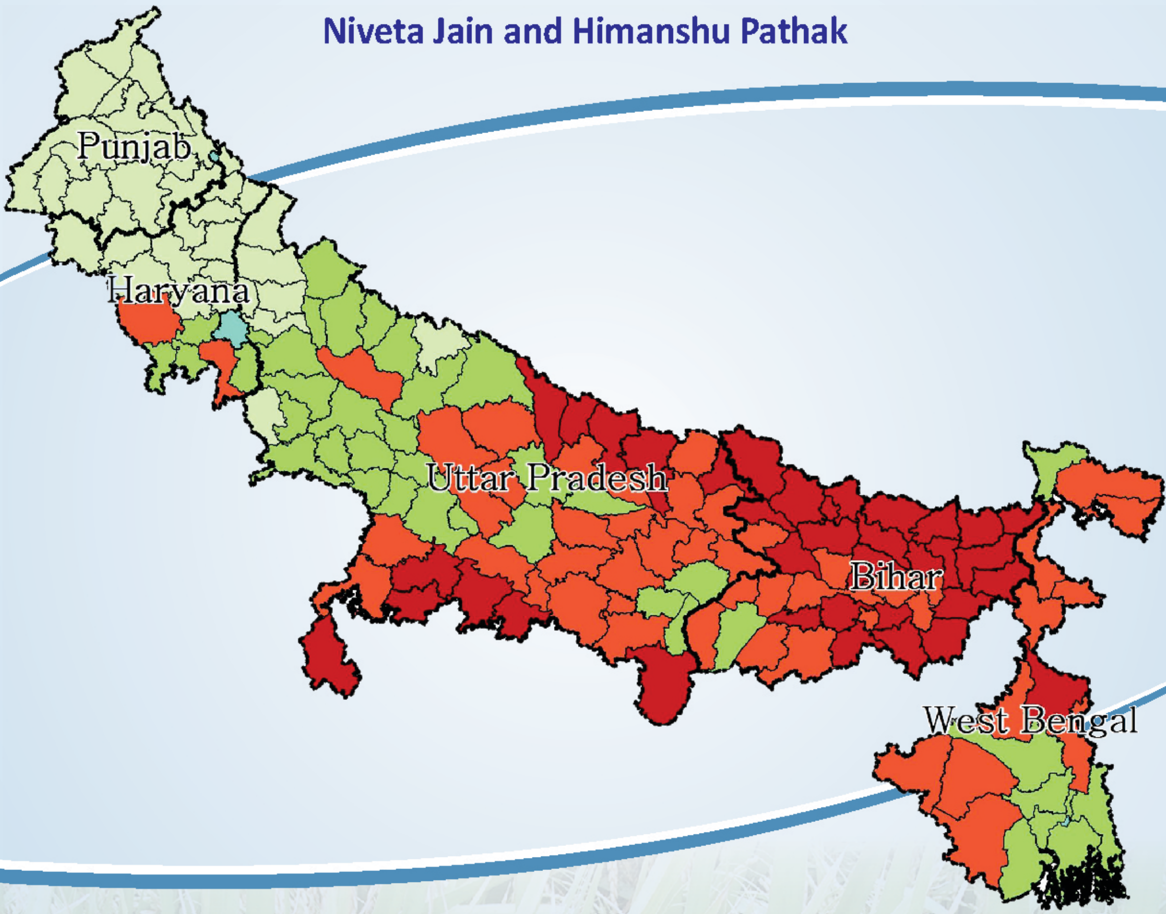
Vulnerability of Agriculture to Climate Change

District Level Assessment in the Indo-Gangetic Plains

Vinay K Sehgal, Malti R Singh, Anita Chaudhary
Niveta Jain and Himanshu Pathak



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ISBN: 978-81-88708-97-0

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Printed in June, 2013

Suggested citation:

Sehgal VK, Singh MR, Chaudhary A, Jain N and Pathak H (2013) Vulnerability of Agriculture to Climate Change: District Level Assessment in the Indo-Gangetic Plains. Indian Agricultural Research Institute, New Delhi p 74.

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ISBN: 978-81-88708-97-0

Printed at:

Venus Printers and Publishers, B-62/8, Naraina Industrial Area, Phase-II, New Delhi 110028, Ph.: 45576780, Mobile: 9810089097, Email: pawannanda@gmail.com

Foreword

Indian agriculture has made significant progress during the past five decades achieving the level of self-sufficiency in food production. However, it is now facing several challenges like stagnating net sown area, plateauing yield levels, deteriorating land quality and reducing farm size. A recent and more challenging addition is the impact of climate change on agriculture. Therefore, to ensure food security of the country, appropriate mitigation and adaptation strategies need to be adopted. A pre-requisite for developing climate-resilient strategies and making policy intervention is an integrated assessment of the vulnerability of agriculture to climate change in a region. This information is crucial for strategic planning and prioritizing allocation of resources to address the adverse impacts of climate change.

The current study has suggested a methodology for assessing and mapping composite vulnerability of agriculture to climate variability and change in a region and has demonstrated its applicability in the Indo-Gangetic Plains (IGP) of India at the district level. Based on the findings in the study, a list has been prepared of all the districts in the IGP on their vulnerability ranking. It has facilitated identification of most vulnerable districts in the IGP which need priority support, a key information for the policy planners and stakeholders.

I appreciate the efforts made by the authors in carrying out the study and bringing out this book. I am sure this book will be equally useful for students, researchers and policy-makers in the field of vulnerability of agriculture to climate change and climatic variability.

(HS Gupta)
Director
Indian Agricultural Research Institute
New Delhi

Acknowledgments

We are extremely grateful to Dr. H.S. Gupta, Director, IARI and Dr. Malavika Dadlani, Joint Director (Research) of the IARI, New Delhi, for their guidance in executing the research work on climate change at the Institute and bringing out this publication. Our sincere thanks are due to Dr. Ravender Singh, Head of the Division of Agricultural Physics, and Dr. R.K. Rattan, In-Charge, Centre for Environment Science and Climate Resilient Agriculture of IARI for their constant encouragement in carrying out the study.

We are thankful to ICAR National Initiative on Climate Resilient Agriculture (NICRA) project for providing financial support to carry out this study. The help and cooperation, extended by our esteemed colleagues and friends at IARI in bringing out this book, is sincerely acknowledged. The help and cooperation extended by our esteemed colleagues Dr. SK Bandyopadhyay, Dr. A Bhatia, Dr. S Chander, Dr. DK Das, Dr. TK Das, Dr. MK Khanna, Dr. RN Padaria, Dr. TJ Purokayastha, Dr. A Singh, Dr. SD Singh, Dr. S Naresh Kumar, Dr. P Sinha, Anjali Singh and Priyanka Negotia in carrying out this study are sincerely acknowledged.

We thank Dr. B. Venkataswarlu, Director, CRIDA, Hyderabad and National Coordinator, National Initiative on Climate Resilient Agriculture (NICRA), ICAR, for his guidance in bringing out this book.

Our sincere thanks are also due to Dr. A.K. Singh and Dr. A.K. Sikka, former and present Deputy Directors General (Natural Resource Management) of the ICAR, New Delhi, respectively for their guidance and encouragement in publishing this book.

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June 2013,
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Abbreviations

AHP	Analytical hierarchy process
AWHC	Available water holding capacity
BADC	British Atmospheric Data Centre
CEC	Cation exchange capacity
CI	Consistency index
CR	Consistency ratio
CRU TS 3.0	Climatic Research Unit time series version 3.0
ENVI™	Environment for visualizing images
FAO	Food and Agriculture Organisation
GA	Geographical area
GDP	Gross domestic product
GIS	Geographic information system
GMIA	Global map of irrigated areas
GUI	Graphical user interface
HDI	Human development index
IDL™	Interactive data language
IGP	Indo-Gangetic Plains
IPCC	Inter-Governmental Panel on Climate Change
MCDA	Multi-criteria decision analysis
MCDM	Multi-criteria decision-making
netCDF	Network common data format
NSA	Net sown area
RI	Random index
UNDP	United Nations Development Programme
UNFCCC	United Nations Framework Convention on Climate Change

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Executive Summary

The Indian agriculture, despite making significant progress, is facing the challenges of stagnating net sown area, reducing per capita land availability, deteriorating soil health and diminishing natural resources. Additionally, climate variability and changes are the emerging challenges being faced by this sector for ensuring national food security in both short and long terms and making agriculture sustainable and climate-resilient, appropriate adaptation and mitigation strategies have to be developed. Assessing vulnerability of agriculture to climate change is the pre-requisite for developing and disseminating climate-smart technologies. Decision-makers and planners need this information to prepare strategy for addressing the adverse impacts of climate change and prioritize vulnerable regions for resources allocations. With this background the present study was undertaken to demonstrate a methodology to assess and map the composite vulnerability of agriculture to climate variability and changes in the Indo-Gangetic Plains (IGP), which is one of the most populous and productive agricultural ecosystems in the world.

The vulnerability of Indian agriculture has been determined at the district level in the IGP using three core components: (i) exposure to hazards, (ii) sensitivity to climate change, i.e. the amount of damage expected to be caused by a particular event, and (iii) adaptive capacity to recover from stress. A novelty of this study is that it has considered climatic, physical and socio-economic factors together to arrive at vulnerability rating. A total of 8 indicators have been computed using gridded meteorological data for the period 1951-2009 for exposure. Sensitivity has been computed from 6 indicators based on crop and soil characteristics. Computation of adaptive capacity has been based on socio-economic indicators of agricultural technology, infrastructure and human development. These spatial datasets of the key indicators contributing to agricultural vulnerability have been generated for the 161 districts in the IGP. These indicators were ranked; weight of each factor was estimated using multi-criteria decision-making techniques such as analytic hierarchal process and finally, the vulnerability maps of agriculture to climate change in the IGP districts were developed. These districts have been tabulated as per the vulnerability rank based on which highly vulnerable, medium vulnerable and less vulnerable districts have been identified. It has been found that the districts located in the eastern and southern parts of Uttar Pradesh and

Bihar are most vulnerable, whereas the districts in Punjab and Haryana are having low vulnerability due to their higher adaptive capacity to recover from the climatic stresses.

The study also computed state-wise normalized vulnerability rating of each district separately so as to rank districts relatively with-in a state only. The study has provided a methodology to identify the vulnerability of any district/ region to climate change and has demonstarted its utility in the identification of vulnerability status of the districts in the Indo-Gangetic Plains. The study has provided vulnerability rank of each district in the following modes: (i) vulnerability rank-wise, (ii) state-wise and (iii) district-wise (in alphabetic order) to make the findings user-friendly. The districts which are most vulnerable to climate change, need support on a higher priority. The findings of the study will be useful for targeting financial resources and better management of resources towards adaptive capacity. In the regions, which have been found to be highly vulnerable, policy makers should enact measures to support effective management of environmental resources (e.g., soil, vegetation and water resources); promote increased market participation, especially within the large subsistence farming sector; stimulate both agricultural intensification and diversification of livelihoods away from risky agriculture; and enact programs and extention services on health, education and social welfare, which can help in maintaining and augmenting both physical and intangible human capital.

Vulnerability of Indian Agriculture to Climate Change: District Level Assessment in the Indo-Gangetic Plains

Introduction

Agriculture is crucial for food, nutritional and livelihood security in India. It engages almost two-thirds of the workforce in gainful employment and accounts for a significant share in India's gross domestic product (GDP). Several industries depend on agricultural production for their requirement of raw materials. Due to its close linkages with other economic sectors, growth in agricultural sector has a multiplier effect on the economy of the country.

The Indian agriculture has made significant progress in recent years. However, currently it is facing the challenges of stagnating net sown area, deteriorating land quality, reducing per capita land availability and growing climate change. The problem is highly challenging because more than 80% of Indian farmers are marginal (cultivating up to 1 hectare land) and small (cultivating 1-2 hectares land) with poor coping capacity. The farms are diverse, heterogeneous and unorganized. Indian agriculture, with almost 60% of its net cultivated area as rainfed, is exposed to stresses arising from climatic variability and climate change. India has the unenviable problem of ensuring food security for the projected most populous country in 2050 with one of the largest malnourished populations.

Climate is the primary determinant of agricultural productivity. Over the past few decades, the man-induced changes in the environment have intensified the risk of climate-dependent crop production. The most imminent of the climatic changes is the increase in atmospheric temperature due to the rising levels of greenhouse gases in the atmosphere (IPCC 2007). It has been manifested in terms of frequent occurrence of events like droughts, floods, storms, melting of glaciers and rise in sea levels. The amount of rainfall and its distribution has become highly uncertain. These changes are already appearing on the horizon and causing serious threat to food security of the nation (Pathak et al. 2012). In coming years, such uncertainties and threats are going to intensify widely.

The global mean surface temperature is projected to rise by 1.4 – 5.8 ^{o}C by 2100 as per the report of Inter-Governmental Panel on Climate Change (IPCC 2001). Increased temperature, uneven rainfall, decrease in irrigation water and extreme weather events are the potential consequences of the rise in global mean surface temperature. This will have a direct impact on agriculture sector, non-agriculture sector and natural resources which are directly linked to national economy. The destruction of agriculture and infrastructure has been observed by climate variability (like droughts and floods) which has a negative impact on human health and livelihood security. The rural people are particularly vulnerable to climate variability and changes owing to their heavy dependence on agriculture for food and livelihood. For preparing people to face these challenges, decision-makers and policy planners need information on climate change. A close assessment of the vulnerability i.e., the degree to which agriculture is susceptible to the adverse effects of climate change, including climate variability and extremes is needed to allocate resources effectively and reduce the impacts.

Indian agriculture is primarily dependant on weather and any variation in its pattern affects agricultural production. Some areas of the country are more vulnerable than the others depending on their adaptive capacity and socio-economic status. To address climatic vulnerability, decision-makers need to prioritize their responses for different regions as the resources are limited. The decision-makers should plan climate adaptation strategies based on vulnerability assessment and mapping regions for vulnerability. The current study was undertaken to demonstrate a methodology for assessing and mapping composite vulnerability of agriculture to climatic variability and climate change in the region of Indo-Gangetic Plains (IGP) of India, with the following objectives:

- To adopt a conceptual framework for assessing the vulnerability of agriculture to climatic variability and climate change.
- To generate spatial datasets of key factors contributing to vulnerability of agriculture to climatic variability and climate change in the IGP.
- To assess the vulnerability of agriculture to climatic variability and climate change in different districts of the IGP.

Indo-Gangetic Plains

IGP, the food bowl of India, spread across the states of Punjab, Haryana, Uttar Pradesh, Bihar and West Bengal and comprising of 161 districts was selected for the study of agricultural vulnerability to climate change (Fig. 1). The IGP has two drainage basins: the western part contains plains of Punjab and Haryana, and the eastern part comprises the Ganges–Brahmaputra drainage systems. The plains of Punjab and Haryana are irrigated using waters from the rivers Ravi, Beas and Sutlej. The middle Ganges extend from the Yamuna river in the west to the state of West Bengal in the east. The Indo-Gangetic Plains are the world's most intensely farmed area with main crops as rice and wheat. Some other crops like maize, sugarcane and cotton are also grown in this area. Due to its fertile soil for farming, the IGP ranks among the world's most densely populated areas, and is home to nearly 1 billion people (about 1/7th of the world population). The big cities of the IGP are Chandigarh, Delhi, Kanpur, Lucknow, Allahabad, Varanasi, Patna and Kolkata.

The IGP is a relatively homogeneous ecological region in terms of vegetation, but based on physiography and bioclimate, it has been subdivided into 5 broad transects (Narang and Virmani 2001). The Trans-Gangetic Plains (transects 1 and 2) occupy large areas of Pakistan and of Punjab and Haryana in India. Transects 3 and 4 comprise areas in Uttar Pradesh, Bihar and Nepal. The lower parts of the Gangetic Plains in West Bengal (India) and parts of Bangladesh constitute transect 5. The IGP is located within the subtropical to warm temperate climates characterized by cool and dry winters and warm and wet summers (Timsina and Connor 2001). In the IGP, rice is usually grown during the wet summer season called kharif (May-June to October-November) and wheat during the dry winter season called rabi

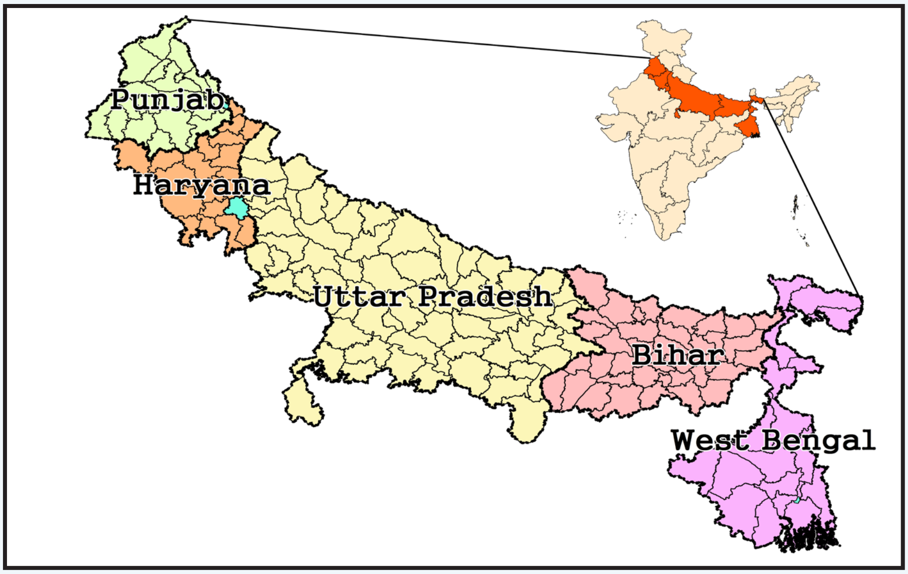

Fig. 1. The study area of the Indo-Gangetic Plains of India showing state and district boundaries

(November-December to March-April). The annual rainfall in the upper-IGP is around 550 mm, while lower-IGP receives 1200 mm rainfall. Temperature during the kharif season is higher in the upper-IGP, while during rabi, it is much lower. Organic carbon content of soils is more in the lower-IGP than in the upper-IGP. Clay contents vary from 20% (upper-IGP) to 35% (lower-IGP), while pH varies from 7.7 (upper IGP) to 6.5 (lower IGP). Consumption of nitrogenous fertilizer in rice and wheat is high in the upper-IGP and low in the lower-IGP. The average yield of rice and wheat crops is higher in the upper parts of the IGP (Pathak et al. 2003, Pathak and Aggarwal 2012).

Conceptual framework of vulnerability assessment

Vulnerability to climate change is the degree to which an agricultural unit has the capacity to sustain the damage due to climate change, including climate variability and extremes. The process of identification, quantification and prioritization of vulnerability in a system is referred to as vulnerability assessment. The study of vulnerability or the degree to which the people, environment or agriculture is affected, requires mainly three types of information: (1) exposure, i.e. patterns of exposure to occurrences of hazards such as droughts and floods; (2) sensitivity, i.e. the degree to which the system can experience damages due to a particular event; and (3) adaptive capacity, i.e. the capacity of a system to recover from disaster and hazards.

Vulnerability is mainly focussed on the internal coping and external exposure. However, The Intergovernmental Panel on Climate Change (IPCC) Second Assessment Report (SAR) and Moser (1998) shifted the focus of vulnerability to two different factors: sensitivity and adaptive capacity. Vulnerability is defined as the degree to which the system can be adversely affected due to climate change. Therefore, in addition to sensitivity of the system, the ability to adapt to new climatic situations also governs vulnerability (Watson et al. 1996). Later, the combined function of exposure, sensitivity and adaptive capacity was termed as vulnerability (McCarthy et al. 2001). The IPCC Third Assessment Report (TAR) defines vulnerability as the degree to which an agricultural system is susceptible or unable to cope up with adverse effects of climate change including climate variability and extremes. The Fourth Assessment Report (AR4) by IPCC stays consistent on the definition of vulnerability with that of TAR (IPCC 2007). A system which is very sensitive to modest climatic change will be highly vulnerable under this framework where the sensitivity includes the potential for substantial harmful effects and for which the ability to adapt is severely constrained. Vulnerability to climate change is a multi-dimensional concept affected by various indicators and can be defined as a function of exposure, sensitivity and adaptive capacity of a particular system, i.e.

$$V_{its} = f(E_{its}, A_{its}) \quad \text{...(1)}$$

where, V_{its} is the vulnerability of a system i to climate stimulus s in time t; E_{its} is the exposure of the system i to stimulus s in time t and A_{its} is the adaptive capacity of system i to deal with stimulus s in time t.

The IPCC gave a simpler way to define vulnerability (V) of a system as a function of exposure (E), sensitivity (S) and adaptive capacity (A), i.e.

Vulnerability = f (Exposure, Sensitivity, Adaptive capacity) ...(2)

Vulnerability = f (Potential Impact – Adaptive capacity) ...(3)

A higher adaptive capacity is associated with a lower vulnerability, while a higher impact is associated with a higher vulnerability. Given the above equation, vulnerability is defined as a function of a range of biophysical and socio-economic factors, aggregated into three components: exposure, sensitivity and adaptive capacity to climate variability and change. This study adopted the IPCC framework of vulnerability (Fig. 2).

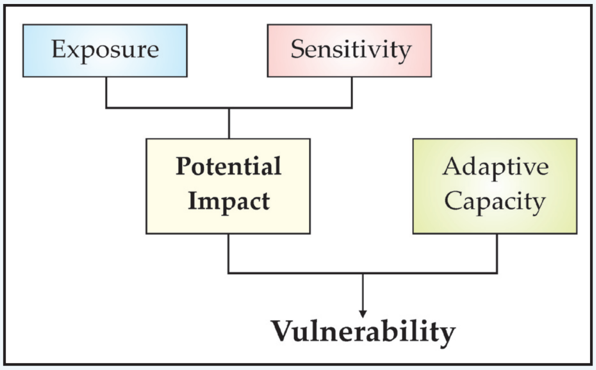

Fig. 2. Conceptual framework of assessing the vulnerability of agriculture to climate change (Source: IPCC 2007)

Exposure

The effects of climate change will be different at different locations. Some regions will be warmer than the others. Also, the precipitation patterns shift in different areas will be varying resulting in uneven distribution of rainfall. Some regions will see prolonged dry periods and some will experience both warm and intense rainfall. In correlations with the above statements, exposure relates to the degree of climate stress at a particular location. The exposure can also be determined by the long-term climatic changes or the variation in climate including the magnitude and frequency of hazards (O'Brien et al. 2004).

Sensitivity

The relative importance of the effects of climate change differs for different regions, groups and sectors in society. For example, highly intense rainfall may lead to devastating results in some region, whereas the same may not be of much harm in some other region. The degree to which a system is modified or affected by internal, external, or sometimes both disturbances is defined as sensitivity (Gallopin 2003). The measure that reflects the responsiveness of a system to climatic influences determines the degree to which a group will be affected by the environmental stress (SEI 2004).

