VULNERABILITY OF PEOPLE OF MADHYA PRADESH TO CLIMATE CHANGE: A MESO-LEVEL ANALYSIS

Ph.D. Thesis

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DISCIPLINE OF ECONOMICS
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VULNERABILITY OF PEOPLE OF MADHYA PRADESH TO CLIMATE CHANGE: A MESO-LEVEL ANALYSIS

A THESIS

Submitted in partial fulfillment of the requirements for the award of the degree
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ALINDA GEORGE

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I hereby certify that the work which is being presented in the thesis entitled **VULNERABILITY OF PEOPLE OF MADHYA PRADESH TO CLIMATE CHANGE: A MESO-LEVEL ANALYSIS** in the partial fulfillment of the requirements for the award of the degree of **DOCTOR OF PHILOSOPHY** and submitted in the **SCHOOL OF HUMANITIES AND SOCIAL SCIENCES, Indian Institute of Technology Indore**, is an authentic record of my own work carried out during the time period from July 2017 to June 2024 under the supervision of Dr. Pritee Sharma, Professor, Indian Institute of Technology Indore

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

25/6/2024

Signature of the student with date

Alinda George

This is to certify that the above statement made by the candidate is correct to the best of my/our knowledge.

Pritee Sharma 28.6.2024

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Alinda George has successfully given his/her Ph.D. Oral Examination held on ..28/6/2024

Pritee Sharma 28.6.2024

Signature of Thesis Supervisor #1 with date

Prof. Pritee Sharma

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Alinda George

Dedicated to

the four pillars of my life:

Pappa, Mummy

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SYNOPSIS

Vulnerability of People of Madhya Pradesh to Climate Change: A Meso-level Analysis

Introduction

The state of Madhya Pradesh has higher exposure to changes in climatic variables, as evident from historical changes in climatic parameters and the projections by various researchers. National level studies on vulnerability to climate change in India have identified state of Madhya Pradesh, as well as its districts, as highly vulnerable to climate change due to several factors like high climate sensitivity, high population growth rate, higher share of marginalized communities and marginal workers, high dependence on agriculture, high unemployment rate, high poverty, lack of education and basic civic amenities (O' Brien et al., 2004b; Sharma et al., 2015b; Chakraborty & Joshi, 2016; Sendhil et al., 2018). The projected changes in climatic conditions in the next couple of decades and the higher vulnerability condition identified in Madhya Pradesh in the literature (Das,2013; Yenneti et al.,2016; Azhar et al.,2017) make a detailed study of vulnerability to climate change a necessity in this state.

Most national-level vulnerability assessments have attributed social vulnerability as the major reason for vulnerability to different stressors in Madhya Pradesh. However, there is no consensus regarding drivers of vulnerability, as the study context differs in each study. As social vulnerability or contextual vulnerability is the internal property of a population, irrespective of the stressor, a detailed study of the reasons contributing to their vulnerability needs to be understood. This requires comparing the social vulnerability of the Madhya Pradesh population with the population of other states. Also, the factors contributing to social vulnerability need to be understood to identify what makes the state population more vulnerable than other states of India.

The projected changes in climatic conditions in the next couple of decades and the higher social vulnerability condition identified in Madhya Pradesh in the literature make an integrated assessment of vulnerability to climate change necessary in this state. As biophysical and social vulnerability has dynamic properties, an assessment of their spatiotemporal pattern is needed to understand whether climate change vulnerability increases or decreases over time. The factors contributing to the change must be identified to facilitate targeted interventions to reduce vulnerability.

The benefits of economic growth of Madhya Pradesh remain concentrated in certain pockets of the state, as is evident from the higher rural-urban disparities prevailing in the state. As per the Census of India (2011), the ratio of rural to urban population in Madhya Pradesh is 72:28. There exist considerable disparities between these rural and urban areas in access to water and sanitation facilities, poverty ratio, literacy rate, etc. (Chaudhuri & Roy, 2017; IIPS & ICF,2017; GoMP,2015; Chaurasia,2011; Chaubey & Chaubey,1998). In the context of the increasing impacts of climate change, the disparities can accentuate vulnerabilities in some areas. Moreover, rural and urban Madhya Pradesh has been identified as highly vulnerable to climate change in studies like Yenneti et al. (2016) & Rao et al. (2016). Due to the high disparities and identification of both areas as highly vulnerable, an assessment of the spatiotemporal pattern of social vulnerability is essential in rural as well as urban areas of Madhya Pradesh.

