8662	47
Muzzafarnagar	0.8609	65	0.9053	44	0.9232	48	0.8430	48
Amroha	0.8954	54	0.9113	41	0.9688	37	0.8379	49
Bhiwani	0.9142	48	0.8791	49	0.9616	39	0.8317	50
Sriganganagar	1.0307	17	0.8492	55	1.0728	29	0.8071	51
Muktsar	1.0830	9	0.7958	60	1.0898	20	0.7891	52
Jind	0.9541	35	0.7951	61	0.9694	36	0.7799	53
Sirsa	0.8355	70	0.8952	46	0.9683	38	0.7624	54
Kaithal	0.9066	50	0.7397	68	0.9747	33	0.6716	55
Moga	0.9741	23	0.7847	64	1.1097	14	0.6491	56
Panipat	0.8217	73	0.8747	51	1.0508	31	0.6457	57
Saharanpur	0.7385	82	0.8500	54	0.9483	45	0.6403	58
Bhatinda	0.9625	31	0.7993	59	1.1270	12	0.6347	59
Fatehabad	0.8649	62	0.7389	69	0.9735	34	0.6303	60
Sonipat	0.8654	60	0.8455	56	1.1023	17	0.6086	61
Faridkot	0.9468	38	0.7701	67	1.1320	9	0.5849	62
Ambala	0.8716	56	0.7846	65	1.0742	27	0.5820	63
Sangrur	0.9688	29	0.6795	79	1.0682	30	0.5800	64
Panchkula	0.7799	79	0.8703	52	1.0794	25	0.5707	65
Tran Taran	0.9521	37	0.7131	71	1.1020	18	0.5632	66
Yamunagar	0.7816	78	0.8512	53	1.0757	26	0.5571	67
Amritsar	0.9616	32	0.7005	73	1.1126	13	0.5495	68
Hisar	0.8540	66	0.7871	63	1.0928	19	0.5483	69
Barnala	0.9419	39	0.6801	78	1.0810	23	0.5410	70
Mansa	0.8181	75	0.7839	66	1.0895	21	0.5125	71
Karnal	0.8963	53	0.7993	58	1.1864	4	0.5091	72
Firozpur	0.9741	24	0.6119	83	1.1410	8	0.4449	73
Kurukhetra	0.8641	63	0.6877	75	1.1084	16	0.4434	74
Patiala	0.8522	67	0.7161	70	1.1285	11	0.4398	75
Ludhiana	0.9386	40	0.6595	80	1.1932	1	0.4048	76
Jallandhar	0.9759	21	0.6139	82	1.1864	5	0.4034	77
Kapurthalla	0.9171	46	0.6539	81	1.1867	3	0.3843	78
SAS Nagar	0.7825	77	0.6821	77	1.1084	15	0.3562	79
Nawasahar	0.7385	81	0.6859	76	1.0732	28	0.3513	80
FG Sahib	0.8653	61	0.6020	84	1.1310	10	0.3362	81
Hoshiarpur	0.7122	84	0.7938	62	1.1898	2	0.3162	82
Ropar	0.7669	80	0.6929	74	1.1485	7	0.3113	83
Gurudaspur	0.7214	83	0.7051	72	1.1828	6	0.2438	84

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Declarations

Conflict of interest The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

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