Adaptive capacity

Depending upon sensitivity and exposure, the extent of response to the effects of climate change differs across regions. For example, frequent droughts can be addressed by some farmers by using appropriate irrigation technology, whereas other farmers may not be able to afford such technology or may lack the skills to operate it. Therefore, the ability to adapt to certain changes in condition is very important to determine the vulnerability of a system towards the change. Adaptability, coping ability, stability, management capacity, flexibility, robustness and resilience, all together form the ability of a system to adapt to the changes effectively. Therefore, 'Adaptive capacity' is a significant factor in characterizing vulnerability (Smit and Wandel 2006). Adaptive capacity is also defined as the potential or ability of a system, region or community to adjust to the effects or impacts of climate change (IPCC, 2001). Different countries, communities, social groups, individuals and times have different capacities to adapt (IPCC 2001, Smit and Wandel 2006). The adaptive capacity of a system or society is to deal with the changes in conditions to modify its own characteristics and behaviour (Brooks 2003).

The increase in literacy levels enhances the capability of people to access information and cope up with adversities, resulting in reduced vulnerability (Leichenko and O'Brien 2002). The farms with larger agricultural income, land area, farm value assets and latest technology are able to prepare and respond better as compared to the farms with lower technology. Also, the farms with traditional technologies are assumed to be less economically diversified and more vulnerable to climatic events. The availability of facilities like electricity, education, health care, etc. determines the state of poverty in a region. When two different agricultural regions having the same crops and similar climate are compared with each other, the exposure to climate changes might be similar, but the adaptive capacity and vulnerability could be very different based on the socio-economic factors.

In addition to identification of threat, the analysis of vulnerability also involves resilience or responsiveness of the system and its ability to exploit opportunities and recover from the environmental and climatic changes. Therefore, asset ownership goes hand in hand with vulnerability. The people having more assets are less vulnerable to climate change.

Multi-criteria decision-making (MCDM) technique

The data from various domains and sources like meteorology, soil science, social science, etc. are processed to form an integrated approach to vulnerability. The various domains and streams coined as exposure, sensitivity, and adaptive capacity are grouped accordingly. The factors and attributes involved in each of these groups are not equally important for vulnerability. Some of the criteria contribute heavily towards it, whereas the others may have minimal importance for it. These criteria are grouped and organized in different hierarchies to address the relative degree of importance towards vulnerability. Multi-criteria evaluation techniques can be used to determine the suitability by evaluating the relative importance of these parameters (Ceballos-Silva and Lopez-Blanco 2003). These techniques are well equipped to make decisions for agricultural applications with their ability to provide rational, objective and non-biased approach.

Framework for decision-making

Fig. 3 illustrates a general framework for assessing vulnerability by using decision-making process in the following three phases:

- ***Intelligence phase:*** This is the initial phase of identifying the problems for decision-making. The situation is analyzed for the problem and various prospects. As this phase also involves evaluation of the criteria according to the defined problems, this phase is also called as problem formulation phase.
- ***Design phase:*** When the problems are defined, we need to understand them and generate alternatives, select crieria, establish relationship among them and assess the importance of given criteria. The design is basically formulated on multi-criteria decision-making methods.
- ***Decision choice:*** Once the design phase is over, we need to evaluate the options and make decisions to deal with problems using multi-criteria decision rules.

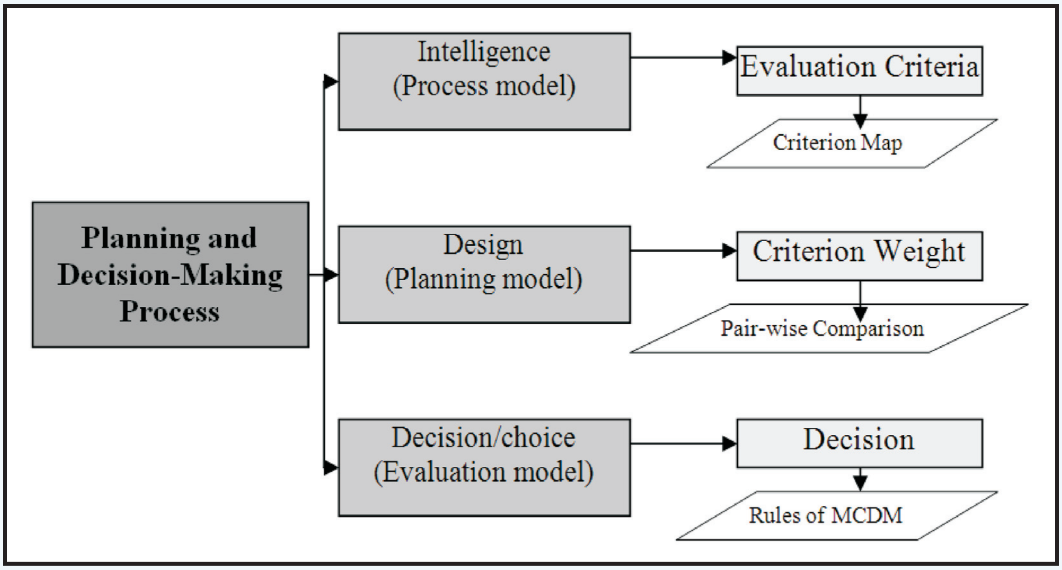

Fig. 3. Framework for locating and planning a decision-making process (Source: Sharifi 2002)

Analytical hierarchy process

There are various types of comparisons between two elements; however, when the comparison is about the relative importance, the Analytical Hierarchy Process (AHP) is the best method for decision-making, introduced by Saaty (1977). As the name suggests, this method uses the analytical approach of decomposing the complex problems into its hierarchies and simpler groups. The empirical studies suggest that more than three criteria can not be compared at a given time (Rommelfanger 2003). Therefore, the decomposition of complex decision-making processes into a hierarchical organization of criteria is helpful for decision-making. Another benefit of using a hierarchical organization is that the structure helps to maintain consistency amongst comparisons along with incorporation of decisions and expert knowledge from various domains.

The decisions about the relative importance of criterion 'A' over some other criteria 'B', 'C', 'D', and 'E' are used to prepare a pair-wise comparison matrix which is the basic input to AHP. Ratio matrix of criteria is produced along with the relative weight of each criterion using pair-wise comparisons. The relative importance of a particular criterion over other criteria in consideration is termed as the 'weight' of that criterion. The criterion is more important if the weight is higher (Malczewski 1999). Eigen-value of the ratio-matrix is used to determine the weights by normalizing the Eigen-vectors associated with a criterion.

Development of pair-wise comparison matrix

The AHP method employs an underlying scale according to the relative importance of the indicators (criteria). With this scale, one can simultaneously compare and consistently rank the criteria. The criteria are compared and ranked in a reciprocal comparison matrix. If the preference to a particular criterion A is twice to that of criterion B, it is said that the criterion B is only half preferred in comparison to criterion A (Malczewski 1999). In simple words, if criterion A has a score of 2 relative to criterion B, then B will have a score of ½ when compared to A.

Past studies on vulnerability of agriculture to climate change

Several vulnerability assessment studies have been done in different fields including climate, agricultural sciences, social sciences, geography and environmental sciences. Some analysts have used theoretical perspectives to define the nature of vulnerability (Cutter 1996, Villa and McLeod 2002, Turner et al. 2003), while the others have developed some quantitative measures for vulnerability (Gogu and Dassargues 2000, Cutter et al. 2003). Vulnerability assessments are subjective and difficult to quantify due to the complexity of issues. Table 1 summarizes some previous studies on vulnerability to climate change showing the framework adopted and indicators used.

Table 1. Previous studies on vulnerability assessment, conceptual frameworks and indicators used to construct vulnerability maps

Study	Concept	Major indicators
Climate change vulnerability mapping for Southeast Asia (Yusuf and Francisco 2009)	Vulnerability as a function of the character, magnitude and rate of climate variation to which a system is exposed, its sensitivity and its adaptive capacity	• Drought • Flood • Cyclone • Human development index • Poverty incidence • Income inequality • Use of electricity • Irrigation • Road density • Communication
Mapping climate vulnerability and poverty in Africa (Thornton et al. 2006)	Vulnerability is assessed based on livelihood assets	• Suitability for crop production • Soil degradation • Internal water resources by sub-basin • Accessibility to markets • Human poverty index • Governance

Assessment of vulnerability to climate change for India and Indian states (Moss et al. 2001, Brenkert and Malone 2005, Patnaik and Narayanan 2005)	Vulnerability of a region as a function of three factors: exposure, sensitivity and adaptive capacity	• GDP per capita • Income equity • Dependency ratio • Literacy rate • Population density • Unmanaged land • Population at flood risk from sea level rise • Population without access to clean water/ sanitation • Cereal production/crop land area • Protein consumption per capita • Managed land • Fertilizer use/cropland area • Completed fertility • Life expectancy • Water use
Regional vulnerability to climate change in combination with other global stressors (TERI 2003, O'Brien et al. 2004)	Vulnerability as a function of exposure to climate and globalization, sensitivity and adaptive capacity	• Depth of soil cover • Severity of soil degradation • Amount of replenishable groundwater • Adult literacy rate • Degree of gender equity • Workforce employed in agriculture • Landless laborers in agricultural workforce • Net irrigated area • Infrastructure development index

Methodology

The process and methodology used in this study can be sub-divided into four phases of adopting a conceptual framework of vulnerability, generating spatial datasets of key factors, estimating the weights of various factors contributing to vulnerability and generating the vulnerability ranking maps of the districts in the study area. The novelty of this study is that it has considered climatic, physical and socio-economic factors together to arrive at the vulnerability rating. The methodology of vulnerability assessment is based on the integration of various climatic, environmental and socio-economic factors following the multi-criteria decision-making technique in a geographical information system (GIS). Various steps of methodology include (1) identification of indicators, (2) ranking of indicators, and (3) calculation of vulnerability index.

Identification of indicators

Expert judgement was used along with extensive review of previous literature (Aandahl and O'Brien 2001, Brooks et al. 2005, Moss et al. 2001, O'Brien et al. 2004, TERI 2003 and Thornton et al. 2006) to select the indicators. Fig. 4 shows the indicators finalized for this study and their relationship with vulnerability.

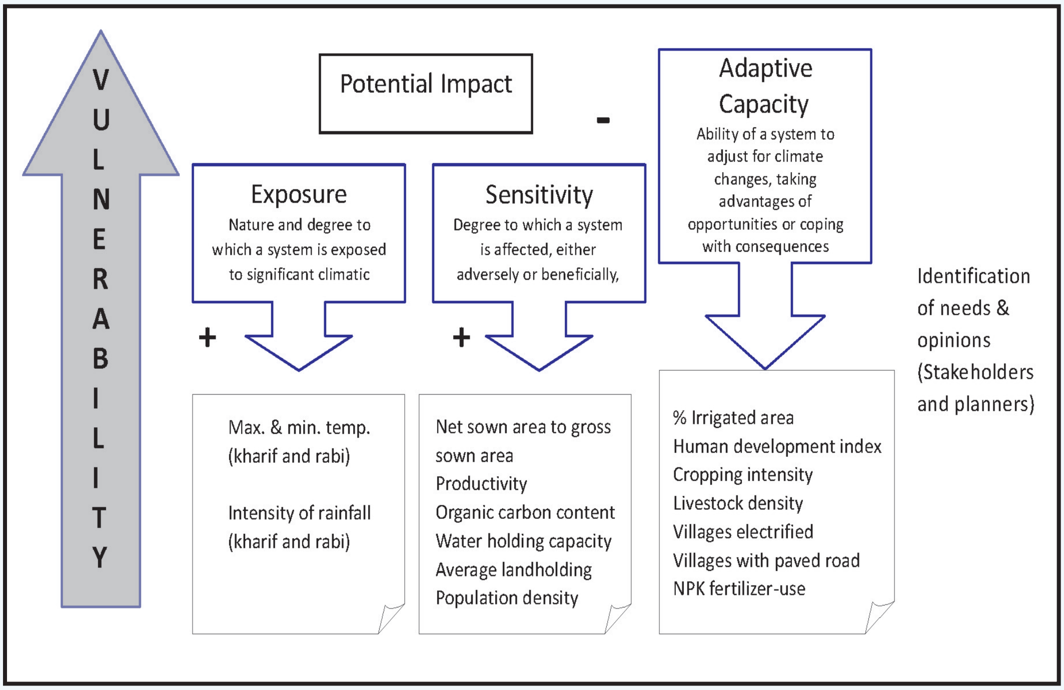

Fig. 4. Indicators of vulnerability used in the study

Datasets

A list of datasets used, their units, period of measurement, hypothesized relationships with vulnerability and data sources are summarized in Table 2. A brief description of these datasets is given below.

Climatic data

The study has used gridded monthly precipitation, maximum temperature and minimum temperature, time series data constructed by Climatic Research Unit (CRU TS 3.0) at a spatial resolution of 0.5 x 0.5 degree for the time period 1951 – 2009. The dataset was provided in the netCDF file format by BADC (http://badc.nerc.ac.uk). A program was written to extract netCDF format data into

Table 2. Description of parameters/indicators used for vulnerability assessment

Parameters/Indicators	Units	Year	Relationship with vulnerability	Data source
Exposure				
1. Rate of change in maximum temperature (kharif)	°C per year	1951 - 2009	+	CRU TS 3.0
2. Rate of change in minimum temperature (kharif)	°C per year	1951 - 2009	+	CRU TS 3.0
3. Rate of change in maximum temperature (rabi)	°C per year	1951 - 2009	+	CRU TS 3.0
4. Rate of change in minimum temperature (rabi)	°C per year	1951 - 2009	+	CRU TS 3.0
5. Frequency of low rainfall events (kharif)	Count SPI 4 < -1	1951 - 2009	+	CRU TS 3.0
6. Severity of low rainfall events (kharif)	Sum SPI 4 < -1	1951 - 2009	+	CRU TS 3.0
7. Frequency of high rainfall events (kharif)	Count SPI 4 > +1	1951 - 2009	+	CRU TS 3.0
8. Severity of high rainfall events (kharif)	Sum SPI 4 > +1	1951 - 2009	+	CRU TS 3.0
9. Frequency of low rainfall events (Rabi)	Count SPI 3 < -1	1951 - 2009	+	CRU TS 3.0
10. Severity of low rainfall events (rabi)	Sum SPI 3 < -1	1951 - 2009	+	CRU TS 3.0
11. Frequency of high rain-fall events (rabi)	Count SPI 3 > +1	1951 - 2009	+	CRU TS 3.0
12. Severity of high rainfall events (rabi)	Sum SPI 3 > +1	1951 - 2009	+	CRU TS 3.0
Sensitivity				
13. Net sown area / Geographical area	ha ha^{-1}	2001	+	Census of India (2001)
14. Productivity of food grains	kg ha^{-1}	2000 - 2006	_	DES, DAC (2008)
15. Organic C content of soil	kg m^{-2}	2000	_	FAO Soil Map
16. Available water-holding capacity of soil	mm m^{-1}	2000	_	FAO Soil Map
17. Average landholding of farmer	ha	2001	_	State Department of Agriculture

18. Human population density	No. of person km^{-1}	2001	+	Census of India (2001)
Adaptive capacity				
19. Irrigated area	%	2000	_	FAO, GMIA
20. Human development index	0 - 1	2001 - 2006	_	UNDP
21. Cropping intensity	%	2003 - 2006	_	State Department of Agriculture
22. Livestock density	No. of livestock km^{-1}	2003	_	Livestock Census
23. Villages electrified	%	2001	_	Census of India (2001)
24. Villages with paved roads	%	2001	_	Census of India (2001)
25. NPK fertilizer consumption	kg ha^{-1} yr^{-1}	2003 - 2006	_	Fertiliser Association of India (2008)

Note: *+ indicates higher the value, higher is the vulnerability level; - indicates higher the value, lower is the vulnerability level. SPI is Standardized Precipitation Index, SPI4 is SPI of June, July, August and September, and SPI3 is SPI of January, February and March.*

ENVI™ format images as well as subset data for user given bounds through a GUI for further analysis. The images were geographically referenced automatically using the geographical extent read from the netCDF file. The gridded dataset of monthly terrestrial surface climate over land areas as constructed by New et al. (2000), and a detailed description of the datasets is given by Mitchell and Jones (2005) were used.

The gridded temperature data were used to calculate the rate of change over the years 1951-2009 by fitting the linear time trend, separately for kharif and rabi seasons. The monthly rainfall data were used to calculate Standardized Precipitation Index (SPI) (Mckee et al. 1993), an index of rainfall deviation for kharif and rabi seasons over the period 1951-2009. Since precipitation is not normally distributed, the long-term precipitation record was first fitted to an incomplete-gamma probability distribution, which was then transformed into a normal distribution to calculate SPI. The frequency of years when SPI was -1 or below was calculated for low rainfall, while the frequency of years when SPI was +1 and more was calculated for high rainfall. Besides, the severity of low rainfall was calculated by summing up all the SPI values whenever it was -1 or less for each grid. Similarly, the severity of high rainfall was calculated by summing up all the SPI values of +1 and more. The intensity of low and high rainfall was calculated by multiplying the corresponding frequency with modulus of severity. This way an index of rainfall variability was developed for kharif and rabi seasons. The district boundary layer was overlaid on rainfall intensity images and temperature trend images to compute district-wise average values.

Water-holding capacity and organic C content of soils

Available water-holding capacity (AWHC) of soil was estimated by taking the difference in water content between field capacity and permanent wilting point. The water-holding capacity of the soil mostly depends on soil porosity, which in turn, depends on soil texture, structure and bulk density. The organic C content of soil is an indicator of its fertility. The Digital Soil Map of the World and Derived Soil Properties (Version 3.5) produced by FAO (FAO, 1995) were used in this study. The soil map was produced at a finer resolution of 5′ x 5′ cell size (9 x 9 km at equator) by using the World Inventory of Soil Emissions (WISE) database. The digital maps of soil moisture storage capacity (mm) for 1 m profile depth and soil organic carbon content (kg m^{-2}) were extracted for the study area. The district boundary layer was overlaid on it and the average values of soil moisture storage capacity and soil carbon content for each district were calculated using ArcGIS™.

Irrigated area

The study utilized the FAO Global Map of Irrigation Areas (GMIA) version 4.0.1 having a cell size of 5′ x 5′ (Siebert et al. 2007) for calculating the irrigated area. Each cell of the map depicts the area equipped for irrigation as the percentage of cell area around the year 2000, but for India it refers to the area actually irrigated. The global map of irrigated areas was developed by combining sub-national irrigation statistics with geospatial information on the position and extent of irrigation schemes to compute the fraction of arc-minute cells that were equipped for irrigation, is called irrigation density. A more detailed description of the dataset, development and validation is given in Siebert et al. (2005). The global ASCII data were unzipped, imported into ENVI™, geo-coded and sub-setted for the study area. The district layer was overlaid on it and the average value of percent irrigated area was calculated.

Agricultural statistics

The district-wise statistics on net sown area and geographical area were compiled from the Census of India (2001). District-wise productivity of food grains was obtained from the Agricultural Statistics published by the Directorate of Economics and Statistics, Department of Agriculture and Cooperation, Ministry of Agriculture, Government of India for the period 2001 to 2006. Livestock density was compiled from the 17th Livestock Census (2003) published by the Department of Animal Husbandry and Dairying, Government of India. The average size of landholding and cropping intensity statistics were compiled from the reports published by the Departments of Agriculture of respective states. The annual N, P and K fertilizer consumption statistics were obtained from the Fertilizer Statistics published by the Fertilizer Association of India.

Socio-economic statistics

The district-wise statistics of human population density, number of villages electrified and the number of villages with paved roads were compiled from the Census of India (2001). The human development index (HDI) was obtained from the Human Development reports of respective states, as produced by the UNDP.

As shown in Table 2, two types of functional relationships are possible between the indicators and vulnerability. The vulnerability is directly proportional to the value of some indicators and inversely proportional to the value of some other indicators. For example, for indicators such as change in maximum and minimum temperature, the higher is the value of these indicators; more will be the vulnerability of the region to climate change as variation in climatic variables increases the vulnerability of agriculture. Thus, the indicators have positive functional relationship with vulnerability. On the other hand, for the HDI, a higher value implies more education, better health, and more income resulting in more awareness to cope with the climate change. As a result, the vulnerability will be lower and thus the HDI has a negative functional relationship with vulnerability.

Ranking of indicators

Each indicator of exposure, sensitivity and adaptive capacity was classified into 5 classes to assign the ranks (Table 3). In this study, the five-point ordered scale was used to rank each factor from very low to extreme value (Table 3). The value 0 was left in scaling to define mask value. Thus, each factor was having an equivalent measurement basis or scale before any weight was applied. The ranks were assigned to the indicators according to their functional relationship with vulnerability, i.e. if the indicator was directly related to vulnerability; higher ranks were given for higher values. However, in case the indicator was inversely related, lower ranks were given for higher values.