The state is characterized by a large share of natural resources, and historically, a large part of the population had been dependent on these resources for livelihood. 70% of the working population in Madhya Pradesh depends on agriculture as cultivators and labourers. Though agriculture sector of the state performs better than many other Indian states due to an increase in irrigated area, increased power supply for agriculture, increased agricultural mechanization, development of road network, effective procurement mechanism and Minimum Support Price for wheat (Gulati et al., 2021), the performance is not even across the state. Regional disparities in land distribution, land use patterns, cropping patterns, access to inputs like fertilizers, irrigation, and mechanization, as well as increased government support towards commercialization, have resulted in the uneven development of this sector. (Singh et al.,2018; Dutta et al.,2020; Shevalkar,2020). The high share of rainfed cultivation, high fragmentation of landholding, lower access to credit, low investment capacity and lack of reach of extension services among tribal farmers, who constitute a major share of farmers in Madhya Pradesh, also add to the issues in the agricultural sector in the state. These existing issues compound with changes in climatic parameters and their extremes, resulting in adverse impacts. Hence, identifying major factors contributing to climate change vulnerability of this sector is necessary to reduce the state's overall vulnerability to climate change. Also, identifying the pattern of vulnerability and its subcomponents is essential to understand the sector's vulnerability changes over time.

Madhya Pradesh is commonly known as the tribal state of India, as it has the highest share of the tribal population in India (14.64%, as per GoI (2011). 21% of the population of the state belongs to Scheduled Tribes (ST), and 16% to Scheduled Castes (SC). These social groups are characterized by a high concentration of poverty, low educational attainments, low infrastructural access and primitive modes of agriculture. 73% of SC and 93% of ST live in rural areas, and their basic social, institutional and infrastructural facilities are very low. If the historical and projected changes in climate in the state are compounded by the poorest socioeconomic characteristics, lower infrastructural facilities, low asset base, and primitive mode of agriculture of these social groups, it can lead to loss of livelihood and income and may result in acute poverty. This necessitates the identification of the vulnerability of these social groups to climate change and the formulation of policy measures to reduce it.

Literature Review and identification of research gap

Studies that assess generic social vulnerability at the district level for the whole of India are limited. Vittal et al. (2020) first attempted district-level vulnerability of whole districts of India but suffers from the limited coverage of variables. Vittal et al. (2020) and Das et al. (2021) used the inductive approach to construct vulnerability indices. However, aggregating all dimensions of social vulnerability to a single index may mask the areas where the actual focus is required. Holand et al. (2011) segregated social vulnerability into the socioeconomic vulnerability index and built environment vulnerability index to avoid the issues of a single index. Mazumdar & Paul (2016) attempted this classification in India, but their study is confined to eastern coastal states, and a nationwide application is not attempted.

The studies assessing vulnerability to climate change in India through an integrated approach mainly follow the IPCC Third Assessment definition, i.e., vulnerability as the function of exposure, sensitivity and adaptive capacity (Bahinipati, 2011; Tripathi,2014; Jeganathan et al.,2021). The district-level vulnerability analysis conducted in Madhya Pradesh (MPSKMCCC, 2018) also used the IPCC approach. This model suffers from the segregation of variables into different subindices, and this definition has undergone modification in recent assessment reports. These differences in the definition of vulnerability in the IPCC report and the inability of this framework to identify major drivers of vulnerability constrain its usage in vulnerability assessment. Though the Livelihood Vulnerability framework of Hahn et al. (2009) is very suitable for assessing vulnerability to climate change, the lack of secondary data constrains its usage at higher scales of analysis like district, state etc. At the same time, the place-based vulnerability assessments based on the Hazard of Place model have the advantage of application in any scale of analysis. This model integrates biophysical and social vulnerability and creates subindices for both vulnerabilities, along with the overall vulnerability index. Though this model is used in vulnerability studies in other countries, it is not applied in the Indian context.