Table 3. Ranking of the indicators of exposure, sensitivity and adaptive capacity on a five point scale for assessing vulnerability

Indicator	Scale	Value	Rank	Indicator	Scale	Value	Rank
Exposure							
1. Rate of change in max. temp. (kharif)	Very low	< 0.0	1	5. Intensity of low rainfall events (kharif)	Very low	< 120.0	1
	Low	0.001 - 0.006	2		Low	120.1 - 140.0	2
	Moderate	0.007 - 0.008	3		Moderate	140.1 - 160.0	3
	High	0.009 - 0.010	4		High	160.1 - 180.0	4
	Extreme	> 0.010	5		Extreme	> 180.0	5
2. Rate of change in min. temp. (kharif)	Very low	< 0.0	1	6. Intensity of high rainfall events (kharif)	Very low	< 120.0	1
	Low	0.001 - 0.006	2		Low	120.1 - 140.0	2
	Moderate	0.007 - 0.008	3		Moderate	140.1 - 160.0	3
	High	0.008 - 0.010	4		High	160.1 - 180.0	4
	Extreme	> 0.010	5		Extreme	> 180.0	5
3. Rate of change in max. temp. (rabi)	Very low	< 0.0	1	7. Intensity of low rainfall events (rabi)	Very low	< 120.0	1
	Low	0.001 - 0.006	2		Low	120.1 - 140.0	2
	Moderate	0.007 - 0.008	3		Moderate	140.1 - 160.0	3
	High	0.008 - 0.010	4		High	160.1 - 180.0	4
	Extreme	-	5		Extreme	> 180.0	5
4. Rate of change in min. temp. (rabi)	Very low	< 0.0	1	8. Intensity of high rainfall events (rabi)	Very low	< 120.0	1
	Low	0.001 - 0.015	2		Low	120.1 - 140.0	2
	Moderate	0.016 - 0.020	3		Moderate	140.1 - 160.0	3
	High	0.021 - 0.025	4		High	160.1 - 180.0	4
	Extreme	> 0.025	5		Extreme	> 180.0	5
Sensitivity							
1. Net sown area to geographical area	Very low	< 0.50	1	4.Available water-holding capacity of soil	Extreme	< 224	5
	Low	0.51 - 0.60	2		High	225 - 229	4
	Moderate	0.61 - 0.70	3		Moderate	230 – 234	3
	High	0.71 - 0.80	4		Low	235 - 239	2
	Extreme	> 0.81	5		Very low	> 240	1

Indicator	Scale	Value	Rank	Indicator	Scale	Value	Rank
2. Productivity of food grains	Extreme	< 1499	5	5.Average land holding size per farmer	Extreme	< 0.60	5
	High	1500 – 1999	4		High	0.61 - 0.80	4
	Moderate	2000 – 2499	3		Moderate	0.81 - 1.0	3
	Low	2500 - 2999	2		Low	1.1 - 2.0	2
	Very low	> 3000	1		Very low	> 2.1	1
3.Organic carbon content of soil	Extreme	< 8.0	5	6. Human population density	Very low	< 500	1
	High	8.1 - 9.0	4		Low	501 - 650	2
	Moderate	9.1 - 10.0	3		Moderate	651 - 800	3
	Low	10.1 - 11.0	2		High	801 - 950	4
	Very low	> 11.1	1		Extreme	> 951	5
Adaptive Capacity							
1. Percent irrigated area	Very low	< 29	1	5. No. of villages electrified	Very low	< 29	1
	Low	30 - 44	2		Low	30 - 49	2
	Moderate	45 - 59	3		Moderate	50 - 69	3
	High	60 – 74	4		High	70 - 89	4
	Extreme	> 75	5		Extreme	> 90	5
2.Human development index	Very low	< 0.50	1	6. No. of villages with paved road	Very low	< 30.0	1
	Low	0.51 - 0.55	2		Low	30.1 - 50.0	2
	Moderate	0.56 - 0.60	3		Moderate	50.1 - 70.0	3
	High	0.61 - 0.65	4		High	70.1 - 90.0	4
	Extreme	> 0.65	5		Extreme	> 90.1	5
3. Cropping intensity	Very low	< 139	1	7. Annual NPK fertilizer cons.	Very low	< 79	1
	Low	140 – 149	2		Low	80 - 119	2
	Moderate	150 - 159	3		Moderate	120 – 159	3
	High	160 – 169	4		High	160 - 199	4
	Extreme	> 170	5		Extreme	> 200	5
4. Livestock density	Very low	< 180	1				
	Low	181 - 230	2				
	Moderate	231 - 280	3				
	High	281 - 300	4				
	Extreme	> 300	5				

Pair-wise comparison matrix

Earlier researchers have used expert judgement (Brooks et al. 2005, Moss et al. 2001) along with various other methods such as arbitrary choice of equal weight (Lucas and Hilderink 2004, O'Brien et al. 2004) and statistical method like principal component analysis (Thornton et al. 2006) to assign weights to indicators. The current study has used the scales listed in Table 4 (Saaty 1980) for the pair-wise comparison. AHP logic was used for the pair-wise comparison. Statistical multi-criteria process using Analytic Hierarchy Process was used with expert judgement to generate the weights of indicators in this study. The vulnerability indicators were assigned their weights after standardization of data and ranks. The relative importance of different indicators is represented as pairwise comparison matrix in Tables 5, 6, 7 and 8.

Table 4. Scales for pair-wise comparison matrix

Importance	Definition	Explanation
1	Equal importance	Two indicators are of equal value
2	Moderate importance	Experience slightly favours one indicator over the other
3	Strong importance	Experience strongly favours one indicator over the other
4	Very strong importance	A indicator is strongly favoured and its dominance is demonstrated in practice

Table 5. Determining relative weights of exposure (I), sensitivity (II) and adaptive capacity (III) by pairwise comparison

Indicator	Step 1			Step 2			Step 3			
	I	II	III	I	II	III	Average	Weighted sum vector	Consistency vector	Weight
I	1			0.2	0.14	0.25	0.19	0.59	3.03	0.2
II	2	1		0.4	0.28	0.25	0.31	0.95	3.05	0.31
III	2	2	1	0.4	0.57	0.5	0.49	1.51	3.07	0.49
Consistancy ratio = 0.04										

Table 6. Pairwise comparison matrix of different indicators of exposure

Indicator	Step 1								Step 2								Step 3			
	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	Average	Weighted sum vector	Consistency vector	Weight
1	1								0.09	0.19	0.10	0.17	0.05	0.05	0.09	0.09	0.10	0.94	9.11	0.10
2	1/3	1							0.03	0.06	0.10	0.17	0.04	0.04	0.09	0.09	0.08	0.69	8.96	0.07
3	1	1	1						0.09	0.06	0.10	0.04	0.15	0.15	0.18	0.18	0.12	1.04	8.65	0.11
4	1	1	4	1					0.09	0.06	0.40	0.17	0.15	0.15	0.27	0.27	0.20	1.73	8.83	0.19
5	3	4	1	1	1				0.26	0.25	0.10	0.17	0.15	0.15	0.09	0.09	0.16	1.44	9.07	0.16
6	3	4	1	1	1	1			0.26	0.25	0.10	0.17	0.15	0.15	0.09	0.09	0.16	1.44	9.07	0.16
7	1	1	1/3	1/3	1	1	1		0.09	0.06	0.05	0.06	0.15	0.15	0.09	0.09	0.09	0.81	8.72	0.09
8	1	1	1/2	1/3	1	1	1	1	0.09	0.06	0.05	0.06	0.15	0.15	0.09	0.09	0.09	0.81	8.72	0.09
Consistancy ratio = 0.09																				

Note: *Indicator name corresponding to its number is same as given in Table 3.*

Table 7. Pairwise comparison matrix of different indicators of sensitivity

Indicator	Step 1						Step 2						Step 3			Weight
	1	2	3	4	5	6	1	2	3	4	5	6	Average	Weighted sum vector	Consistency vector	
1	1						0.13	0.11	0.14	0.14	0.15	0.12	0.13	0.8	6.04	0.131
2	2	1					0.25	0.22	0.29	0.29	0.23	0.18	0.24	1.46	6.07	0.241
3	1/2	1/4	1				0.06	0.05	0.07	0.07	0.08	0.09	0.07	0.43	6.03	0.07
4	1/2	1/3	1	1			0.06	0.07	0.07	0.07	0.08	0.09	0.07	0.45	6.05	0.074
5	1	1/2	2	2	1		0.13	0.11	0.14	0.14	0.15	0.18	0.14	0.85	6.03	0.141
6	3	2	4	4	2	1	0.38	0.44	0.29	0.29	0.31	0.35	0.34	2.08	6.11	0.343
Consistancy ratio = 0.09																

Note: *Indicator name corresponding to its number is same as given in Table 3.*

Table 8. Pairwise comparison matrix of different indicators of adaptive capacity

Indicator	Step 1							Step 2							Step 3			
	1	2	3	4	5	6	7	1	2	3	4	5	6	7	Average	Weighted sum vector	Consistency vector	Weight
1	1							0.17	0.21	0.21	0.11	0.22	0.17	0.42	0.22	1.71	7.89	0.22
2	1/3	1						0.05	0.07	0.05	0.08	0.11	0.11	0.05	0.08	0.55	7.22	0.07
3	1/2	2	1					0.08	0.14	0.11	0.16	0.11	0.17	0.05	0.12	0.85	7.19	0.11
4	3	4	2	1				0.52	0.28	0.21	0.32	0.22	0.22	0.28	0.3	2.28	7.71	0.3
5	1/4	1/2	1/2	1/4	1			0.04	0.03	0.05	0.08	0.06	0.06	0.03	0.05	0.38	7.3	0.05
6	1/3	1/2	1/3	1/4	1	1		0.05	0.03	0.04	0.08	0.06	0.06	0.03	0.05	0.37	7.34	0.05
7	1/3	3	3	1/2	4	4	1	0.05	0.21	0.32	0.16	0.22	0.22	0.14	0.19	1.4	7.33	0.18
Consistancy ratio = 0.05																		

Note: *Indicator name corresponding to its number is same as given in Table 3.*

Computation of weights of different criteria

A simple method for determining the weights of different criteria was suggested by Saaty (1980), which involves the following steps:

1. Compare two criteria at a time and assign scores to them.
2. Prepare a pair-wise comparision matrix. Each value of element in the matrix is divided by the sum of values in that column. The resultant matrix is called normalized pair-wise comparison matix and is used as an estimate of the Eigen value of the matrix.
3. Calculate the relative weights of the factors/criteria by computing the average of each element in each row of the normalized matrix.

Estimation of consistency ratio

The estimation of consistency ratio involves the following steps:

1. Determine the weighted sum vector by multiplying the weights for their corresponding values of pair-wise comparison matrix followed by summation of values over each row.
2. Divide the weighted sum vector by criterion weight to determine the consistency vector.

The values for lambda (λ) and the consistency index (CI) were computed using the calculated consistency vector. The average of consistency vector using the following equation gives the value of lambda (as an example from Table 5):

$$\lambda = (3.03+3.05+3.07)/3 = 3.05 \quad \ldots (4)$$

The value of λ is always greater than the number of criteria (n) under consideration, except under the scenario where $\lambda = n$, if the pair-wise comparison matrix is a consistent matrix. This observation and reciprocal matrix were used to calculate CI. The degree of inconsistency can be determined as $\lambda - n$ and is normalized as follows:

$$CI = (\lambda - n) / (n - 1) = (3.05 - 3) / (3 - 1) = 0.03 \quad \ldots (5)$$

The CI provides a measure of departure from consistency.

The probability that matrix ratings were randomly generated indicates the consistency ratio (CR) and was determined by the equation:

$$CR = CI / RI = 0.03 / 0.58 = 0.04 \quad \ldots (6)$$

Here, random index (RI) represents the consistency index of randomly generated pair-wise comparison matrix which depends on the number of elements. The value of CR indicates the consistency in pair-wise comparisons. Higher is the value of CR, lower is the consistency in assiging importance to indicators. CR > 0.10 needs to be recalculated whereas CR < 0.10 is considered a reasonable level of consistency. Tables 5 to 8 show that reasonable level of consistency was achieved in the pair-wise comparison in this study with CR values ranging between 0.04 to 0.09.

Fig. 5 shows the relationship of parameters with vulnerability and weights of each parameter to compute the composite vulnerability. The potential impact of exposure and sensitivity is positively related with vulnerability; on the other hand, adaptive capacity is inversly related to vulnerability; more the socio-economic progress, less is the agricultural vulnerability. The rate of change in minimum temperature during rabi season got the highest weight (0.19) in exposure and human population density got the highest weight (0.34) in sensitivity parameter. Human development index which was computed using education, income and health, secured the highest weightage in adaptive capacity which again had a higher weightage of 0.49 in overall computation of composite vulnerability.

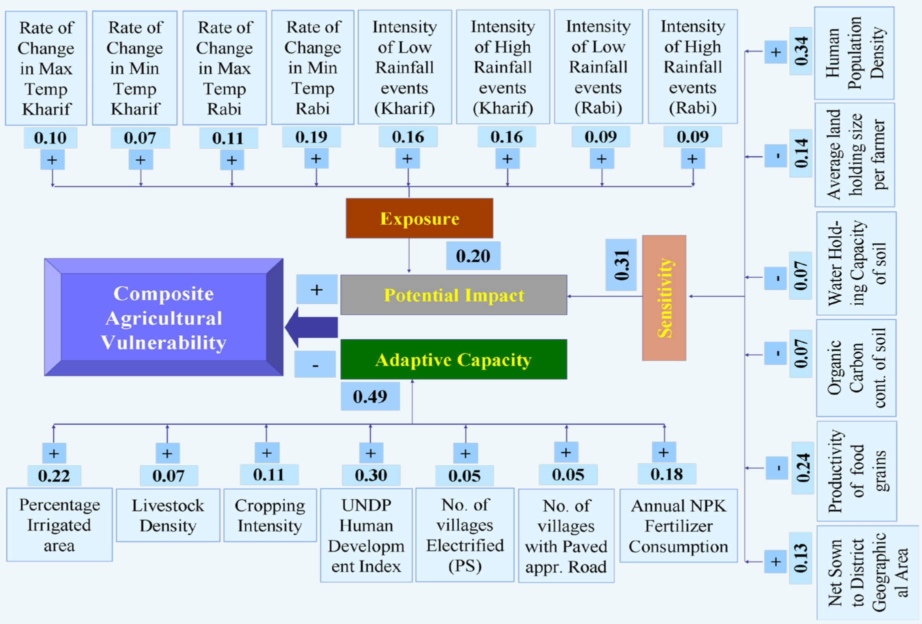

Fig. 5. Schematic diagram showing relationships of parameters of vulnerability and their weights for computing composite vulnerability of agriculture to climate change

Calculation of vulnerability index

Once the weight of each indicator was determined, exposure, sensitivity and adaptive capacity maps were prepared by taking weighted some of the rank of all relevant indicators. These three parameters and maps along with their functional relation with vulnerability resulted in the final calculation of vulnerability map varying from 1 to 4 (low, moderate, high and extreme). The composite vulnerability rating maps were produced in GIS.

Results and Discussion

Exposure indicators

Eight indicators of exposure were computed using meteorological data for a period of 50 years (1951-2009). The indicators included the rate of change in maximum and minimum temperatures, the frequency and severity of high and low rainfall events in kharif and rabi seasons. The maps were developed for each of these indicators of climatic exposure.

Rate of change of maximum and minimum temperatures during kharif and rabi seasons

Figures 6 to 9 show the pattern of rate of change of maximum and minimum temperatures for kharif and rabi seasons in all the districts of the IGP. The rate of change of maximum temperature for the kharif season was high in southern Uttar Pradesh (UP), southern Bihar and almost entire West Bengal. On the other hand, the rate of change of minimum temperature was high in south-western and upper UP, northern Bihar and northern West Bengal during kharif season. The rest of UP and Bihar had almost similar patterns of rate of change in maximum and minimum temperatures during kharif season. Punjab and Haryana showed the lowest rate of change for both maximum and minimum temperatures during kharif season.

The rate of change of maximum temperature in rabi season was low, which ranged from -0.014 to 0.010 for the entire IGP (Fig. 8). The rate of change of minimum temperature was high, ranging from -0.015 to 0.032 in almost the entire UP, Bihar and West Bengal. The rate of change of maximum temperature decreased as one moves towards the northern and western parts of the IGP. Punjab and Haryana again showed a very low rate of change of minimum temperature for the rabi season.

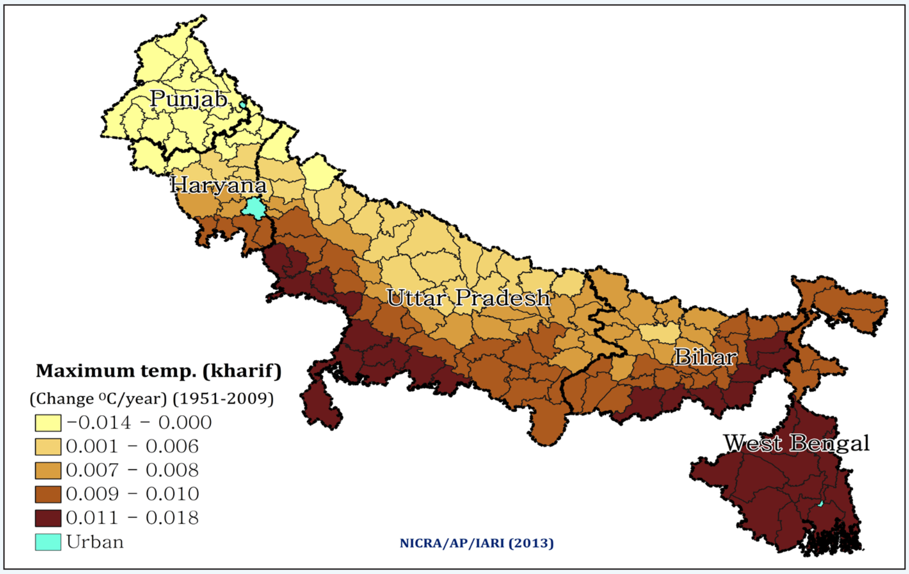

Fig. 6. Rate of change of maximum temperature during kharif season in different districts of Indo-Gangetic Plains

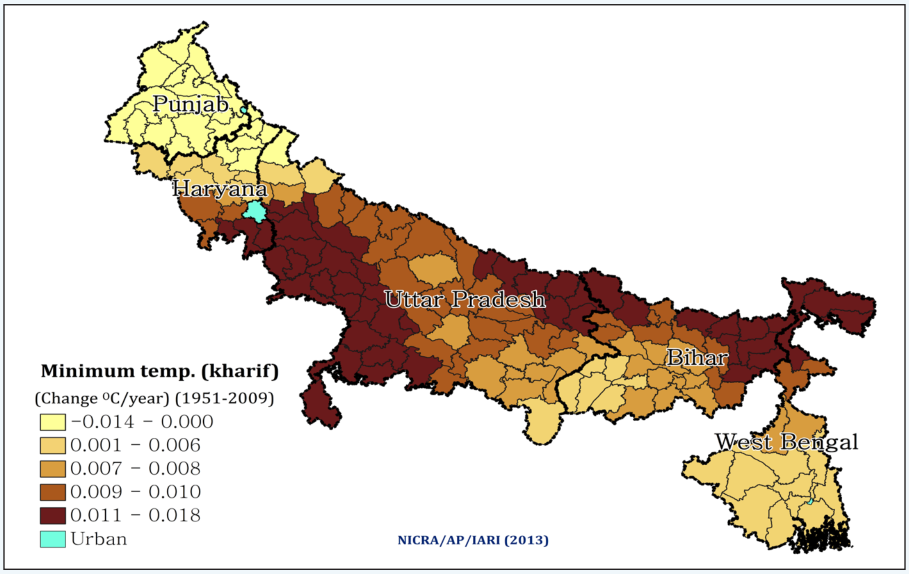

Fig. 7. Rate of change of minimum temperature during kharif season in different districts of Indo-Gangetic Plains

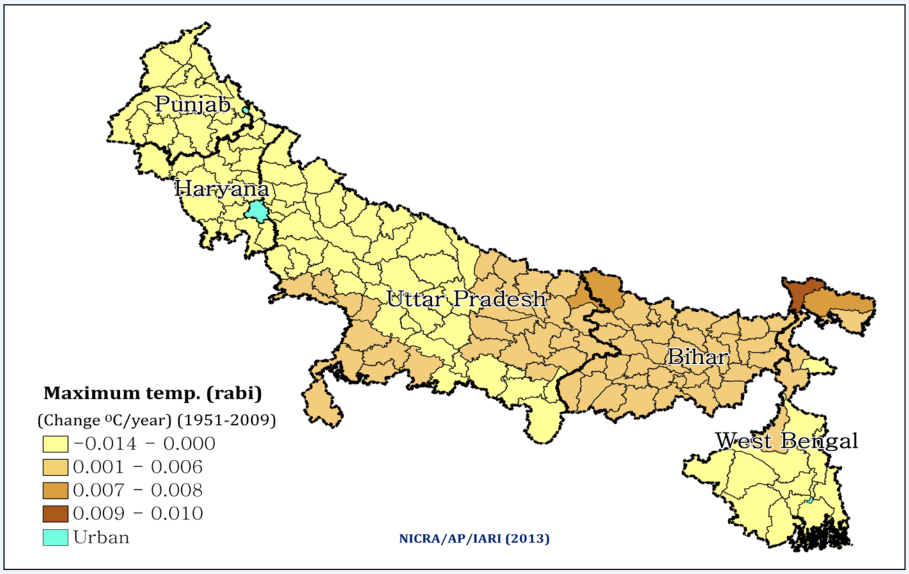

Fig. 8. Rate of change of maximum temperature during rabi season in different districts of Indo-Gangetic Plains

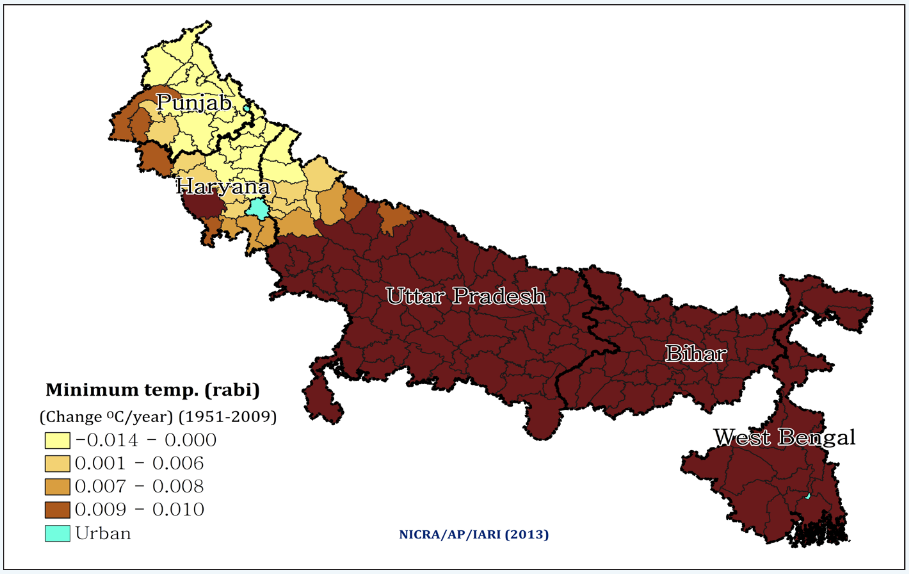

Fig. 9. Rate of change of minimum temperature during rabi season in different districts of Indo-Gangetic Plains

Rainfall variability during kharif and rabi seasons

Figures 10 to 13 show the index of intensity of low and high rainfall during kharif and rabi seasons in all the districts of States in the IGP. The higher the value of the intensity index, higher is the seasonal rainfall variability. The intensity of low rainfall in kharif season was higher in the central part of the IGP comprising the districts of central and eastern UP and a couple of districts of Haryana and Bihar. The rest of UP, Haryana and West Bengal had low to moderate intensity of low rainfall during kharif season, ranging between 160-180. The rest of the study area showed a very low intensity of low rainfall, less than 120 in kharif season. On the other hand, the intensity of high rainfall in kharif season varied in the opposite manner. The western part of IGP comprising Punjab, Haryana, and southern parts of West Bengal showed higher intensity of high rainfall during kharif season. The central part of the IGP had a relatively lower intensity of high rainfall during kharif season and almost the entire Bihar had the lowest intensity of high rainfall during kharif season with index value less than 120.