The concept of vulnerability is dynamic and context-specific. However, the studies on vulnerability to climate change generally consider vulnerability at a particular point in time only (Maiti et al., 2015; Jeganathan et al.,2021; Menezes et al.,2018). A temporal assessment of vulnerability can capture the dynamics of the community over time and can track the progress in reducing social inequalities which cause vulnerability (Mavhura et al., 2017). The spatiotemporal studies in different countries (Cutter & Finch,2008; Frigerio et al.,2018; Santos et al.,2022, Das et al.,2021) tried to assess generic social vulnerability to multiple hazards, but this is not attempted for integrated vulnerability approaches which include climatic variables. The rural-urban divide in development planning in India resulted in huge disparities in the patterns of livelihood and access to basic amenities (IIPS & ICF,2017; Chaudhuri & Roy,2017), which led to considerable disparities in coping capacities and rendered the rural population more socially vulnerable to stressors like climate change. Attempts on rural-urban disparity focused only on the social vulnerability dimension (Ge et al.,2021; Wang et al.,2022), and biophysical vulnerability was not considered. Though studies on rural or urban vulnerability to climate change (Rao et al.,2016; Yenneti et al.,2016) exist in India, there is a gap in the literature comparing rural and urban areas at each spatial unit of analysis.

The agriculture sector in India is highly vulnerable to climate change due to the high share of rainfed cultivation, land fragmentation and dominance of small and marginal farmers. Assessments of agricultural vulnerability in India are generally static in nature (Das,2013; Rao et al.,2013). Though Palanisami et al. (2008) attempted to assess the vulnerability of agroclimatic regions for three decades, indices are constructed separately for each decade, and only the ranks of study units are compared. Also, identifying significant contributors is impossible due to simple averaging. Jha & Gundimeda (2019) attempted to identify the major factors contributing to exposure, sensitivity and adaptive capacity through factor analysis, while assessing vulnerability to floods using IPCC approach. But the study was conducted for only one point in time. Assessment of the spatiotemporal pattern of the three subcomponents of vulnerability can identify the changes in each subcomponent over time and the contribution of change of each subcomponent to changes in the agricultural vulnerability index. However, it is not attempted in vulnerability studies in India and other countries.

Marginalized sections of an economy are generally more vulnerable to climate change as their higher social vulnerability due to political and social identities, excessive dependence on natural resource-dependent sectors and limited access to basic facilities compounds with adverse climate in their places of residence. Though vulnerability studies in India identified districts with more marginalized sections as highly vulnerable to climate change (Azhar et al.,2017; Mishra,2015; Bahinipati,2014), a study on these social groups is not conducted in India. In global vulnerability literature and Indian literature, the vulnerability of specific communities like farmers, fishing communities etc., are addressed (Sahana et al.,2021; Huynh & Stringer,2018). But an assessment of differentiated vulnerability among social groups is lacking and is urgently needed in states like Madhya Pradesh, where disparities among social groups are very high.

Research Questions and Objectives

This study tries to answer the following research questions:

1. How far population in MP is socially vulnerable when compared to other states of India?

2. a) Is the vulnerability to climate change in MP increasing or decreasing?

   b) Is rural and urban vulnerability to climate change decreasing simultaneously?

3. Whether the vulnerability of the agriculture sector to climate change is increasing or decreasing, and what contributes to its vulnerability?

4. Why are marginalised sections of the population more vulnerable to climate change?

To address these questions, the following objectives are set for this thesis.

- To assess the social vulnerability of districts of Madhya Pradesh in comparison to other districts of India.
- To identify the spatiotemporal pattern of the vulnerability of districts of Madhya Pradesh to climate change and to identify the role of rural-urban disparities in vulnerability to climate change.
- To assess the spatiotemporal vulnerability of the agriculture sector in Madhya Pradesh to climate change.
- To compare the vulnerability to climate change among social groups in Madhya Pradesh districts (SC, ST and Non SC/ST)