The distribution of intensity of low rainfall during rabi season was similar to that of the kharif season (Fig. 12). The central part of the IGP, northern and western Bihar, eastern West Bengal and a couple of districts in western Punjab showed higher intensity of low rainfall during rabi season with index value above 180. Haryana and south-western UP had the lowest intensity of low rainfall during rabi

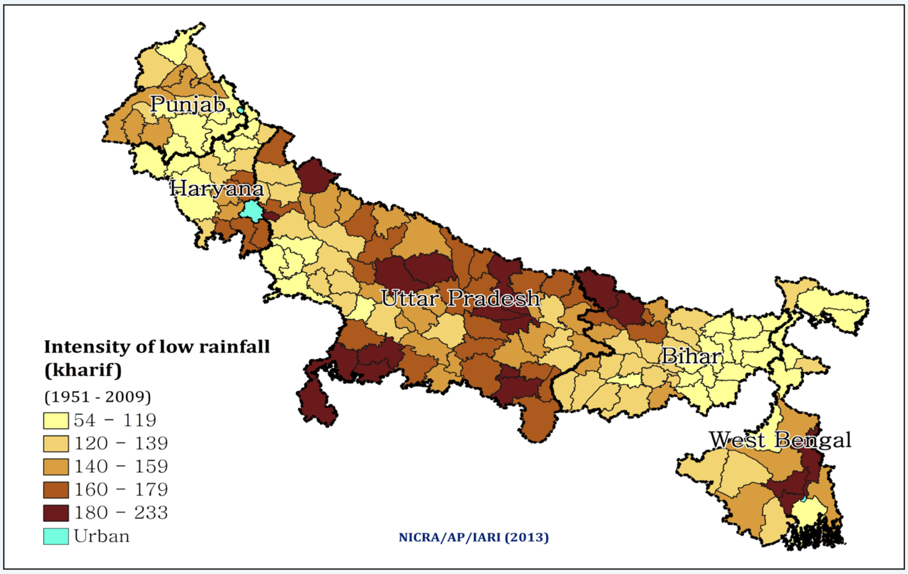

Fig. 10. Intensity of low rainfall during kharif season in different districts of Indo-Gangetic Plains

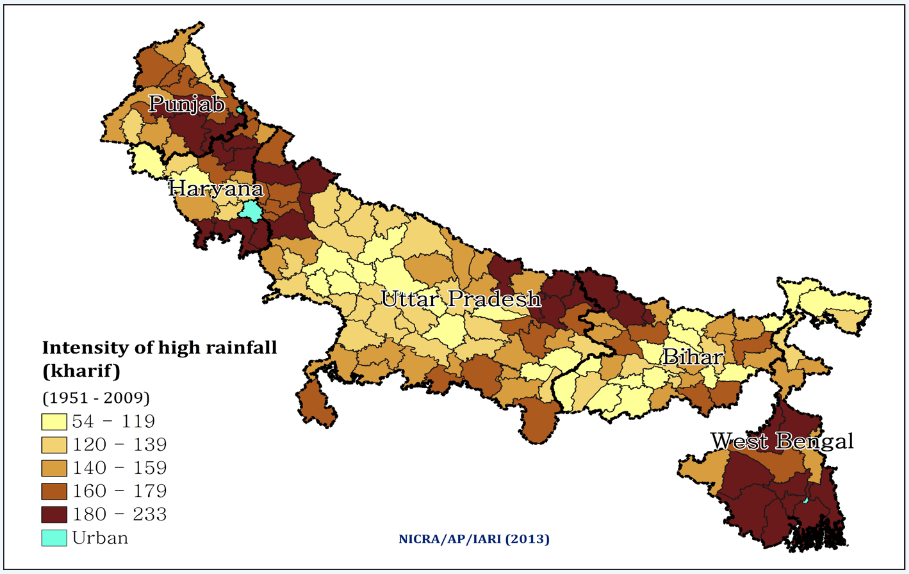

Fig. 11. Intensity of high rainfall during kharif season in different districts of Indo-Gangetic Plains

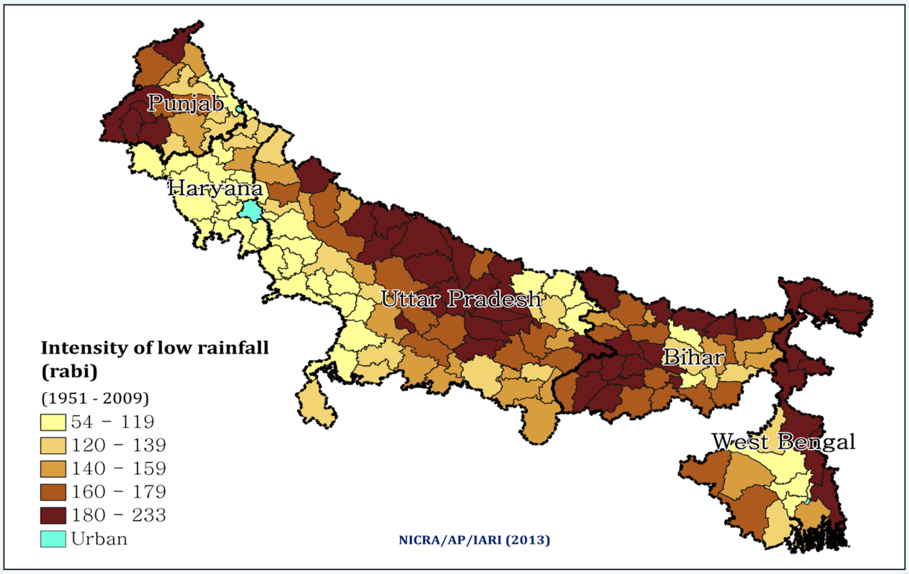

Fig. 12. Intensity of low rainfall during rabi season in different districts of Indo-Gangetic Plains

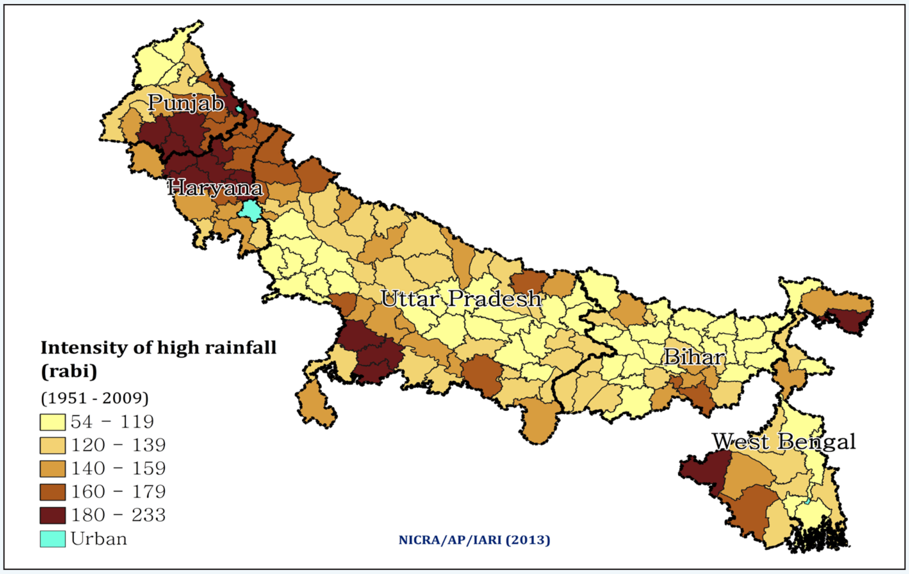

Fig. 13. Intensity of high rainfall during rabi season in different districts of Indo-Gangetic Plains

season with values less than 120. Intensity of high rainfall during rabi season was higher in the districts on the border of Punjab and Haryana. A couple of districts in southern UP and West Bengal also showed higher intensity of high rainfall during rabi season. The remaining study area had a relatively lower intensity of high rainfall during rabi season with index value less than 140.

Composite exposure

Composite exposure (Fig. 14) was computed spatially using the above indicators of exposure, viz., maximum and minimum temperatures, and the intensity of low and high rainfall during kharif and rabi seasons by assigning weightage to each indicator given in the pair-wise comparison matrix (Table 6). The district-wise exposure values are given in Annexure-1. The districts of Paschim and Purbi Champaran and Sheohar in northern Bihar and Balrampur, Kushinagar, Hamirpur and Mahoba in eastern UP had extreme composite exposure. The higher rate of minimum temperature in kharif and rabi seasons and higher intensity of low and high rainfall in kharif season resulted in extreme exposure in the districts of Bihar. Similarly, the extreme exposure areas in southern UP (parts of Buldelkhand region) were the result of higher rate of maximum and minimum temperatures in kharif season and higher rate of minimum temperature in rabi season and higher intensity of low rainfall in kharif season.

Some districts of southern UP, eastern Bihar and parts of West Bengal were also rated high on exposure. Moderate to low exposure occurred in areas in central and western UP, Bihar and most of Haryana and central parts of Punjab. Districts such as Sirsa, Hisar and Fatehabad in Haryana and Hosiarpur, Gurdaspur, Nawanshahar, Mansa and Rupnagar in northern Punjab experienced very low exposure. The reasons behind such a low exposure in the above mentioned areas were lower rate of change of maximum and minimum temperatures in kharif and rabi seasons and very low to moderate rainfall intensity.

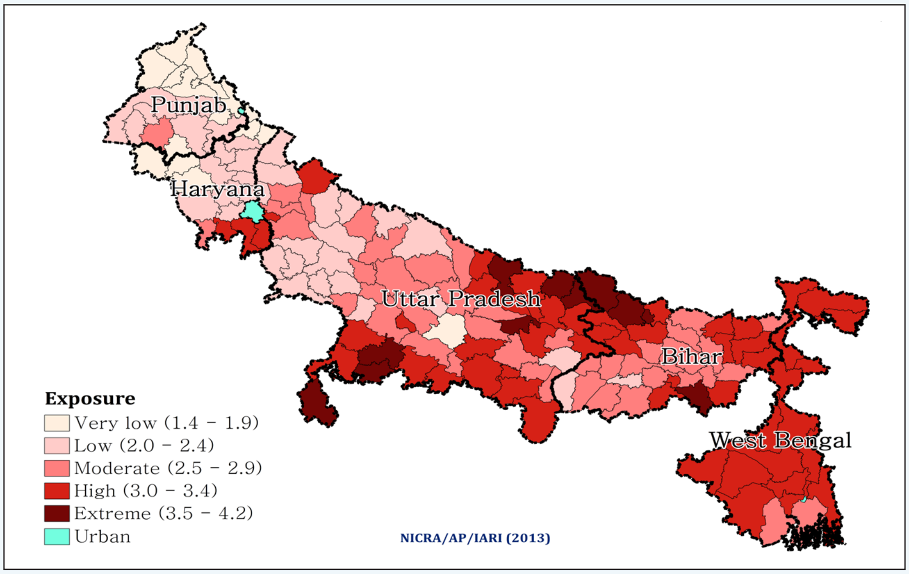

Fig. 14. Composite exposure map of different districts of Indo-Gangetic Plains

Sensitivity indicators

Sensitivity was computed from six indicators based on crop (net sown area to geographical area and productivity of food grains), soil characteristics (organic carbon content and water-holding capacity) and socio-economics (human population density and average landholding of farmers).

Net sown area to geographical area

The net sown area represents the area sown with crops at least once in any of the crop seasons of a year, regardless the number of times it is used for cultivation in the year. Here, district-wise distribution of net area sown to their respective geographical area was calculated and the map was developed. This indicator is positively related to vulnerability, i.e., the higher is the ratio of net sown area to geographical area, the more sensitive and hence more vulnerable is the district to climate change.

Southern parts of Bihar, adjoining districts of Uttar Pradesh, and southern parts of West Bengal had less net sown area compared to geographical area, whereas the districts of Punjab, Haryana and eastern Uttar Pradesh had high net sown area to geographical area (Fig. 15). Almost the entire state of Punjab; the districts of Sirsa, Fatehabad, Jind, Kaithal, Kurukshetra, Bhiwani, Rohtak and Sonipat in Haryana; a few eastern districts of Ghaziabad, Gautam Buddha Nagar, Moradabad, Aligarh, Muzaffarnagar, Mathura and Rampur of Uttar Pradesh; Buxar of Bihar and Uttari and Dakshini Dimapur of West Bengal had very high net sown area compared to geographical area with values ranging from 0.81 to 1.0 ha ha^{-1}. The remaining districts of Haryana; western, southern and eastern Uttar Pradesh; western Bihar and a couple of districts from West Bengal were under high net sown area with values ranging from 0.7 to 0.8 ha ha^{-1}. Southern Bihar; Mirjapur, Sonbhadra from Uttar Pradesh, and Purulia, Bankura, Medinipur and 24 South Parganas from West Bengal had net sown area to geographical area less than 0.5 ha ha^{-1}.

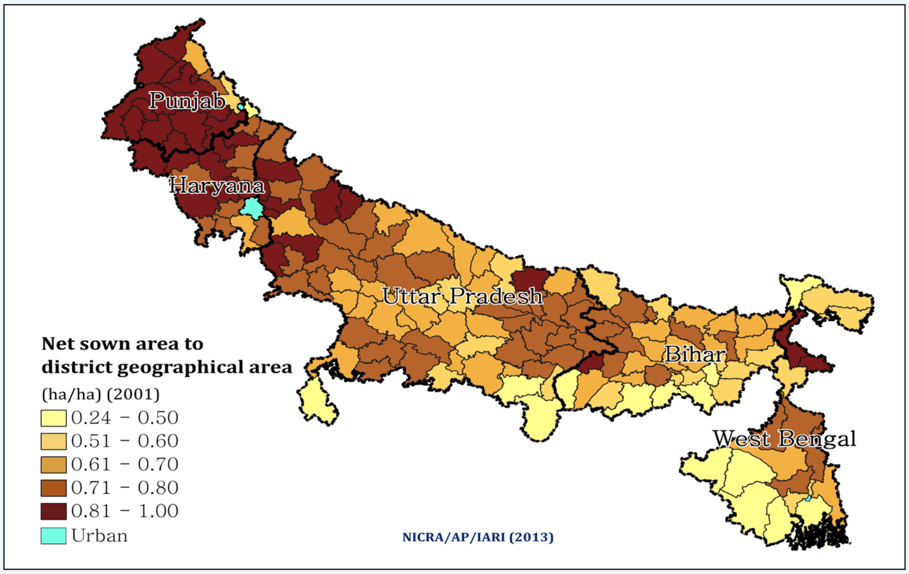

Fig. 15. Net sown area to respective geographical area of different districts in Indo-Gangetic Plains

Productivity of food grains

The productivity of food grains represents the average amount of grains produced at least once in any crop season in a year. The productivity is inversely related to vulnerability, i.e., the higher is the crop productivity, the lower is the sensitivity and hence vulnerability.

The foodgrain productivity showed an east-west gradient across the IGP, with higher values in western states and lower values in eastern states (Fig. 16). The entire states of Punjab and Haryana had high productivity of > 3000 kg ha^{-1}, except southern districts of Bhiwani, Rohtak, Mahendragarh, Jhajjar, Rewari and Gurgaon, which had low to medium productivity ranging between 1500 and 3000 kg ha^{-1}. The districts of Muzaffarnagar, Baghpat, Meerut, and Ghaziabad in UP also had very high productivity. The productivity decreased as one moves towards the eastern UP. The southern districts of Jalaun, Hamirpur, Jhansi, Lalitpur, Mahoba, Banda and Chitrakoot in UP had a productivity less than 1500 kg ha^{-1}. The districts in western and central Bihar had a productivity ranging between 1500 and 2500 kg ha^{-1} and the rest of Bihar had very low productivity. West Bengal showed a significantly high productivity in the districts of Birbhum, Burdwan, Bankura and Hugli; the rest of the state showed the productivity ranging from 2000 to 2500 kg ha^{-1}.

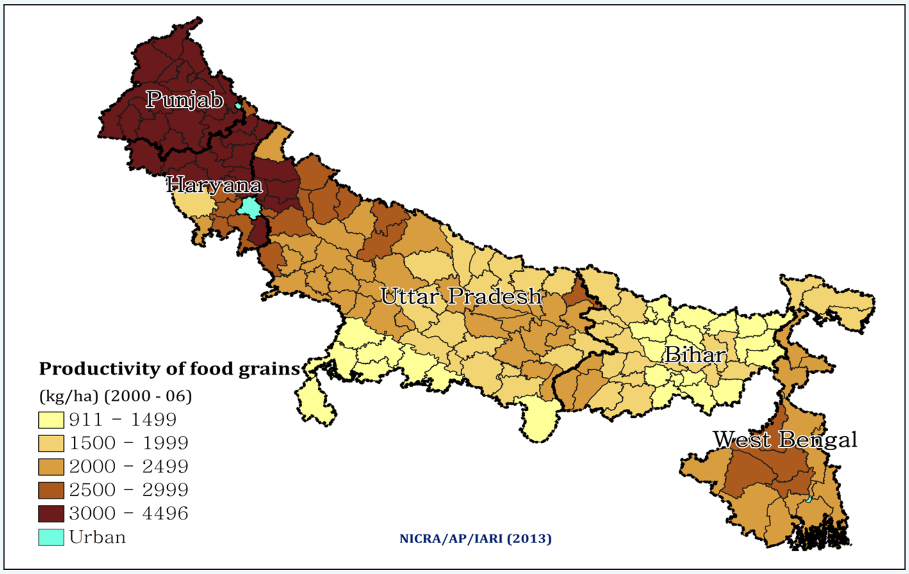

Fig. 16. Average productivity of food grains in different districts of Indo-Gangetic Plains

Organic carbon content of soil

Soil organic carbon is composed of a wide range of different materials with different chemical and physical properties and different extents of decomposition. Soil carbon improves the physical properties of soil. It increases the cation exchange capacity (CEC) and water-holding capacity and contributes to the structural stability of soil by helping it to bind particles into aggregates that are of importance to plant growth. Organic carbon content of soil is inversely related to vulnerability, i.e., higher is the value lower is the sensitivity and hence lower is the vulnerability.

Soils of almost the entire states of Punjab, Haryana and western UP had an organic carbon content in the range of 3.6 and 8.0 kg m^{-2}, which is considered to be very low (Fig. 17). The entire state of UP, except the central part consisting of the districts of Hardoi, Sitapur, Lucknow, Barabanki, Raebareli, Gonda, Faizabad, Sultanpur, Basti, Ambedkar Nagar and Azamgarh, which showed organic carbon content higher than 11.1 kg m^{-2}, had organic carbon content between 10.1 and 11.0 kg m^{-2}. The districts of northern Bihar showed higher organic carbon content in soil compared to rest of Bihar, which had organic carbon content ranging from 8.1 to 10.0 kg m^{-2}. The northern and southern districts of West Bengal had higher organic carbon content and rest of West Bengal showed organic carbon content ranging between 3.6 and 10.0 kg m^{-2}.

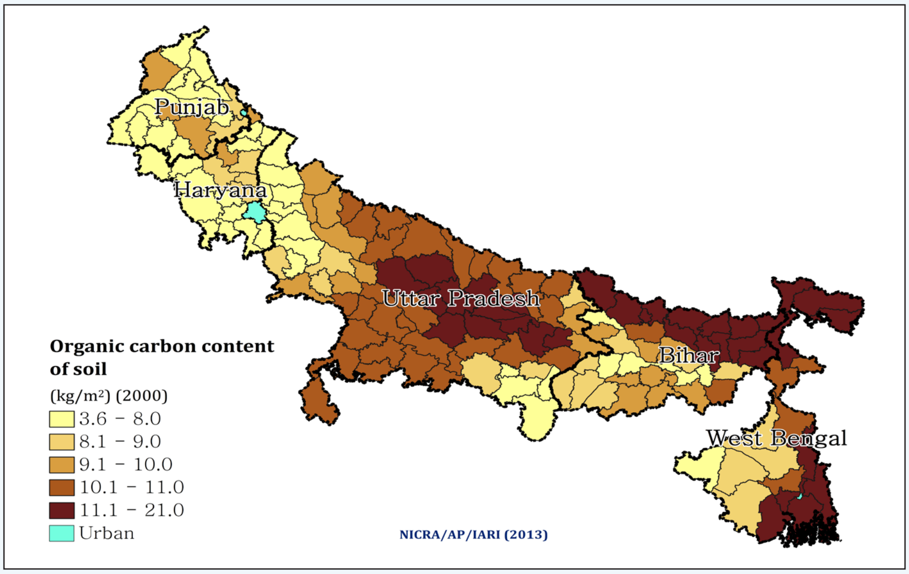

Fig. 17. Organic carbon content of soil in different districts of Indo-Gangetic Plains

Water-holding capacity of soil

The water-holding capacity of soil is inversely related to vulnerability, i.e., the higher the value, the lower is the vulnerability. Very few districts in the study area of the IGP had very high water-holding capacity (Fig. 18). Only Gurdaspur, Hosiarpur and Nawanshahr from northern Punjab; Ambala and Yamunanagar from northern Haryana; Shaharanpur, Bijnor, Rampur, Kishanganj and Ballia from UP; and central Bihar and northern and eastern West Bengal showed water-holding capacity higher than 240 mm m^{-1} soil depth.

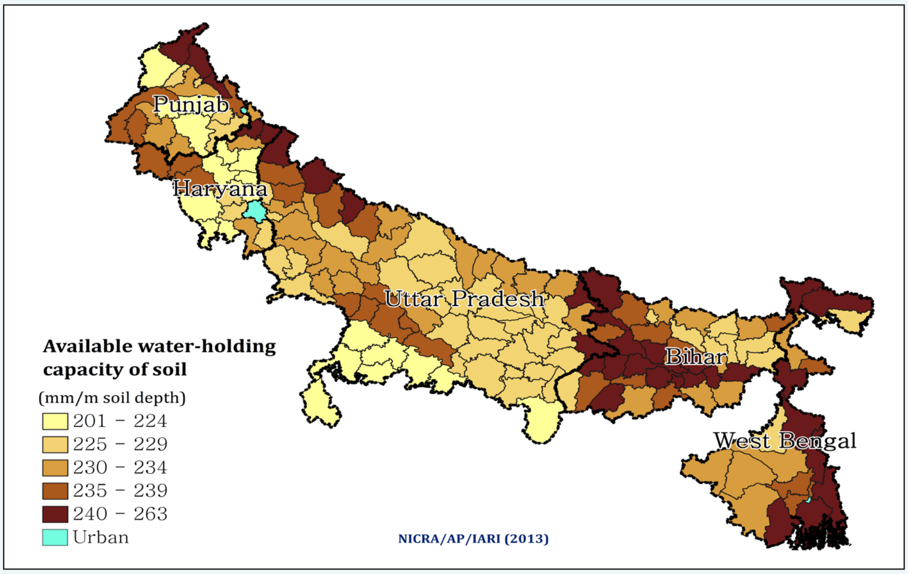

Fig. 18. Water-holding capacity of soil in different districts of Indo-Gangetic Plains

Most of the districts of Punjab, Haryana, UP and northern Bihar had water-holding capacity ranging from 225 to 235 mm m^{-1} soil depth. Amritsar, Moga, Ludhiana and Sangrur in Punjab; Kaithal, Jind, Karnal, Panipat and Sonipat in Haryana; and the districts of southern UP and northern Bihar showed water-holding capacity less than 225 mm m^{-1} soil depth.