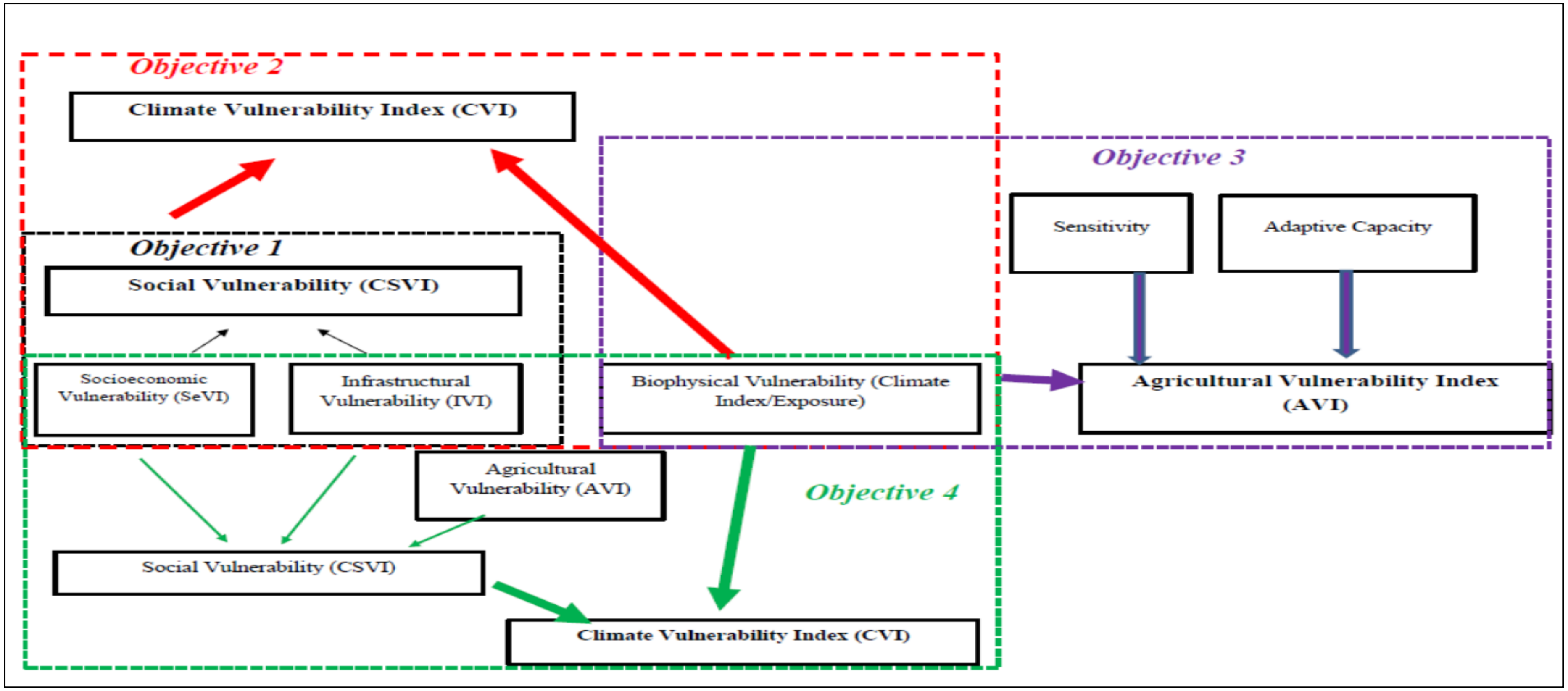
Data and Methodology

The study involves quantifying the vulnerability of Madhya Pradesh districts by preparing vulnerability indices. The subindices of vulnerability to climate change are prepared using inductive approach and averaged with weightage to construct the climate vulnerability index. The study is conducted at the district level, as it is the smallest unit for administrative purposes and implementation of any targeted interventions. As three out of four objectives assess the vulnerability of the district population, the Census of India is used as the major data source. Agricultural Census and ICRISAT district-level database and IWRIS database are also used as data sources in the study. The study mainly uses Principal Component Analysis during the construction of vulnerability indices. Spatial autocorrelation techniques like Moran's I and LISA (Local Indicators of Spatial Autocorrelation) are also used in two objectives to identify the spatial clustering of vulnerability.

As the first objective of this study deals with the assessment of the generic social vulnerability of the population, it adapts the Social Vulnerability Index developed by Cutter et al. (2003). It assesses the social vulnerability of all districts of India using a Composite Social Vulnerability Index constructed out of two subindices: the Socioeconomic Vulnerability Index (SeVI) and the Infrastructural Vulnerability Index (IVI) for each district of India. The second objective deals with the climate change vulnerability of the Madhya Pradesh population for three decades. Hence, it uses a place-based vulnerability approach initially developed from the Hazard of Place model of Cutter et al. (1996). In this objective, Climate Vulnerability Index is constructed as a weighted average of the Climate Index and Composite Social Vulnerability Index. Composite Social Vulnerability Index, in turn, is an aggregate of the Socioeconomic Vulnerability Index and Infrastructural Vulnerability Index. The first part of this objective aims to assess the spatiotemporal pattern of vulnerability to climate change by preparing Climate Vulnerability Index and its subindices for districts of Madhya Pradesh for three decades (1991,2001, and 2011). The second part of this objective tries to understand whether climate change vulnerability differs in rural and urban areas of Madhya Pradesh. Hence, Climate Vulnerability Index and its subindices have been prepared for rural and urban areas for three decades (1991,2001 and 2011).

In contrast to the first two objectives, which deal with the vulnerability of the population, the third objective deals with the vulnerability of a particular sector, viz. agriculture sector of Madhya Pradesh. As vulnerability in the agriculture sector is conceptualised as what is left behind after adaptation, the framework of vulnerability used in the third assessment report of

IPCC is used in this objective and Agricultural Vulnerability Index is constructed out of subindices: Exposure Index, Sensitivity Index and Adaptive Capacity Index. As this objective also deals with spatiotemporal assessment, AVI and subindices are prepared for five decades (1970-1979,1980-1989,1990-1999,2000-2009 and 2010-2015).



Source: Author's preparation

Figure 1 Conceptual framework of thesis

In the fourth objective, place-based vulnerability is used, and the climate vulnerability index is prepared for three social groups, viz. SC, ST and Non-SC/ST in Madhya Pradesh. As agriculture is the primary source of livelihood for marginalised social groups such as SC & ST, the composite social vulnerability index contains a subindex for agricultural vulnerability along with socioeconomic and infrastructural vulnerability indices.

Major findings

1. The socioeconomic and infrastructural vulnerability of the Indian population is concentrated more in bigger states, especially the Empowered Action Group States, to which Madhya Pradesh belongs (Chapter 4).
2. The central zone of India, where Madhya Pradesh is located, possesses the second highest socioeconomic and infrastructural vulnerability compared to other zones of India (Chapter 4).
3. Socioeconomic vulnerability is more pronounced in districts of Indian states or union territories, as evident from the higher number of districts and population share under the very high vulnerability category. However, when districts of Madhya Pradesh are considered alone, more districts are found to possess infrastructural vulnerability than socioeconomic vulnerability (Chapter 4).
4. Half of the districts of Madhya Pradesh and 42 % of its population possess high or very high socioeconomic vulnerability. Whereas 38 out of 50 districts and 72% of its population possess high or very high infrastructural vulnerability. 34 districts, and around 60% of its population possess high or very high social vulnerability (Chapter 4).
5. The higher dependence on the agricultural and allied sectors and illiteracy contribute more to socioeconomic vulnerability in India. Limited access to infrastructure and assets is identified as the major driver of infrastructural vulnerability (Chapter 4).
6. Social vulnerability to climate change in Madhya Pradesh has decreased over the decades (1991 to 2011) due to decreased socioeconomic and infrastructural vulnerability. However, overall climate vulnerability has increased, though not significantly, in the most recent decade due to a significant change in climate in the recent 30-year period (Chapter 5a).
7. Similar to the result of the first objective, spatiotemporal analysis also found more prominence of infrastructural vulnerability in Madhya Pradesh. The number of districts

and percentage of the population under high and very high IVI is more than twice that of SeVI in 2011 (Chapter 5a).