Average landholding of farmers

The size of landholding is an important factor affecting land use, cropping pattern, productivity and farm employment. Fig. 19 shows the correlation between crop productivity and landholding size in the IGP. As landholding of the farmers increases, the productivity also increases. Small landholding farmers (farmers with landholding less than 1 ha) are more sensitive to climate change and climatic variability. They use less capital-intensive technologies and have limited capacity to use best management practices. Thus, a region with a large number of small landholding farmers will be more climate-sensitive.

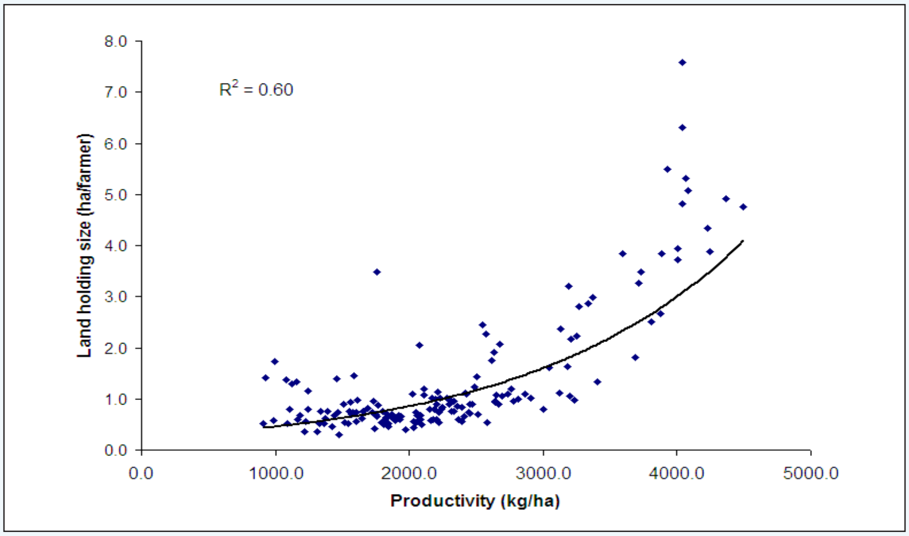

Fig. 19. Correlation between average landholding of farmers and crop productivity in Indo-Gangetic Plains

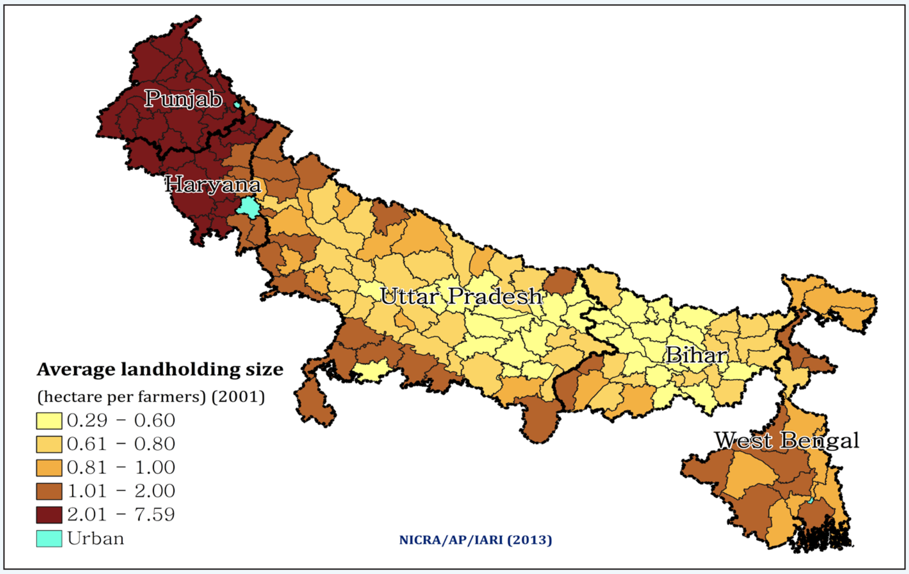

Fig. 20. Average landholding of farmers in different districts of Indo-Gangetic Plains

The entire states of Punjab and Haryana, except for the Karnal, Panipat, Sonipat, Faridabad and Gurgaon districts, had the average landholding of farmers more than 2.01 ha per farmer (Fig. 20). The districts of Sahranpur, Muzaffarnagar, Meerut, Bijnor, Aligarh, Mathura and Agra in western and southern UP and Dinajpur, Purulia, Birbhum, Hugli and Medinipur in West Bengal showed the average landholding ranging between 0.8 and 2.0 ha per farmer. The rest of the IGP had the average landholding of less than 0.8 ha per farmer.

Human population density

The districts with more population density are more sensitive to climate change as more population is exposed to climatic extremes and therefore these districts need more humanitarian assistance.

The districts of Deoria, Kushinagar, Gorakhpur, Mau, Sharwasti, Lucknow, Kanpur, Moradabad, Meerut, Gautam Buddha Nagar, Jaunpur and Varanasi in UP had a population density of more than 951 person km^{-2} (Fig. 21). Similarly high population density was seen in western Bihar and Murshidabad, Burdwan, Nadia, Hugli and Howrah districts of West Bengal. The rest of the districts in UP (except southern UP, where the population density was lower than 500 person km^{-2} in the districts of Jalaun, Hamirpur, Banda, Chitrakoot, Jhansi, Mahoba, Lalitpur,

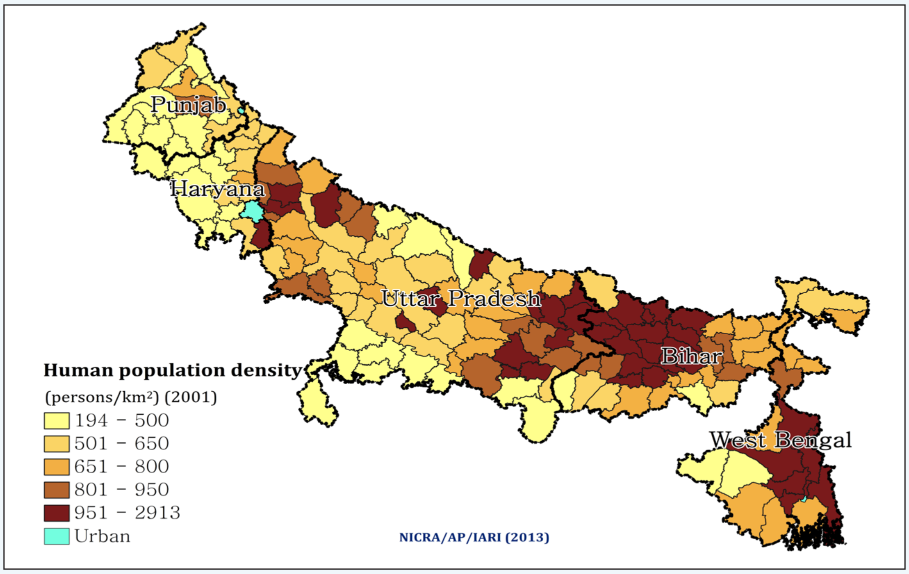

Fig. 21. Human population density in different districts of Indo-Gangetic Plains

Mirzapur and Shonbhadra), Bihar and West Bengal showed the population density ranging from 651 to 950 persons km^{-2}. Southern UP; Purulia and Bankura districts of West Bengal; Jamui from Bihar and most of the districts of Punjab and Haryana showed population density of less than 500 person km^{-2}.

Composite sensitivity

The composite sensitivity of agriculture to climate change varied from very low to extreme with values ranging from 1.5 to 4.5. The district-wise values of sensitivity are given in Annexure-1. The north-western parts of Bihar (Darbhanga, Sheohar, Nalanda, Samastipur) and adjoining UP districts (Sant Kabir Nagar, Gorakhpur) were extremely sensitive to climate change owing to high population density (Fig. 22). The small landholdings of farmers in these areas also added to higher sensitivity. The districts of eastern UP and northern Bihar showed higher sensitivity owing to lower productivity and landholding size and higher population density. The rest of the area showed moderate to low sensitivity owing to average net sown area, productivity and low population density. On the contrary, most districts of Punjab and Haryana were less sensitive to climate change owing to higher productivity, large average landholding size and lower population density.

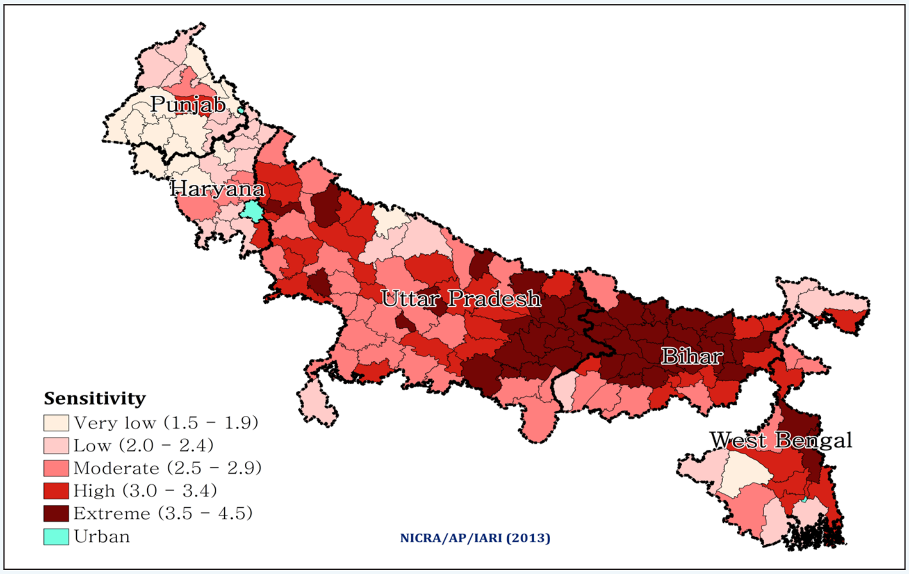

Fig. 22. Composite sensitivity map of different districts of Indo-Gangetic Plains

Adaptive capacity indicators

Adaptation in agriculture is a continuous process, whereas diversity in agriculture is actually the manifestation of climatic and also to some extent, of socio-economic adaptation. Farmers and society have always adapted to the climatic changes when allowed by technological availability, their socio-economic capacity and the economics of producing a given commodity. Induced adaptation has been aided by innovation and the Green Revolution of 1960s was one of the striking examples. In order to overcome the challenges, traditional adaptation and coping strategies practised by farmers included growing crop varieties that were less sensitive to climatic stresses, resource conservation, diversified cropping and heat stress improvement by irrigation. The induced adaptation options included changing varieties/crops, altering fertilizer rates to maintain grain or fruit quality that was more suited to the prevailing climate, changing the timings of irrigation and quantity of irrigation water, more effective use of water including rain-water harvesting and conserving soil moisture through different ways including crop residue retention incorporation, altering the timing or location of cropping activities and diversifying income including through animal husbandry.

Adaptive capacity plays an important role in assessing vulnerability. The indicators of adaptive capacity included human development index (HDI), adoption of agricultural technology (percent irrigated area and annual NPK fertilizer consumption) and access to infrastructure to cope with adverse effects of climate change.

Percent irrigated area

Improving irrigation infrastructure, facilitating more equitable distribution of water and improving on-farm water management increase agricultural production and farm income.

The western part of the IGP was better irrigated than the eastern part. Almost the entire Punjab and Haryana and western UP had a significantly higher percentage of irrigated area (60.1 - 94.5%) and most of the Punjab had irrigated areas between 75.1- 94.5% (Fig. 23). Except the districts of Bahraich, Shrawasti, Balrampur, Hamirpur, Lalitpur, Mirjapur and Sonbhadra in UP which had irrigated area lesser than 30 %, the rest of UP had irrigated area ranging between 30.1 to 60.0%. Gopalganj, Siwan, Buxar, Bhojpur and Rohtas districts in Bihar also had high irrigated area (60.1 – 75.0%). The rest of Bihar and almost the entire West Bengal had a much lower (< 30%) irrigated area.

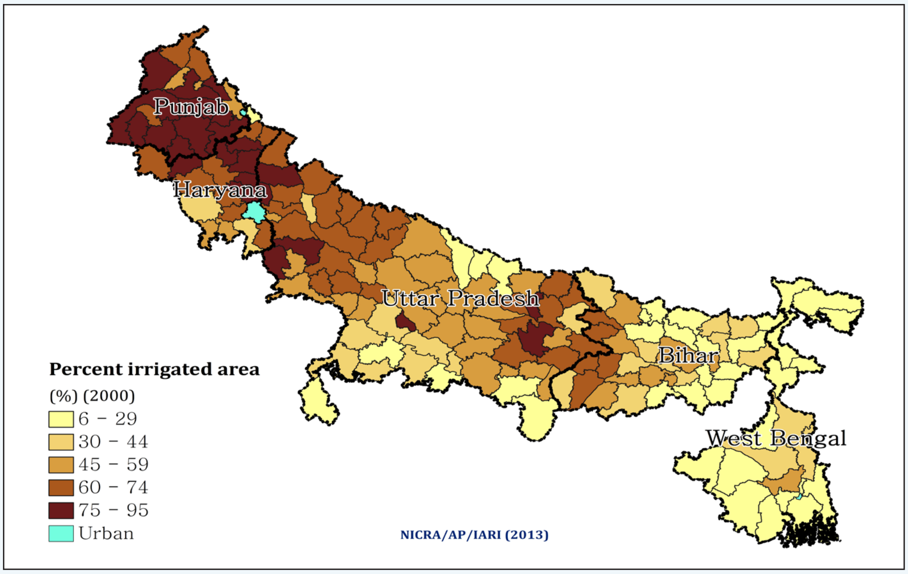

Fig. 23. Percent irrigated area in different districts of Indo-Gangetic Plains

Human development index

Human development index (HDI) was calculated using three socio-economic indicators, viz. health, education and income. It was given higher weightage because the chances of recovery from potential impacts are higher if the value of HDI is higher.

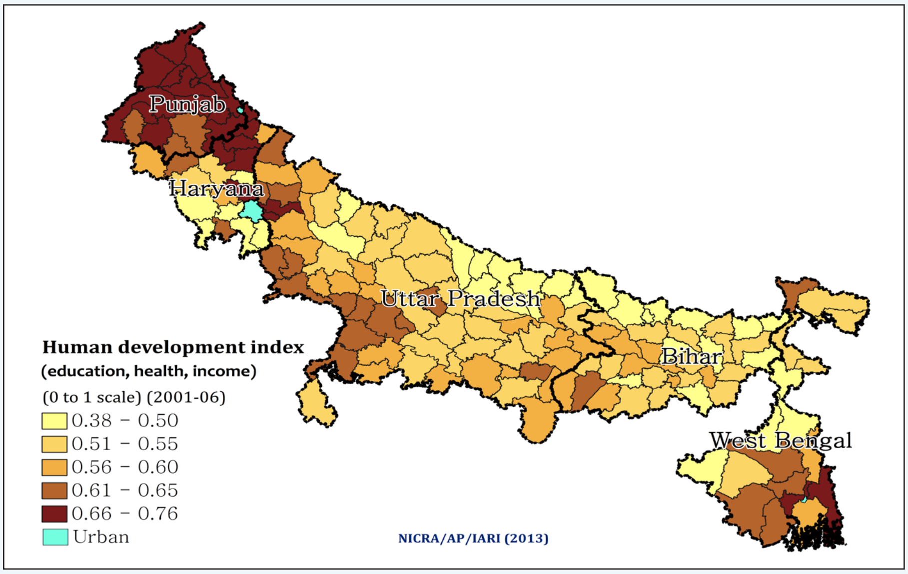

Fig. 24. Human development index in different districts of Indo-Gangetic Plains

All the districts of Punjab; the districts of Panchkula, Ambala, Kurukshetra and Karnal of Haryana; Ghaziabad and Kanpur districts of Uttar Pradesh and Howrah district of West Bengal had a high HDI value ranging between 0.66 and 0.76 on 0 to 1 scale (Fig. 24). The district Mansa in Punjab; Sirsa, Fatehabad, Sonipat and Rewari in Haryana; Shaharanpur, Meerut, Mathura, Hathras, Agra, Etawah, Kanpur, Auraiya, Jalaun, Jhansi, Lucknow and Varansi in UP; Rohtas in Bihar and Burdwan, Hugli, Medinipur and Darjiling in West Bengal had HDI values ranging from 0.61 to 0.65.

The rest of study area had lower HDI values ranging from 0.38 to 0.55 with southern Haryana (Jhajjar, Faridabad, Gurgaon); northern UP (Shrawasti, Bahraich, Balrampur) and northern Bihar (Kishanganj, Sheohar, Pashchim Champaran) falling even below 0.5. The districts of Panchkula in Haryana; and Ludhiana, Rupnagar and Fatehgarh Sahib in Punjab had the highest HDI values (7.4 to 7.6).

Cropping intensity

Cropping intensity denotes the number of crops grown in a year on one piece of land. The agricultural land will be more vulnerable if it is not much used for growing crops. In other words, the vulnerability is inversely proportional to the cropping intensity of that land.

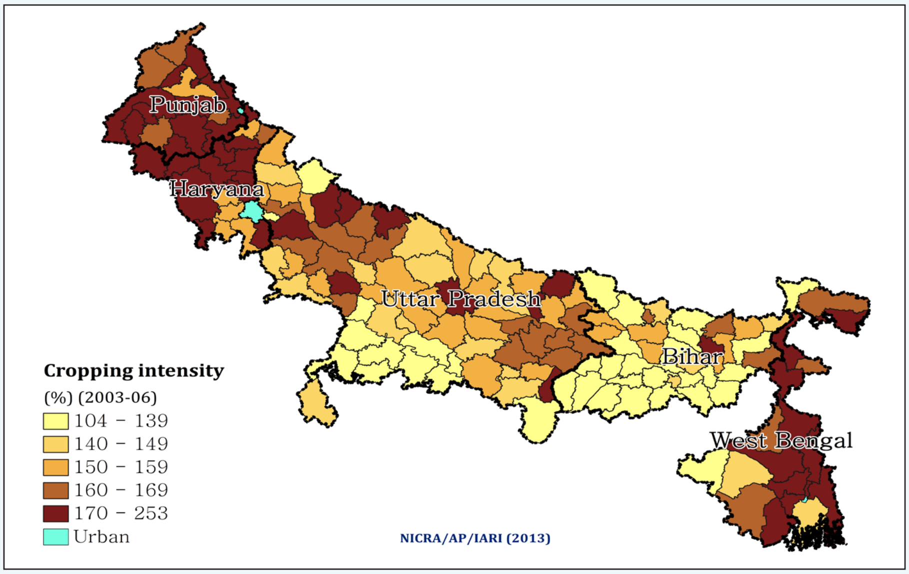

Fig. 25. Cropping intensity in different districts of Indo-Gangetic Plains

Almost all the districts of Punjab and Haryana; eastern districts of West Bengal; Moradabad, Rampur, Pilibhit, Bulandshahar, Mainpuri, Barabanki, Maharajganj and Kaimur districts in UP and Saharsa in Bihar had a cropping intensity higher than 170% (Fig. 25). A few districts in southern Haryana; the entire UP, except the southern part; Gopalganj, Siwan, Muzaffarpur, Vaishali, Supaul, Araria, Saharsa and Katihar districts in Bihar and Jalpaiguri, Birbhum and Medinipur districts in West Bengal had the cropping intensity ranging between 150 and 170%. Almost the entire Bihar and the districts of Auraiya, Jalaun, Jhansi, Hamirpur, Lalitpur, Mahoba, Banda, Chitrakoot, Fatehpur, Kaushambi and Sonbhadra in southern UP and Purulia in West Bengal had the lowest cropping intensity (< 140%).

Livestock population density

The livestock population density is the measure of the number of livestock per sq km. A higher livestock population density supports agriculture through animal power and manure, provides alternative livelihood to farmers and enhances the adaptive capacity of farmers in the time of climatic extremes.

The livestock population density was higher in the eastern part of the IGP compared to that in the western part (Fig. 26). Almost the entire West Bengal; some districts of Bihar; and districts of Ballia, Varanasi, Kaushambi, Rae Bareli, Kannauj, Firozabad and Hathras in UP had the highest density of livestock (more

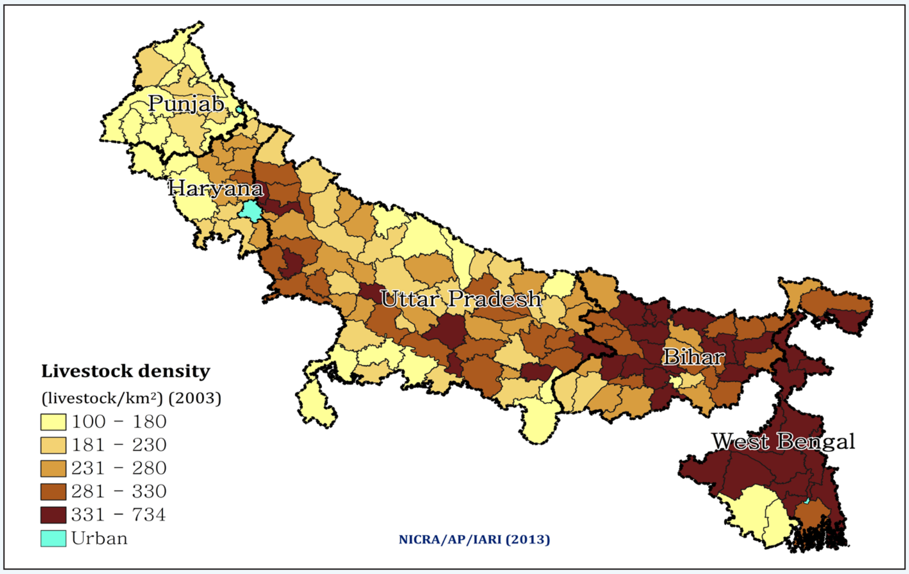

Fig. 26. Livestock population density in different districts of Indo-Gangetic Plains

than 330 livestock km^{-2}). Some districts of UP and Bihar showed the livestock density of 230– 330 livestock km^{-2}. Pilibhit, Kheri, Bahraich, Maharajganj, Jhansi, Hamirpur, Mahoba, Banda, Lalitpur, Sonbhadra and Kaimur districts in southern UP; Medinipur in West Bengal and the entire states of Punjab and Haryana had lower livestock density (< 180 livestock km^{-2}).

Number of villages electrified

The development of infrastructure such as electricity supply and paved roads is an important measure of the relative adaptive capacity of a region. Electricity supply is major input required for growth in the agriculture sector. Electric power plays an important role in the social sectors which has impact on various dimensions of human development focussing on improvement of standard of living, health, education, and poverty reduction.

The western States of the IGP were much ahead of the rest of the States area in terms of electrification of villages (Fig. 27). All the districts in Punjab and Haryana had 100% villages electrified. The districts of Saharanpur, Muzaffarnagar, Baghpat, Meerut, Ghaziabad, Bulandshahar in north western Uttar Pradesh and Rae Bareli, Varanasi and Mau district in central and eastern Uttar Pradesh; and Burdwan, Nadia, Hugli and Howrah districts in West Bengal had high number (90–100%) of villages electrified. A large number of districts in Bihar lagged in village electrification and

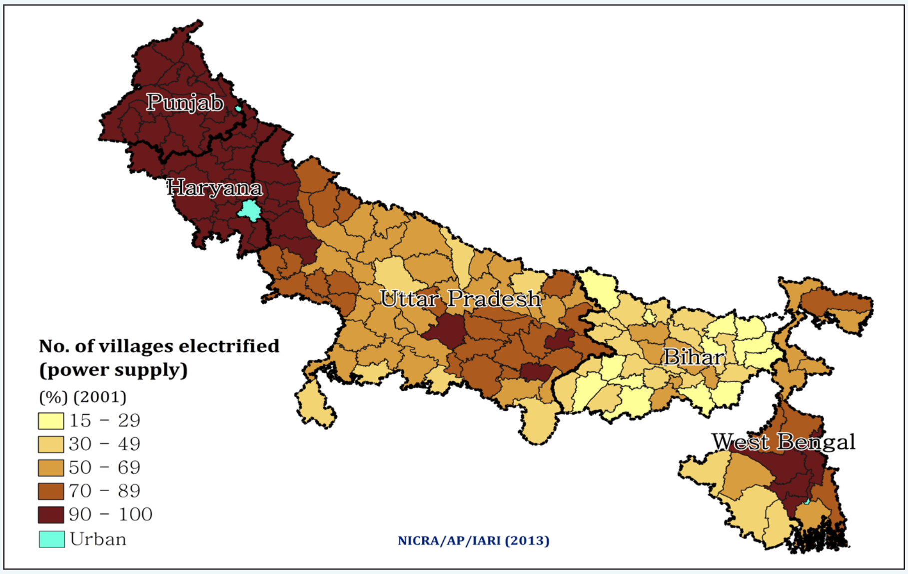

Fig. 27. Number of villages electrified in different districts of Indo-Gangetic Plains

districts of Vaishali, Begusarai, Munger, Samastipur, Muzaffarpur, Nawada and Sheikhpura in Bihar had only 50–70% villages electrified. The rest of Uttar Pradesh, Bihar and West Bengal had 70-90% villages electrified.

Number of villages with paved approach road

The regions with better infrastructure are apparent to adapt to climatic stresses in a better way. Improved road infrastructure reduces transportation cost and strengthens the links between labour and product markets.

Almost all the districts of Punjab and Haryana and the districts Muzaffarnagar and Meerut in Uttar Pradesh had the highest number of villages (about 100%) with paved approach roads (Fig. 28). About 70 - 90% of villages in the districts of Kapurthala, Nawanshahar and Rupnagar in Punjab; Saharanpur, Bijnor, Ghaziabad, Bulandshahar, Aligarh, Mathura, Hathras, Mathura, Agra, Firozabad, Etawah, Kanpur, Lucknow, Kausambi and Varanasi in Uttar Pradesh and Howrah, North and South 24 Paraganas districts in southern West Bengal had paved approach roads. North-western districts of Uttar Pradesh adjoining to Haryana had 70 - 90% number of villages with paved approach roads. Almost all the districts of Uttar Pradesh, Bihar and West Bengal had a lower number of villages with paved

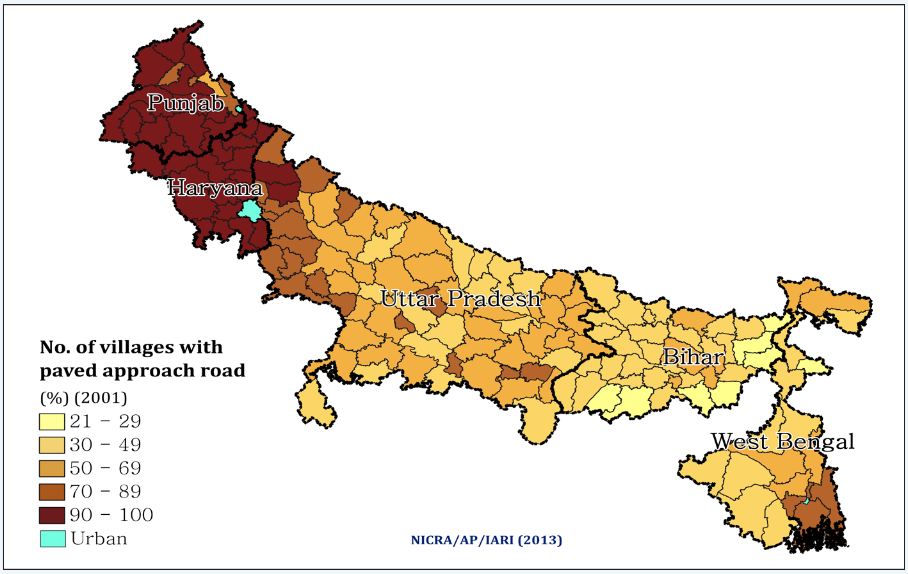

Fig. 28. Number of villages with paved approach road in different districts of Indo-Gangetic Plains

approach roads ranging from 30 to 70%. The districts Banka, Jamui, Katihar and Kishanganj in Bihar and Dakshin Dinajpur in West Bengal had the lowest number of villages (21-25%) with paved approach roads.

Fertilizer consumption

Annual consumption of NPK fertilizers in different districts of the IGP depicted a heterogeneous pattern (Fig. 29).

The districts of Jalandhar, Nawanshahar, Moga, Ludhiana, Rupnagar and Sangrur in eastern Punjab; Ambala, Yamunanagar, Kurukshetra, Saharanpur, Kathial, Karnal, Panipat, Sonipat and Faridabad in Haryana; Saharanpur, Muzaffarnagar, Baghpat, Meerut, Ghaziabad, Moradabad, Pilibhit, Shahjahanpur, Farrukhabad, Maharajganj, Deoria and Varanasi in UP and Hugli and Howrah in West Bengal were among the districts with highest consumption of NPK fertilizers (> 200 kg ha^{-1}). The rest of Punjab, Haryana, western and eastern UP, central Bihar and the rest of West Bengal had NPK fertilizer consumption in the range of 120–160 kg ha^{-1}. The southern UP and the rest of Bihar had the lowest NPK fertilizer consumption (< 80 kg ha^{-1}). Sheohar, Supaul, Kishanganj, Madhubani in Bihar and Banda in UP were the five districts with lowest consumption of NPK fertilizer (20-80 kg ha^{-1}).

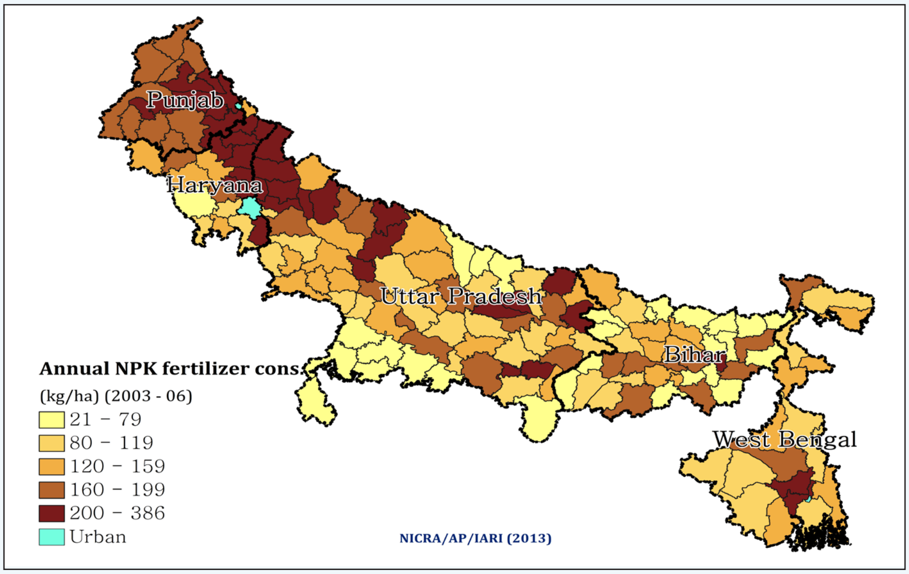

Fig. 29. Annual NPK fertilizer consumption in different districts of Indo-Gangetic Plains

Composite adaptive capacity

The composite adaptive capacity was computed using different indicators of adaptive capacity as discussed above. The district-wise values of adaptive capacity are given in Annexure-1.

The adaptive capacity in the northern (Kishanganj, Madhubani, Sitamarhi and Sheohar) and southern (Banka, Lakhisarai and Jamui) districts of Bihar was low because of low HDI, percent irrigated area and cropping intensity (Fig. 30). However, in the districts of southern UP (Lalitpur, Sonbhadra and Hamirpur), the adaptive capacity was low because of less irrigated area and low fertilizer consumption. Whereas most of the districts in UP, Bihar and West Bengal fell under low to moderate adaptive capacity category, the adaptive capacity of eastern and western UP was high due to higher cropping intensity, higher HDI, and higher irrigated and electrified areas. Sonipat, Karnal, Kaithal and Kurukshetra districts of Haryana and the entire state of Punjab (except Kapurthala district) had extremely high adaptive capacity because of higher percentage of irrigated area, HDI, cropping intensity, number of electrified villages and number of villages with paved approach roads.

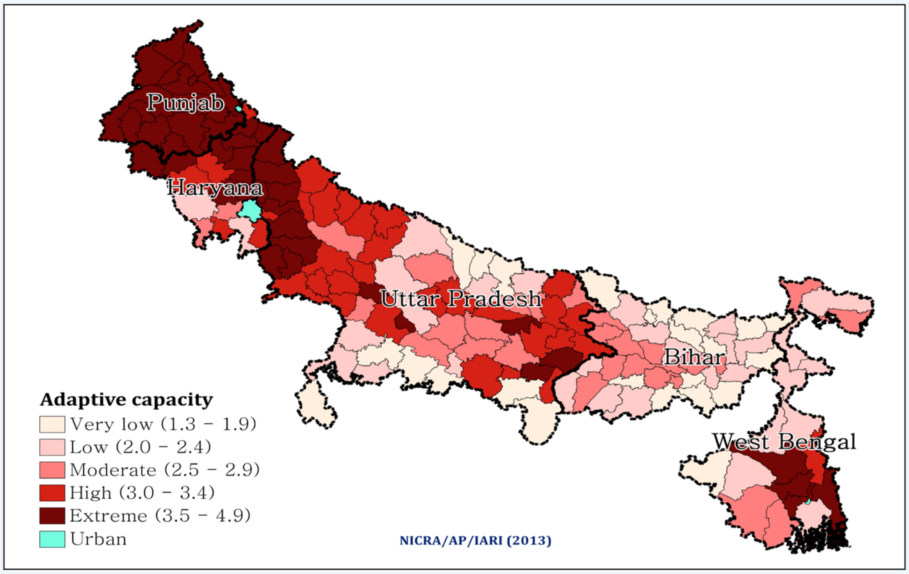

Fig. 30. Composite adaptive capacity to climatic changes in various districts of Indo-Gangetic Plains

Composite vulnerability

The composite vulnerability rating was arrived at by combining the exposure, sensitivity and adaptive capacity using their respective weights. The district-wise values of vulnerability are given in Annexure-1. The agricultural vulnerability increased as one moved from western to eastern parts of the IGP (Fig. 31). Numbers of districts in different vulnerability class in the various States of the IGP are presented in Table 9. The highest number of districts (48%) were highly vulnerable whereas 39% were moderate and 37% each were low and extremly vulnerable. As a ready-reckoner for the readers, different districts of the IGP have been arranged alphabetically in Table 10 and according to vulnerability in Table 11.

The western part of the IGP was less vulnerable because of low exposure, low sensitivity and high adaptive capacity. The northern and southern Bihar and eastern and southern parts of UP were assessed to be most vulnerable regions in the IGP owing to high exposure, high sensitivity and low adaptive capacity. The north-western districts of Bihar (Sheohar, Sitamarhi, Madhubani, Purba Champaran, Darbhanga) were highly vulnerable because of high exposure to climatic stresses and high sensitivity, whereas the districts in southern Bihar (Nawada, Banka, Lakhisarai, Jehanabad and Jamui) were highly vulnerable owing to low adaptive capacity. The north-eastern districts of UP (Shrawasti, Balrampur, Bahraich,

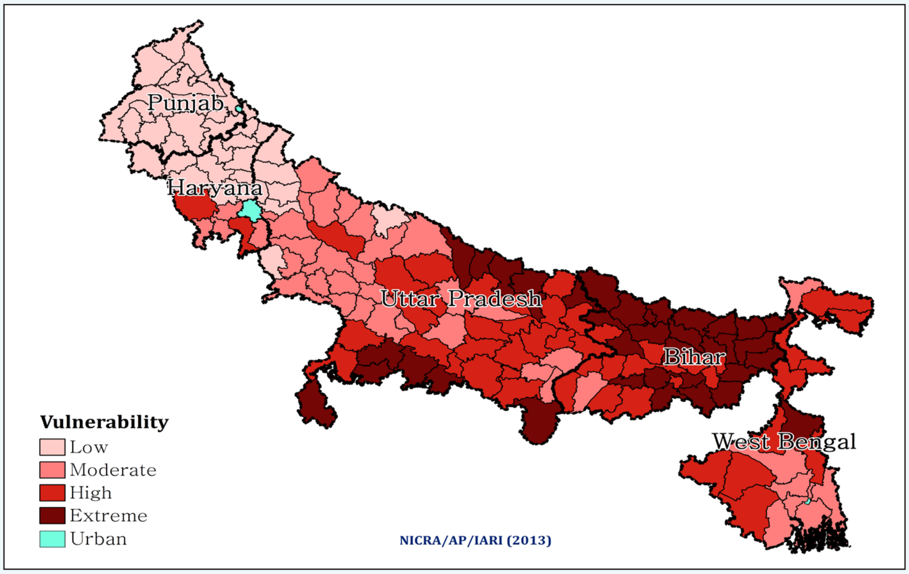

Fig. 31. Vulnerability of agriculture to climatic changes in various districts of Indo-Gangetic Plains

Siddharthnagar) were more vulnerable because of low HDI, irrigated area and fertilizer consumption. Southern districts of UP (Mahoba, Lalitpur, Hamirpur and Banda) were highly vulnerable to climate change because these districts were more exposed to droughts and change in maximum temperature in kharif season and had less adaptive capacity (less amount of fertilizer consumption and low cropping intensity). The five most vulnerable districts of the IGP were: Sheohar, Sitamarhi, Madhubani and Purba Champaran in Bihar and Shrawasti district in UP. Agriculture of the central UP and West Bengal districts was rated low to moderate in vulnerability because of moderate exposure, sensitivity and adaptive capacity. The vulnerability of agriculture in the state of Punjab, the northern parts of Haryana and the adjoining districts of UP was rated low because of higher HDI and higher percentage of irrigated area.

Table 9. Number of districts in different vulnerability class in the various States of the Indo-Gangetic Plains

States	Total districts	No. of districts in different vulnerability class			
		Low	Moderate	High	Extreme
Bihar	37	0 (0)*	1 (3)	12 (32)	24 (65)
Haryana	19	13 (68)	4 (21)	2 (11)	0 (0)
Punjab	17	17 (100)	0 (0)	0 (0)	0 (0)
Uttar Pradesh	70	7 (10)	27 (39)	24 (34)	12 (17)
West Bengal	18	0 (0)	7 (39)	10 (56)	1 (5)
Total	161	37 (23)	39 (24)	48 (30)	37 (23)

*Figures in the parenthesis are percent of districts in different vulnerability class.

Table 10. Vulnerability rank of different districts in the Indo-Gangetic Plains (Districts arranged alphabetically).

District	State	Vulnerability rank*
Agra	Uttar Pradesh	111
Aligarh	Uttar Pradesh	118
Allahabad	Uttar Pradesh	77
Ambala	Haryana	149
Ambedkar Nagar	Uttar Pradesh	81
Amritsar	Punjab	146
Araria	Bihar	11
Auraiya	Uttar Pradesh	103
Aurangabad	Bihar	69
Azamgarh	Uttar Pradesh	76

Baghpat	Uttar Pradesh	134
Bahraich	Uttar Pradesh	23
Ballia	Uttar Pradesh	84
Balrampur	Uttar Pradesh	6
Banda	Uttar Pradesh	28
Banka	Bihar	12
Bankura	West Bengal	78
Barabanki	Uttar Pradesh	92
Burdwan	West Bengal	113
Bareilly	Uttar Pradesh	90
Basti	Uttar Pradesh	75
Bathinda	Punjab	143
Begusarai	Bihar	49
Bhagalpur	Bihar	35
Bhiwani	Haryana	64
Bhojpur	Bihar	58
Bijnor	Uttar Pradesh	97
Birbhum	West Bengal	46
Budaun	Uttar Pradesh	83
Bulandshahr	Uttar Pradesh	124
Buxar	Bihar	38
Chandauli	Uttar Pradesh	99
Chitrakoot	Uttar Pradesh	37
Dakshin Dinajpur	West Bengal	60
Darbhanga	Bihar	7
Darjiling	West Bengal	93
Deoria	Uttar Pradesh	50
E. Medinipur	West Bengal	102
Etah	Uttar Pradesh	105
Etawah	Uttar Pradesh	116
Faizabad	Uttar Pradesh	88
Faridabad	Haryana	95
Faridkot	Punjab	150
Farrukhabad	Uttar Pradesh	98
Fatehabad	Haryana	148
Fatehgarh Sahib	Punjab	158
Fatehpur	Uttar Pradesh	68

Firozabad	Uttar Pradesh	107
Firozpur	Punjab	154
Gautam Buddha Nagar	Uttar Pradesh	87
Gaya	Bihar	53
Ghaziabad	Uttar Pradesh	129
Ghazipur	Uttar Pradesh	108
Gonda	Uttar Pradesh	51
Gopalganj	Bihar	21
Gorakhpur	Uttar Pradesh	67
Gurdaspur	Punjab	144
Gurgaon	Haryana	61
Hamirpur	Uttar Pradesh	25
Howrah	West Bengal	120
Hardoi	Uttar Pradesh	74
Hathras	Uttar Pradesh	117
Hisar	Haryana	135
Hoshiarpur	Punjab	159
Hugli	West Bengal	123
Jalandhar	Punjab	141
Jalaun	Uttar Pradesh	56
Jalpaiguri	West Bengal	70
Jamui	Bihar	24
Jaunpur	Uttar Pradesh	47
Jehanabad	Bihar	16
Jhajjar	Haryana	110
Jhansi	Uttar Pradesh	55
Jind	Haryana	132
Jyotiba Phule Nagar	Uttar Pradesh	115
Kaimur (Bhabua)	Bihar	80
Kaithal	Haryana	160
Kannauj	Uttar Pradesh	114
Kanpur Dehat	Uttar Pradesh	109
Kanpur Nagar	Uttar Pradesh	112
Kapurthala	Punjab	140
Karnal	Haryana	153
Katihar	Bihar	17
Kaushambi	Uttar Pradesh	44

Khagaria	Bihar	65
Kheri	Uttar Pradesh	91
Kishanganj	Bihar	8
Koch Bihar	West Bengal	54
Kurukshetra	Haryana	156
Kushinagar	Uttar Pradesh	34
Lakhisarai	Bihar	13
Lalitpur	Uttar Pradesh	20
Lucknow	Uttar Pradesh	85
Ludhiana	Punjab	139
Madhepura	Bihar	22
Madhubani	Bihar	3
Maharajganj	Uttar Pradesh	82
Mahendragarh	Haryana	86
Mahoba	Uttar Pradesh	18
Mainpuri	Uttar Pradesh	122
Maldah	West Bengal	42
Mansa	Punjab	147
Mathura	Uttar Pradesh	125
Mau	Uttar Pradesh	79
Meerut	Uttar Pradesh	131
Mirzapur	Uttar Pradesh	45
Moga	Punjab	157
Moradabad	Uttar Pradesh	100
Muktsar	Punjab	142
Munger	Bihar	39
Murshidabad	West Bengal	31
Muzaffarnagar	Uttar Pradesh	128
Muzaffarpur	Bihar	10
Nadia	West Bengal	71
Nalanda	Bihar	29
Nawada	Bihar	9
Nawanshahr	Punjab	161
North 24 Parganas	West Bengal	104
Panchkula	Haryana	136
Panipat	Haryana	127
Pashchim Champaran	Bihar	19

Patiala	Punjab	155
Patna	Bihar	41
Pilibhit	Uttar Pradesh	133
Pratapgarh	Uttar Pradesh	57
Purba Champaran	Bihar	5
Purnia	Bihar	27
Puruliya	West Bengal	43
Rae Bareli	Uttar Pradesh	94
Rampur	Uttar Pradesh	101
Rewari	Haryana	121
Rohtak	Haryana	126
Rohtas	Bihar	96
Rupnagar	Punjab	151
Saharanpur	Uttar Pradesh	130
Saharsa	Bihar	14
Samastipur	Bihar	15
Sangrur	Punjab	145
Sant Kabir Nagar	Uttar Pradesh	36
Sant Ravidas Nagar	Uttar Pradesh	59
Saran	Bihar	32
Shahjahanpur	Uttar Pradesh	119
Sheikhpura	Bihar	63
Sheohar	Bihar	1
Shrawasti	Uttar Pradesh	4
Siddharthnagar	Uttar Pradesh	26
Sirsa	Haryana	137
Sitamarhi	Bihar	2
Sitapur	Uttar Pradesh	66
Siwan	Bihar	40
Sonbhadra	Uttar Pradesh	33
Sonipat	Haryana	152
South 24 Parganas	West Bengal	89
Sultanpur	Uttar Pradesh	62
Supaul	Bihar	30
Unnao	Uttar Pradesh	72
Uttar Dinajpur	West Bengal	52

Vaishali	Bihar	48
Varanasi	Uttar Pradesh	106
West Medinipur	West Bengal	73
Yamunanagar	Haryana	138

**Rank 1 is the highest and 161 is the lowest vulnerability.*

Table 11. Vulnerability rank of different districts in the Indo-Gangetic Plains (Arranged according to vulnerability).