8. The spatial pattern of climate vulnerability and subindices in 2011 shows an apparent clustering of low vulnerability in central Madhya Pradesh and high vulnerability in the peripheral districts. Tribal districts like Alirajpur and Jhabua remain very highly vulnerable to climate change throughout the study period due to the very high socioeconomic vulnerability and high infrastructural vulnerability coupled with higher exposure to climate change. The higher share of a marginalized population, low access to education, high agriculture sector dependence, the high growth rate in population, a large share of dependent population, limited access to infrastructure, etc., make them very highly vulnerable to climate change. Though districts like Indore, Bhopal, Gwalior, and Jabalpur possessed high or moderate exposure to climate change in the study period, their low social vulnerability due to high access to education, low dependence on the agriculture sector, a lower share of children and marginalized communities and higher access to basic infrastructure leads to their lower vulnerability to climate change (Chapter 5a).
9. Rural areas in Madhya Pradesh possess significantly higher vulnerability to climate change than their urban counterparts due to significant differences in the social vulnerability index and its subindices between rural and urban areas. The social vulnerability index and its subindices of rural and urban areas have significantly decreased over the decades of study. However, the climate vulnerability in rural and urban areas has significantly increased from 2001 to 2011 due to an increased climate index in the recent decade (Chapter 5b).
10. The decrease in the share of children, improvement in overall literacy rate and reduction of the gender gap in literacy, decreased dependence on the agriculture sector, and increased access to infrastructure have reduced socioeconomic and infrastructural vulnerability of both rural and urban areas over the decades. The lesser share of children in urban population, higher literacy rate and low gender gap in literacy, low agriculture dependence and better access to infrastructure in urban areas resulted in lower socioeconomic and infrastructural vulnerability than urban counterparts (Chapter 5b).
11. The agriculture sector in Madhya Pradesh faced high exposure to climate change in recent decades, especially from 2000-09. Though 2010-15 has a mean exposure less than 2000-09, it is higher than the eighties and nineties. The sensitivity component is found to have no change, and the adaptive capacity is increasing over the decades. The

agricultural vulnerability decreased in the most recent decade of study, due to the higher adaptive capacity, despite the increased exposure (Chapter 6).

12. The variation in rainfall is identified as a major contributor to exposure. In contrast, the yield of major crops and net cropped area contributes the most to sensitivity and input availability, and cropping intensity contributes the most to adaptive capacity. The study in Chapter 6 also identified the prominence of vulnerability in eastern and northern districts, similar to the overall vulnerability of the population in Objective 2 (chapter 5).
13. Social groups possess different levels of vulnerability to climate change in districts of Madhya Pradesh due to differences in composite social vulnerability characterized by differences in socioeconomic characteristics, infrastructural access and agricultural characteristics. Intergroup comparison using combined indices and their ANOVA indicates the significant differences among social groups in vulnerability index scores. Non SC/ST was found to be the least vulnerable among all groups, and ST has the highest vulnerability in Climate vulnerability and its subdimensions except Agricultural Vulnerability, which is highest among SC (Chapter 7).

The results of the thesis are valid as the districts identified as very highly vulnerable in each objective, and the major drivers of vulnerability match the previous literature. The study contributes to the literature in the following ways:

1. Application of a segregated social vulnerability index for the first time for the whole Indian population (Chapter 4). The segregated social vulnerability index facilitated the identification of the dimension to which each district population in India is vulnerable and will aid targeted policymaking.
2. The grouping of vulnerability indices for each state in objective 1 facilitated identification of where the district stands in over all vulnerability in India and where it stands among its neighbouring districts (chapter 4).
3. Spatiotemporal assessment of vulnerability to climate change for 3 decades, using an integrated approach for the first time globally (Chapter 5a).
4. Identifying rural-urban disparity in vulnerability to climate change for the first time in India (chapter 5b). This will aid identification of priority areas for targeted interventions.
5. Identification of spatiotemporal pattern of agricultural vulnerability for the first time globally (chapter 6). The patterns of vulnerability and its components are identified to

understand where the focus of policymakers is required. The major factors contributing to each dimension of vulnerability are also identified.

6. Identification of vulnerability of social groups within a population for the first time (chapter 7). It identified the most vulnerable social groups in each district and to which dimension of vulnerability they are more vulnerable.

This study is also not free from limitations. The major limitations are:

1. Non availability of data in other databases for rural and urban areas and social groups in a district led to the usage of population census in 3 out of 4 objectives. Population census is the most comprehensive database for the population of a particular area and is the only data source that facilitates a temporal analysis. The delays in collecting the population census 2021 due to COVID-19 restricted the data available up to 2011 only. The study can be updated once the data becomes available.
2. The segregation of districts during the study period (1991 to 2011) and the lack of data at lower levels for age groups, disabled population, houseless population etc., constrained its usage in spatiotemporal assessment. However, they are considered as important indicators of vulnerability. Census 1991 has not collected data of assets of households like TV, radio, two-wheeler, four-wheeler etc. Hence, they are also omitted from spatiotemporal analysis (chapter 5).
3. The lack of data for many essential variables in the agriculture sector, like mechanization, roads, markets etc., led to the omission of these variables. Moreover, the last decade could be calculated only for 6 years (2010-15) due to the non-availability of data for certain variables considered (chapter 6).
4. In the fourth objective (chapter 7), the population in each district is grouped into three social groups: SC, ST and Non SC/ST. The Non SC/ST groups include information about several population groups, including the social groups other than SC and ST and religious minorities in India. Generally, the surveys conducted by National Sample Survey Organization and other agencies collect data from Other Backward Caste (OBC) groups with lower socioeconomic backgrounds than upper caste Hindus. As the data on OBC is not available separately in the Census of India (2011), this study could not identify whether the vulnerability of OBC to climate change differs from other social groups. The study can be advanced further if a data source with separate data for SC, ST, OBC, and others is used.
5. The lack of agriculture census data for ST of Bhind constrained the calculation of AVI, CSVI and CVI of ST in this district (Chapter 7). Though the district is classified as very

high in the climate index, the CVI of ST in that district could not be calculated due to the lack of data for variables of AVI. The CVI of this social group can be calculated once the data becomes available.

Conclusion and Policy Implications

The study found that Madhya Pradesh state faces higher exposure to climate change, and more than half of its population is socially vulnerable compared to other states of India. Though social vulnerability is decreasing in the state over the decades, exposure to climate change is significantly increasing. Hence overall vulnerability to climate change can be reduced only by reducing social vulnerability with major focus on socioeconomic and infrastructural vulnerability. The social vulnerability can be reduced by improving education, livelihood diversification, skill development and enhanced access to basic facilities. Though the overall vulnerability of the agriculture sector is decreasing over time, certain districts remain highly vulnerable owing to the higher regional disparities in the state. Therefore, a balanced development of the agriculture sector is advocated for reducing the vulnerability of the sector and its dependents. As marginalised sections are identified as the most vulnerable social groups, the intervention measures should target marginalised sections, especially scheduled tribes.

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ACRONYMS

ACI	Adaptive Capacity Index
ANOVA	Analysis of Variance
AVI	Agricultural Vulnerability Index
CI	Climate Index
CSVI	Composite Social Vulnerability Index
C.V.	Coefficient of Variation
CVI	Climate Vulnerability Index
EI	Exposure Index
GoI	Government of India
GoMP	Government of Madhya Pradesh
ICRISAT	International Crops Research Institute for the Semi-Arid Tropics
IMD	India Meteorological Department
IPCC	Intergovernmental Panel on Climate Change
IVI	Infrastructural Vulnerability Index
IWRIS	India Water Resources Information System
KMO value	Kaiser-Meyer-Olkin Value
LISA	Local Indicators of Spatial Association
MoEFCC	Ministry of environment, Forest and Climate change
MPSKMCCC	Madhya Pradesh State Knowledge Management Centre on Climate Change
OBC	Other Backward Castes
PCA	Principal Component Analysis
QGIS	Quantum Geographic Information System
SC	Scheduled Castes
S.D.	Standard Deviation
SeVI	Socioeconomic Vulnerability Index
SI	Sensitivity Index
ST	Scheduled Tribes
UT	Union Territory
WMO	World Meteorological Organization

Chapter 1

Introduction

According to the Intergovernmental Panel on Climate Change (IPCC), the term "weather" means "the conditions of the atmosphere at a cer-tain place and time with reference to temperature, pressure, humid-ity, wind, and other key parameters (meteorological elements)" (Cubasch et al.,2013). It also includes "the presence of clouds, precipitation and the occurrence of special phe-nomena, such as thunderstorms, dust storms, tornados and others" (Cubasch et al.,2013). Whereas climate is defined as "the average weather" or "the statistical description in terms of mean and variability of temperature, precipitation and wind over a period of time ranging from months to thousands or millions of years" (Cubasch et al.,2013). World Meteorological Organization has defined the period for averaging this variable as 30 years.

IPCC defines *climate change* as "a change in the state of the climate that can be identified (by using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer" (IPCC,2014). IPCC (2014) attribute climate change to "natural internal processes or external forcing such as modulation of solar cycles, volcanic eruptions and persistent anthropogenic changes in the composition of the atmosphere or in land use".