District	State	Vulnerability rank*
Sheohar	Bihar	1
Sitamarhi	Bihar	2
Madhubani	Bihar	3
Shrawasti	Uttar Pradesh	4
Purba Champaran	Bihar	5
Balrampur	Uttar Pradesh	6
Darbhanga	Bihar	7
Kishanganj	Bihar	8
Nawada	Bihar	9
Muzaffarpur	Bihar	10
Araria	Bihar	11
Banka	Bihar	12
Lakhisarai	Bihar	13
Saharsa	Bihar	14
Samastipur	Bihar	15
Jehanabad	Bihar	16
Katihar	Bihar	17
Mahoba	Uttar Pradesh	18
Pashchim Champaran	Bihar	19
Lalitpur	Uttar Pradesh	20
Gopalganj	Bihar	21
Madhepura	Bihar	22
Bahraich	Uttar Pradesh	23
Jamui	Bihar	24
Hamirpur	Uttar Pradesh	25
Siddharthnagar	Uttar Pradesh	26
Purnia	Bihar	27
Banda	Uttar Pradesh	28

Nalanda	Bihar	29
Supaul	Bihar	30
Murshidabad	West Bengal	31
Saran	Bihar	32
Sonbhadra	Uttar Pradesh	33
Kushinagar	Uttar Pradesh	34
Bhagalpur	Bihar	35
Sant Kabir Nagar	Uttar Pradesh	36
Chitrakoot	Uttar Pradesh	37
Buxar	Bihar	38
Munger	Bihar	39
Siwan	Bihar	40
Patna	Bihar	41
Maldah	West Bengal	42
Puruliya	West Bengal	43
Kaushambi	Uttar Pradesh	44
Mirzapur	Uttar Pradesh	45
Birbhum	West Bengal	46
Jaunpur	Uttar Pradesh	47
Vaishali	Bihar	48
Begusarai	Bihar	49
Deoria	Uttar Pradesh	50
Gonda	Uttar Pradesh	51
Uttar Dinajpur	West Bengal	52
Gaya	Bihar	53
Koch Bihar	West Bengal	54
Jhansi	Uttar Pradesh	55
Jalaun	Uttar Pradesh	56
Pratapgarh	Uttar Pradesh	57
Bhojpur	Bihar	58
Sant Ravidas Nagar	Uttar Pradesh	59
Dakshin Dinajpur	West Bengal	60
Gurgaon	Haryana	61
Sultanpur	Uttar Pradesh	62
Sheikhpura	Bihar	63
Bhiwani	Haryana	64
Khagaria	Bihar	65

Sitapur	Uttar Pradesh	66
Gorakhpur	Uttar Pradesh	67
Fatehpur	Uttar Pradesh	68
Aurangabad	Bihar	69
Jalpaiguri	West Bengal	70
Nadia	West Bengal	71
Unnao	Uttar Pradesh	72
West Medinipur	West Bengal	73
Hardoi	Uttar Pradesh	74
Basti	Uttar Pradesh	75
Azamgarh	Uttar Pradesh	76
Allahabad	Uttar Pradesh	77
Bankura	West Bengal	78
Mau	Uttar Pradesh	79
Kaimur (Bhabua)	Bihar	80
Ambedkar Nagar	Uttar Pradesh	81
Maharajganj	Uttar Pradesh	82
Budaun	Uttar Pradesh	83
Ballia	Uttar Pradesh	84
Lucknow	Uttar Pradesh	85
Mahendragarh	Haryana	86
Gautam Buddha Nagar	Uttar Pradesh	87
Faizabad	Uttar Pradesh	88
South 24 Parganas	West Bengal	89
Bareilly	Uttar Pradesh	90
Kheri	Uttar Pradesh	91
Barabanki	Uttar Pradesh	92
Darjiling	West Bengal	93
Rae Bareli	Uttar Pradesh	94
Faridabad	Haryana	95
Rohtas	Bihar	96
Bijnor	Uttar Pradesh	97
Farrukhabad	Uttar Pradesh	98
Chandauli	Uttar Pradesh	99
Moradabad	Uttar Pradesh	100
Rampur	Uttar Pradesh	101
E. Medinipur	West Bengal	102

Auraiya	Uttar Pradesh	103
North 24 Parganas	West Bengal	104
Etah	Uttar Pradesh	105
Varanasi	Uttar Pradesh	106
Firozabad	Uttar Pradesh	107
Ghazipur	Uttar Pradesh	108
Kanpur Dehat	Uttar Pradesh	109
Jhajjar	Haryana	110
Agra	Uttar Pradesh	111
Kanpur Nagar	Uttar Pradesh	112
Burdwan	West Bengal	113
Kannauj	Uttar Pradesh	114
Jyotiba Phule Nagar	Uttar Pradesh	115
Etawah	Uttar Pradesh	116
Hathras	Uttar Pradesh	117
Aligarh	Uttar Pradesh	118
Shahjahanpur	Uttar Pradesh	119
Howrah	West Bengal	120
Rewari	Haryana	121
Mainpuri	Uttar Pradesh	122
Hugli	West Bengal	123
Bulandshahr	Uttar Pradesh	124
Mathura	Uttar Pradesh	125
Rohtak	Haryana	126
Panipat	Haryana	127
Muzaffarnagar	Uttar Pradesh	128
Ghaziabad	Uttar Pradesh	129
Saharanpur	Uttar Pradesh	130
Meerut	Uttar Pradesh	131
Jind	Haryana	132
Pilibhit	Uttar Pradesh	133
Baghpat	Uttar Pradesh	134
Hisar	Haryana	135
Panchkula	Haryana	136
Sirsa	Haryana	137
Yamunanagar	Haryana	138
Ludhiana	Punjab	139

Kapurthala	Punjab	140
Jalandhar	Punjab	141
Muktsar	Punjab	142
Bathinda	Punjab	143
Gurdaspur	Punjab	144
Sangrur	Punjab	145
Amritsar	Punjab	146
Mansa	Punjab	147
Fatehabad	Haryana	148
Ambala	Haryana	149
Faridkot	Punjab	150
Rupnagar	Punjab	151
Sonipat	Haryana	152
Karnal	Haryana	153
Firozpur	Punjab	154
Patiala	Punjab	155
Kurukshetra	Haryana	156
Moga	Punjab	157
Fatehgarh Sahib	Punjab	158
Hoshiarpur	Punjab	159
Kaithal	Haryana	160
Nawanshahr	Punjab	161

**Rank 1 is the highest and 161 is the lowest vulnerability.*

Normalized vulnerability in different states of Indo-Gangetic Plains

The vulnerability is a relative term, which will differ when one compares district in the state against the same district in the whole IGP. The study was taken one step ahead towards determining vulnerability for each state separately. The vulnerability index was normalized on 0 to 1 scale for different districts of each State in study area and then the maps were prepared showing normalized vulnerability for each state.

The normalized vulnerability index was computed using following formula:

$$\text{Normalized Vulnerbility} = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad \ldots(8)$$

where, X is the value of vulnerability index of the district, X_{min} is the minimum vulnerability index in the particular State, X_{max} is the maximum vulnerability index in the particular State.

Fig. 32 shows the normalized vulnerability rating of districts of Bihar. The southern districts of Kaimur, Rohtas, Aurangabad and Khagaria had less than 0.25 normalized vulnerability index due to comparatively higher productivity and higher HDI. On the other hand, districts Purba Champaran, Madhubani, Sitamarhi and Sheohar were found to have extreme normalized vulnerability ranging between 0.8 and 1 because of low average land-holding size (high sensitivity) and low HDI (low adaptive capacity). Rest of the districts in Bihar were found under moderate to high normalized vulnerability ranging between 0.26 and 0.75.

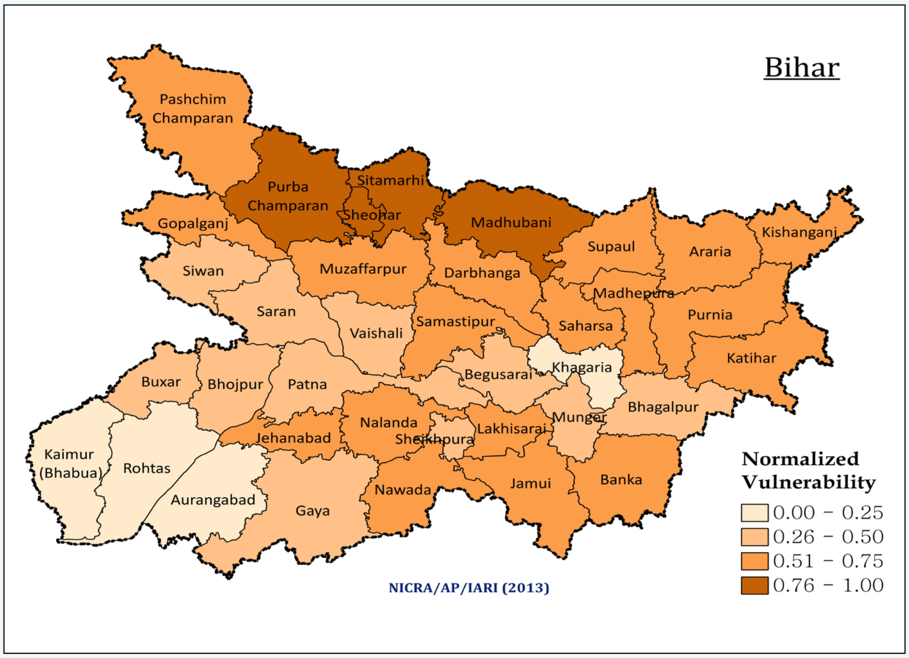

Fig. 32. Normalized vulnerability of agriculture to climate change in various districts of Bihar

The districts in northern half of Haryana had low normalized vulnerability (< 0.25) due to the higher HDI values in the districts (Fig. 33). The normalized vulnerability was higher in the southern districts of Faridabad, Mahendragarh, Bhiwani and Gurgaon (vulnerability ranging from 0.7 to 1.0) due to high population density and low HDI.

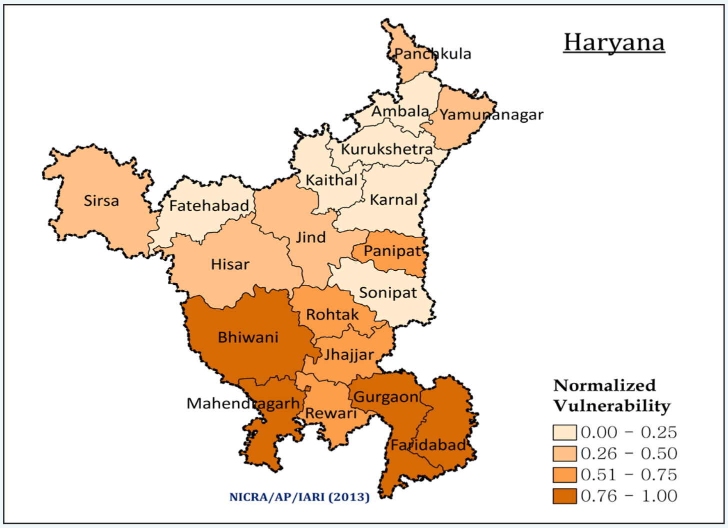

Fig. 33. Normalized vulnerability of agriculture to climate change in various districts of Haryana

The districts of Ludhiana, Kapurthala and Jalandhar in Punjab had extreme normalized vulnerability ranging between 0.7 and 1.0 due to higher population density (Fig. 34). On the other hand, Nawanshahar, Hosiarpur, Fatehgarh Sahib and Moga were least normalized vulnearble districts in Punjab. Rest of the state showed normalized vulnerability index ranging from 0.26 to 0.75.

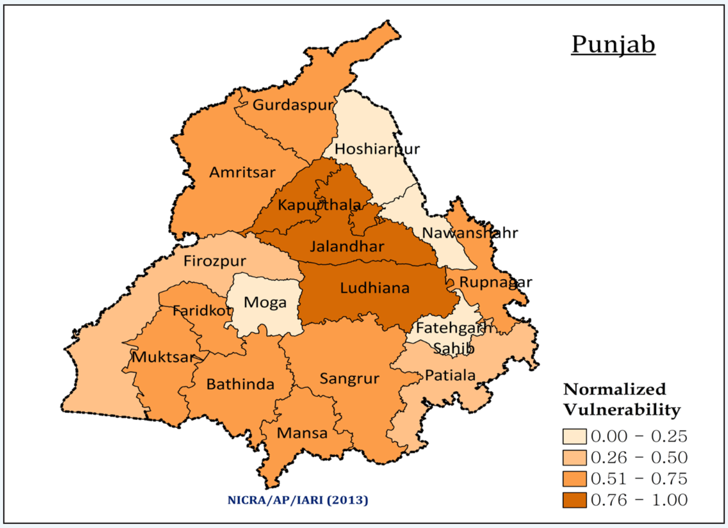

Fig. 34. Normalized vulnerability of agriculture to climate change in various districts of Punjab

The largest state of UP in the IGP had a heterogenous distribution of vulnerability among its districts (Fig. 35). The western border of Uttar Pradesh and couple of districts such as Pilibhit, Shahjahanpur, Mainpuri, Kannauj and Etawah had least normalized vulnerability index ranging from 0 to 0.25 because of higher adaptive capacity. The southern districts Mahoba, Lalitpur and Hamirpur and north-western districts Shrawasti, Balrampur, Bahraich and Siddharthnagar showed extreme normalized vulnerability index ranging between 0.7 and 1.0 due to low percent irrigated area, low HDI and high exposure.

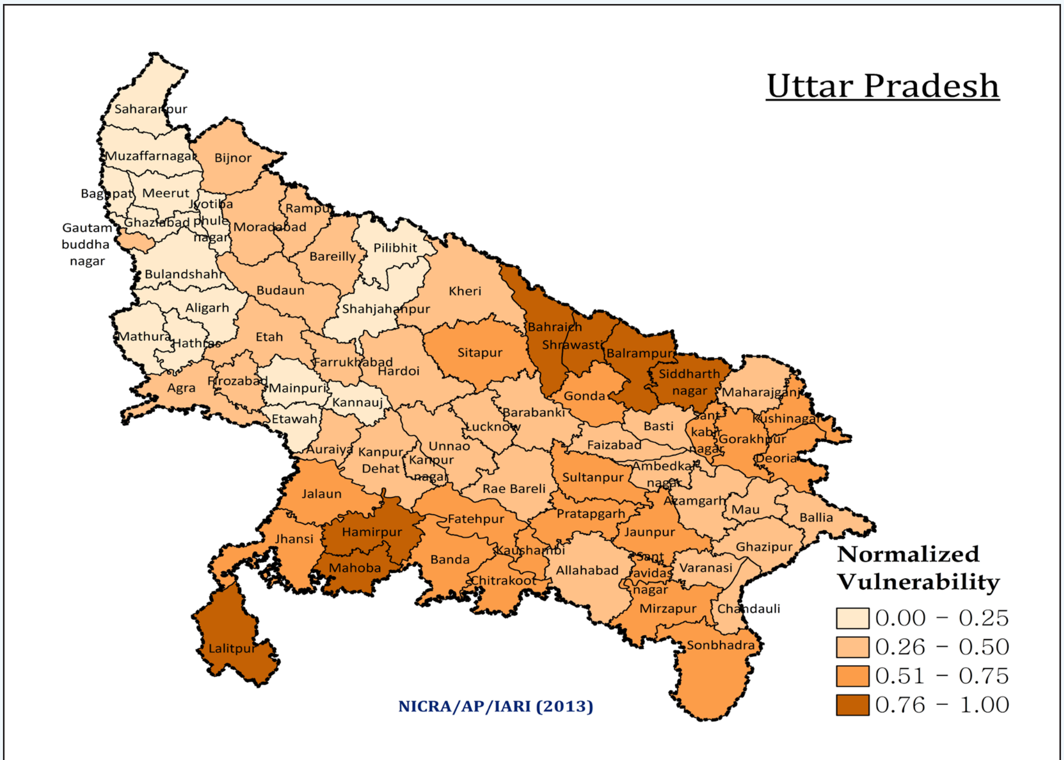

Fig. 35. Normalized vulnerability of agriculture to climate change in various districts of Uttar Pradesh

Only few districts in the state of West Bengal such as Burdwan, Hugli and Howrah showed low normalized vulnerability (Fig. 36). The central part of West Bengal comprising districts of Murshidabad, Maldah, Purulia and Birbhum showed high normalized vulnerability index ranging from 0.8 to 1.0 because of high exposure. Rest of the state had vulnerability index 0.26 to 0.75.

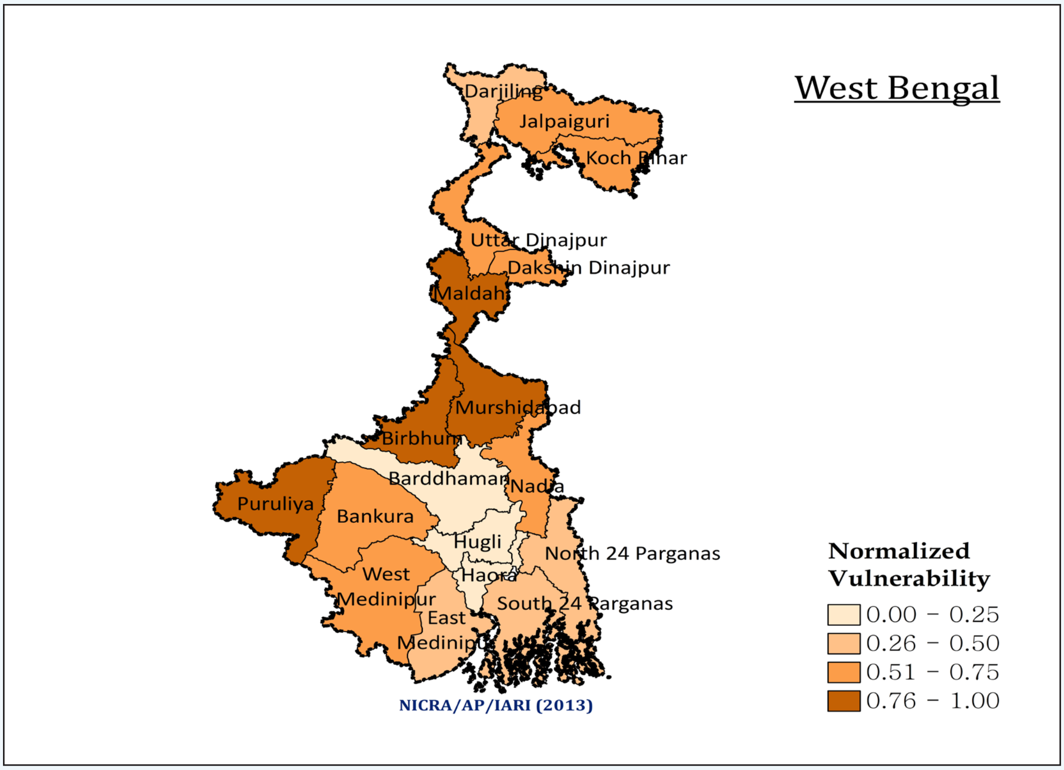

Fig. 36. Normalized vulnerability of agriculture to climate change in various districts of West Bengal

Correlation among the components of vulnerability

Correlation among the three components of vulnerability was analyzed to understand their relationship. The parameter values at district level were used as observations in carrying out this correlation analysis. Exposure and sensitivity were positively related (R^2=0.25) (Fig. 37) while exposure and sensitivity with adaptive capacity were inversely related (R^2=0.41 and 0.12) (Fig. 38 and 39). The districts experiencing high exposure and having high sensitivity or/and high exposure with low adaptive capacity should be targeted on priority for undertaking climate change adaptation measures.

Exposure and sensitivity were positively correlated with vulnerability (R^2=0.61 and 0.45, respectively) (Fig. 40 and 41) whereas a negative correlation of vulnerability with adaptive capacity was observed (Fig. 42). As the relative weight of adaptive capacity was highest among compnents, so a high correlation was observed with vulnerability.

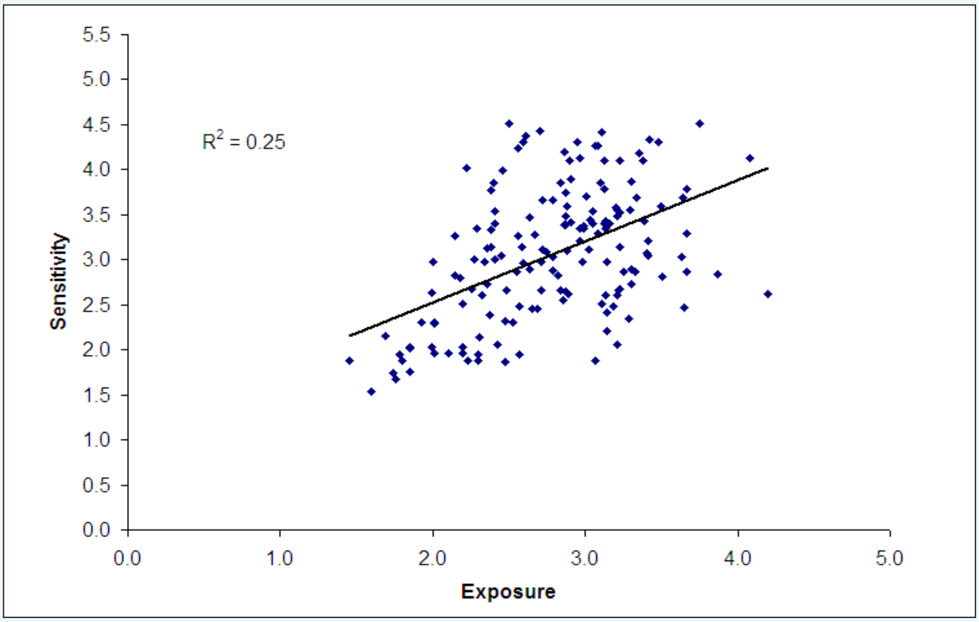

Fig. 37. Correlation between exposure and sensitivity in various districts of the Indo-Gangetic Plains

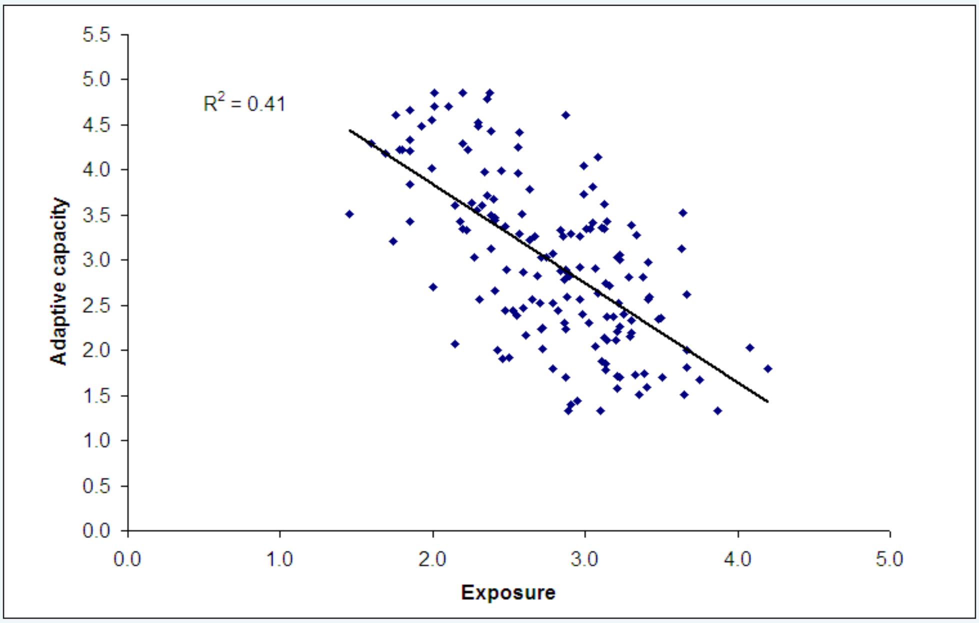

Fig. 38. Correlation between exposure and adaptive capacity in various districts of the Indo-Gangetic Plains

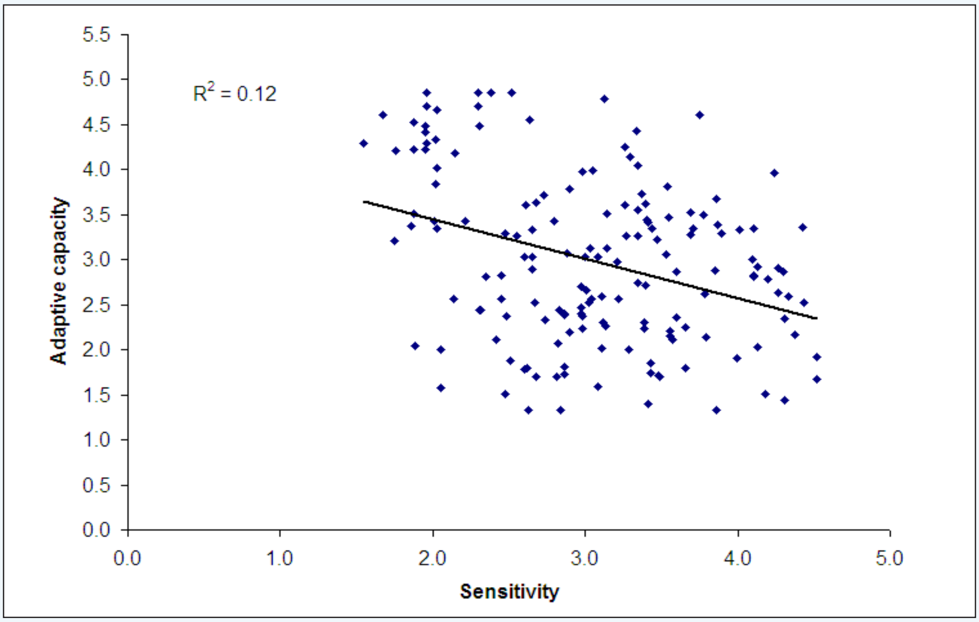

Fig. 39. Correlation between sensitivity and adaptive capacity in various districts of the Indo-Gangetic Plains

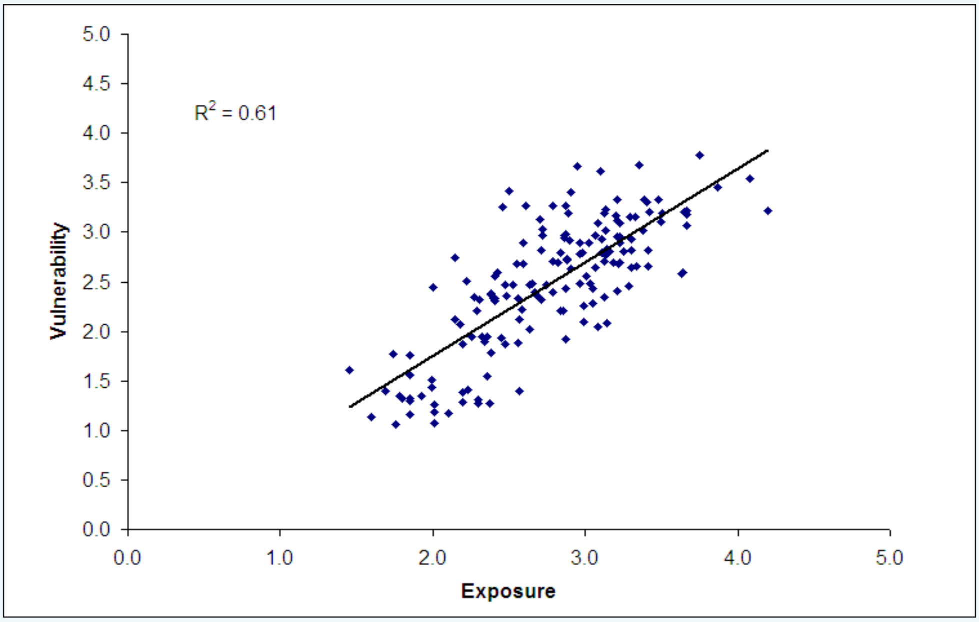

Fig. 40. Correlation between exposure and vulnerability in various districts of the Indo-Gangetic Plains

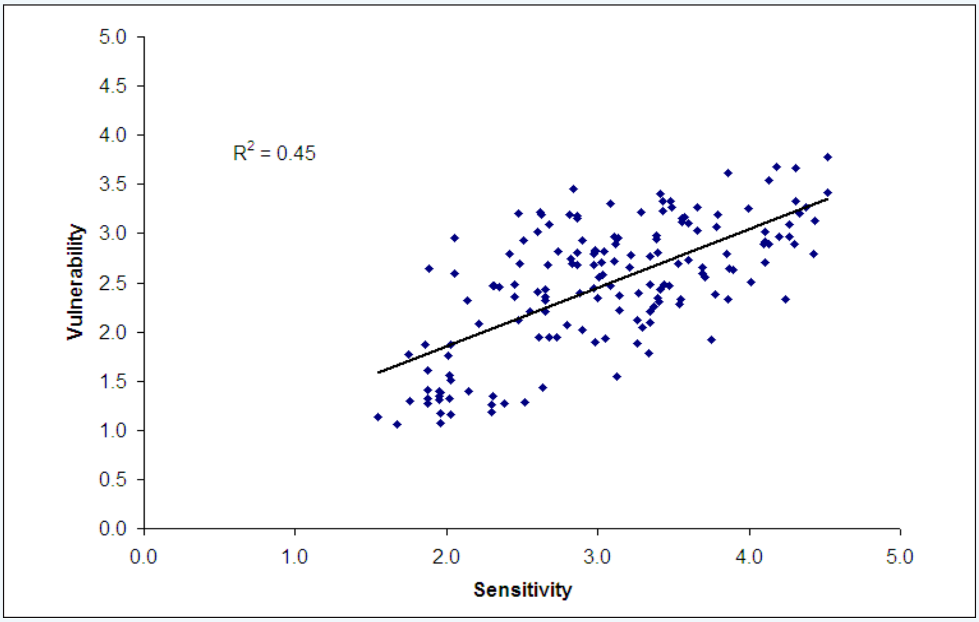

Fig. 41. Correlation between sensitivity and vulnerability in various districts of the Indo-Gangetic Plains

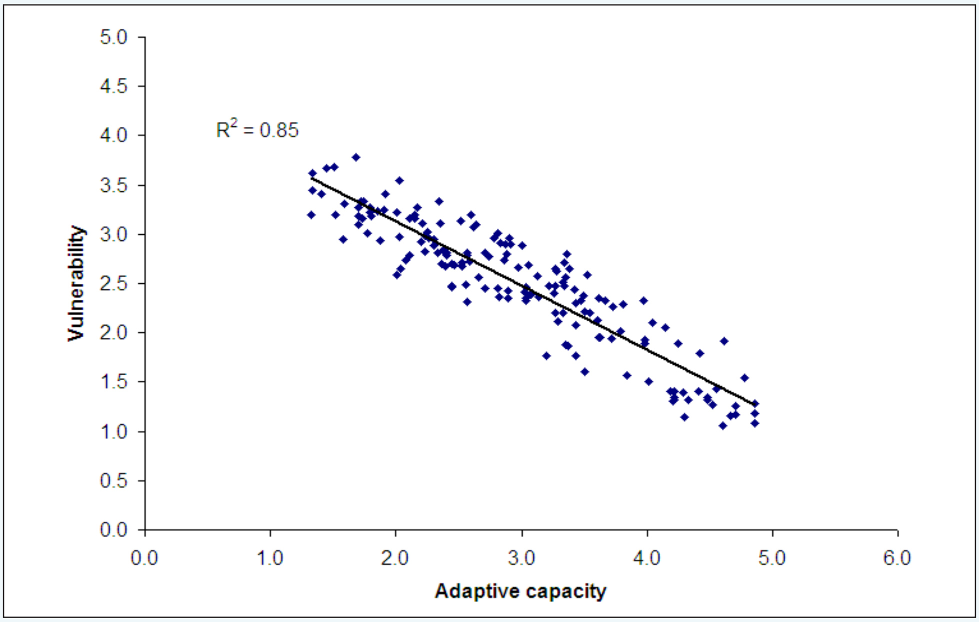

Fig. 42. Correlation between adaptive capacity and vulnerability in various districts of the Indo-Gangetic Plains

Conclusions

Agriculture is crucial for food, nutritional and livelihood security of people of India. It engages almost two-third of the workforce in gainful employment and accounts for a significant share in national gross domestic product (GDP). Indian agriculture has made significant progress during the past five decades or so and has become a self-sufficient nation from the status of food-importing country. However, it is presently facing several challenges like stagnating net sown area, plateauing yield levels, deteriorating soil health, reducing per capita land availability etc. Additionally a new challenge is of vulnerability of agriculture to climate change.

Adaptation to climate change can reduce many of its adverse impacts and can lead to enhanced benefits. The key features of climate change vulnerability and adaptation are related to variability and extremes. The limited economic resources, information and skills, poor infrastructure and insufficient levels of technology make the developing countries like India inadequate to adapt and highly vulnerable. Enhancement of adaptive capacity is necessary for reducing vulnerability to climate changes encountered in the frequency and intensity of extreme events, like floods and droughts which have deep impact on agriculture and livelihood.

The IGP is one of the most populous and productive agricultural ecosystems in the world. This study provides support to the decision makers at all stages of decision making to identify the vulnerable districts of the IGP. The districts, which are most vulnerable to climate change, need policies on a higher priority. The results will be useful for stakeholders such as farmers, policy makers and technical advisors, the scientific community and traders for targeting financial resources and better management of resources towards adaptive capacity. The states of Bihar, some districts of Uttar Pradesh and West Bengal were found most vulnerable to climate change. In the regions, which are highly vulnerable, policy makers should enact measures to support effective management of environmental resources (e.g., soil, vegetation and water resources); promote increased market participation, especially within the large subsistence farming sector; stimulate both agricultural intensification and diversification of livelihoods away from risky agriculture; and enact social programs and spending on health, education and welfare, which can help in maintaining and augmenting both physical and intangible human capital. Finally, investment should be made in the development of infrastructure in rural areas, and in high exposure regions, priority should be given to the development of more accurate systems for early warning of extreme climatic events (e.g., drought or flood) apart from appropriate relief programs and agricultural insurance. In addition to the usefulness of the study for policy makers and stakeholders, the study is expected to act as a baseline to further improve the methodologies for assessing vulnerability of agriculture to climate change.

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Annexure - 1

Calculated values of expsoure, sensitivity, adaptive capacity, composite vulnerability and normalized vulnerability (state-wise) for all the study districts.

District	Exposure	Sensitivity	Adaptive capacity	Composite vulnerability	Normalized vulnerability
		Bihar			
Sheohar	3.75	4.52	1.68	3.78	1.00
Sitamarhi	3.35	4.18	1.5	3.68	0.93
Madhubani	2.94	4.31	1.44	3.67	0.92
Purba Champaran	4.08	4.13	2.03	3.55	0.83
Darbhanga	2.5	4.52	1.92	3.41	0.73
Kishanganj	2.9	3.41	1.4	3.4	0.72
Nawada	3.38	3.43	1.74	3.33	0.67
Muzaffarpur	3.48	4.31	2.34	3.33	0.67
Araria	3.21	3.48	1.72	3.33	0.67
Banka	3.4	3.08	1.59	3.3	0.65
Lakhisarai	2.87	3.48	1.7	3.27	0.63
Saharsa	2.79	3.66	1.79	3.27	0.62
Samastipur	2.61	4.38	2.17	3.27	0.62
Jehanabad	2.46	3.99	1.91	3.25	0.61
Katihar	3.14	3.43	1.86	3.23	0.60
Pashchim Champaran	4.2	2.62	1.8	3.22	0.59
Gopalganj	3.42	4.33	2.6	3.2	0.57
Madhepura	3.12	3.79	2.15	3.2	0.57
Jamui	3.51	2.82	1.7	3.19	0.56
Purnia	3.3	3.56	2.15	3.16	0.54
Nalanda	2.7	4.43	2.52	3.13	0.52
Supaul	3.21	3.56	2.21	3.11	0.51
Saran	3.08	4.26	2.64	3.09	0.50
Bhagalpur	2.72	3.66	2.25	3.03	0.44
Buxar	2.88	3.39	2.23	2.98	0.41
Munger	2.72	3.11	2.02	2.97	0.40
Siwan	3.07	4.27	2.9	2.96	0.40
Patna	2.86	4.2	2.78	2.96	0.40
Vaishali	2.59	4.3	2.87	2.9	0.35
Begusarai	2.97	4.13	2.92	2.89	0.35

Gaya	2.72	2.98	2.23	2.82	0.29
Bhojpur	2.84	3.85	2.88	2.8	0.27
Sheikhpura	3.14	3.34	2.74	2.77	0.25
Khagaria	2.88	3.6	2.86	2.74	0.23
Aurangabad	2.82	2.83	2.44	2.69	0.20
Kaimur (Bhabua)	2.43	2.06	2	2.59	0.12
Rohtas	2.88	2.65	2.9	2.43	0.00
Haryana					
Gurgaon	3.14	2.42	2.11	2.79	1.00
Bhiwani	2.15	2.82	2.08	2.74	0.97
Mahendragarh	2.65	2.45	2.56	2.48	0.82
Faridabad	3.05	3.41	3.42	2.44	0.79
Jhajjar	2.31	2.14	2.56	2.32	0.72
Rewari	3.14	2.21	3.43	2.08	0.58
Rohtak	2.32	2.61	3.61	1.95	0.51
Panipat	2.36	2.73	3.72	1.94	0.50
Jind	2.2	2.03	3.35	1.88	0.47
Hisar	1.74	1.75	3.2	1.77	0.41
Panchkula	1.85	2.01	3.43	1.76	0.40
Sirsa	1.46	1.88	3.51	1.61	0.31
Yamunanagar	1.85	2.02	3.84	1.56	0.28
Fatehabad	1.8	1.88	4.22	1.32	0.14
Ambala	1.85	2.02	4.33	1.32	0.14
Sonipat	2.2	2.51	4.85	1.28	0.12
Karnal	2.37	2.38	4.85	1.28	0.12
Kurukshetra	2.01	2.3	4.85	1.18	0.06
Kaithal	2.01	1.96	4.85	1.08	0.00
Punjab					
Ludhiana	2.36	3.13	4.78	1.54	1.00
Kapurthala	1.99	2.03	4.02	1.5	0.92
Jalandhar	1.99	2.64	4.56	1.43	0.77
Muktsar	2.23	1.88	4.22	1.41	0.72
Bathinda	2.57	1.95	4.41	1.4	0.71
Gurdaspur	1.69	2.15	4.18	1.4	0.71
Sangrur	2.2	1.96	4.29	1.39	0.68
Amritsar	1.92	2.3	4.48	1.35	0.60
Mansa	1.78	1.95	4.22	1.34	0.58
Faridkot	2.3	1.95	4.48	1.31	0.53
Rupnagar	1.85	1.76	4.2	1.3	0.50

Firozpur	2.3	1.88	4.52	1.27	0.44
Patiala	2.01	2.3	4.71	1.25	0.40
Moga	2.1	1.96	4.71	1.17	0.22
Fatehgarh Sahib	1.85	2.03	4.67	1.16	0.20
Hoshiarpur	1.6	1.54	4.3	1.14	0.17
Nawanshahr	1.76	1.67	4.61	1.06	0.00
Uttar Pradesh					
Shrawasti	3.1	3.86	1.34	3.61	1.00
Balrampur	3.87	2.84	1.34	3.45	0.91
Mahoba	3.67	3.29	2	3.22	0.78
Lalitpur	3.65	2.47	1.51	3.2	0.77
Bahraich	2.89	2.63	1.32	3.2	0.77
Hamirpur	3.67	2.86	1.8	3.19	0.77
Siddharthnagar	3.2	3.57	2.11	3.16	0.75
Banda	3.33	2.86	1.73	3.16	0.75
Sonbhadra	3.23	2.68	1.7	3.09	0.71
Kushinagar	3.67	3.78	2.62	3.07	0.70
Sant Kabir Nagar	3.38	4.1	2.82	3.02	0.67
Chitrakoot	3.13	2.6	1.78	3.01	0.67
Kaushambi	2.87	3.39	2.31	2.94	0.63
Mirzapur	3.11	2.51	1.87	2.93	0.63
Jaunpur	2.9	4.1	2.83	2.92	0.62
Deoria	3.23	4.1	3.01	2.89	0.60
Gonda	3.02	3.11	2.31	2.89	0.60
Jhansi	3.31	2.73	2.33	2.81	0.56
Jalaun	3.25	2.86	2.41	2.81	0.56
Pratapgarh	3.16	3.4	2.71	2.81	0.56
Sant Ravidas Nagar	3.11	4.42	3.36	2.79	0.55
Sultanpur	2.96	3.22	2.56	2.78	0.55
Sitapur	2.88	3.1	2.59	2.72	0.51
Gorakhpur	3.13	4.1	3.34	2.71	0.50
Fatehpur	2.79	3.03	2.53	2.71	0.50
Unnao	2.59	2.97	2.46	2.68	0.49
Hardoi	2.55	2.86	2.39	2.68	0.49
Basti	3.41	3.21	2.98	2.66	0.48
Azamgarh	3.34	3.69	3.27	2.65	0.47
Allahabad	3.31	3.87	3.38	2.65	0.47
Mau	2.91	3.89	3.29	2.63	0.46
Ambedkar Nagar	3.64	3.69	3.53	2.59	0.44

Maharajganj	3.63	3.03	3.12	2.58	0.43
Budaun	2.41	3	2.66	2.56	0.42
Ballia	3.01	3.71	3.35	2.56	0.42
Lucknow	2.22	4.01	3.33	2.51	0.39
Gautam Buddha Nagar	3.04	3.44	3.34	2.48	0.38
Faizabad	2.96	3.35	3.27	2.48	0.38
Bareilly	2.64	3.47	3.22	2.47	0.38
Kheri	2.48	2.32	2.44	2.47	0.37
Barabanki	2.74	3.09	3.04	2.47	0.37
Rae Bareli	2	2.97	2.71	2.45	0.36
Bijnor	3.21	2.6	3.03	2.41	0.34
Farrukhabad	2.67	3.27	3.26	2.4	0.33
Chandauli	2.78	2.88	3.08	2.39	0.33
Moradabad	2.39	3.77	3.5	2.38	0.33
Rampur	2.39	3.15	3.13	2.37	0.32
Auraiya	2.48	2.65	2.89	2.35	0.31
Etah	2.27	3	3.04	2.35	0.31
Varanasi	2.56	4.24	3.97	2.33	0.30
Firozabad	2.4	3.54	3.47	2.33	0.29
Ghazipur	2.4	3.86	3.67	2.33	0.29
Kanpur Dehat	2.71	2.65	3.04	2.32	0.29
Agra	2.4	3.41	3.44	2.3	0.28
Kanpur Nagar	3.05	3.54	3.81	2.29	0.27
Kannauj	2.58	3.14	3.51	2.22	0.23
Jyotiba Phule Nagar	2.86	2.55	3.27	2.21	0.23
Etawah	2.84	2.65	3.33	2.21	0.23
Hathras	2.29	3.35	3.55	2.2	0.23
Aligarh	2.15	3.26	3.6	2.12	0.18
Shahjahanpur	2.57	2.48	3.29	2.12	0.18
Mainpuri	2.18	2.8	3.43	2.07	0.16
Bulandshahr	2.64	2.9	3.79	2.02	0.12
Mathura	2.26	2.68	3.63	1.95	0.09
Muzaffarnagar	2.45	3.05	3.99	1.93	0.08
Ghaziabad	2.87	3.75	4.61	1.92	0.07
Saharanpur	2.34	2.98	3.98	1.89	0.06
Meerut	2.56	3.26	4.25	1.89	0.05
Pilibhit	2.48	1.86	3.38	1.87	0.04
Baghpat	2.38	3.34	4.42	1.79	0.00

West Bengal					
Murshidabad	3.5	3.6	2.35	3.11	1.00
Maldah	3.23	3.14	2.26	2.96	0.86
Puruliya	3.21	2.05	1.58	2.95	0.85
Birbhum	3.3	2.89	2.2	2.93	0.83
Uttar Dinajpur	3.14	2.98	2.38	2.84	0.74
Koch Bihar	3.41	3.04	2.56	2.82	0.72
Dakshin Dinajpur	2.99	2.98	2.4	2.79	0.70
Jalpaiguri	3.19	2.48	2.37	2.69	0.61
Nadia	3.23	3.53	3.06	2.69	0.60
West Medinipur	3.22	2.67	2.53	2.68	0.59
Bankura	3.07	1.88	2.04	2.64	0.56
South 24 Parganas	2.53	2.31	2.44	2.47	0.40
Darjiling	3.28	2.35	2.81	2.45	0.38
E. Medinipur	2.69	2.45	2.83	2.36	0.29
North 24 Parganas	3.12	3.4	3.62	2.35	0.28
Burdwan	2.99	3.37	3.73	2.26	0.20
Howrah	2.99	3.34	4.04	2.1	0.05
Hugli	3.08	3.29	4.14	2.05	0.00

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