United Nations Framework Convention on Climate Change (UNFCCC) defines *climate change* as "the change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods". These definitions indicate that human activities are a major reason for climate change, along with the variability caused by natural forces.

The anthropogenic or human-induced climate change is caused mainly by global warming. Global warming is the gradual rise in atmospheric and ground surface air temperature due to the greenhouse effect caused by trapping the sun's radiations and preventing it from radiating back to space. Greenhouse gases (GHG) such as carbon dioxide, methane, nitrogen oxide, halocarbons, and ozone in the lower atmosphere are essential contributors to global warming.

1.1 Climate change scenario: global and national

Climate change is manifested mainly in the form of increased surface air temperature and changes in precipitation. It also results in rising ocean temperature, ocean acidification, sea level rise, glacier melting, and the increased frequency and intensity of extreme events like floods, drought, cyclones, and heat waves.

World Meteorological Organization (WMO) has recorded 2015-2022 as the eight warmest years in its 173-year instrumental record (WMO,2023). The global mean temperature in 2022 was recorded as around 1.15°C above the preindustrial (1850-1900) average (WMO,2023), and an increase of around 1.0°C to 5.7°C in 2081-2100 is predicted under different emission scenarios (IPCC,2021). In India, the annual mean temperature and maximum temperature have increased by 0.15°C per decade, whereas the minimum temperature increased by 0.13°C per decade from 1986 to 2015 (Sanjay et al., 2020). Warm days and nights are becoming more frequent worldwide, including in India (Krishnan et al., 2020; Sanjay et al., 2020). The mean monsoon rainfall in India has a decreasing trend (Dash et al.,2007), while the short-spell rain events with high intensity are increasing (Dash et al., 2011; Tripathi & Govindaraju,2009; Mukherjee et al.,2018). The global mean sea level rise has doubled between 1993-2002, and 2013-2022 (WMO,2023) and its increase of about 52-98 cm is predicted under RCP[1] 8.5.

Climate change can enhance weather variability or extreme weather occurrences (GIZ, 2011). Extreme weather or climate extreme is defined as “the occurrence of a value of a weather or climate variable above (or

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[1] *RCPs (Representative Concentration Pathways) are used to predict the climate in future, depending on the Green House Gas concentrations. IPCC uses four RCPs for climate modelling viz. RCP 2.6, RCP4.5, RCP6, and RCP8.5, which are labelled based on a possible range of radiative forcing values in the year 2100. RCP 8.5 denotes the carbon intensive scenario where no actions are taken to reduce emissions and annual temperature may increase to 4.3 degree Celsius above preindustrial level by 2100. (Mani et al 2018)*

below) a threshold value near the upper (or lower) ends of the range of observed values of the variable" (Field et al., 2012). According to Mohanty (2020), more than 478 extreme events have occurred in the Indian subcontinent since 1970. The frequency of floods and their associated events, such as landslides, extreme rainfall, hailstorms, thunderstorms, and cloudbursts, have been reported to increase in recent decades. The average number of districts affected by floods, drought and cyclones has also increased significantly in recent decades (Mohanty,2020). While heat waves are increasing in India (Pai et al.,2013; Sanjay et al., 2020), cold waves are less frequent (Bhattacharya et al.,2023).

1.2 Climate change scenario in Central India

The climate in India has large spatial variations due to the vast size and varied geography of different regions of the country. Central parts of India are known as the core monsoon zone (CMZ), as it receives a major share of precipitation during the southwest monsoon from June to September (Shrivastava et al., 2017). It is also considered a representative region of the mean performance and variability of the Indian monsoon (Shrivastava et al., 2017). This region experiences a decline in summer monsoon rainfall and rainy days (Roxy et al.,2017; Das et al.,2014). The frequency of extreme precipitation events is reported to be increasing (Mukherjee et al.,2018; Roxy et al.,2017) and is predicted to rise in future (Gupta et al.,2021). At the same time, moderate rainfall events are becoming less frequent (Goswami et al., 2006; Guhatakurta et al., 2011). A significant drying trend is observed over the southwest monsoon in the humid regions of central India (Mujumdar et al.,2020), and the spatial extent of droughts is significantly increasing (Sharma & Mujumdar, 2017). The frequency, total duration and maximum duration of heatwaves are also reported to increase over central India (Rohini et al.,2016).

1.3 Climate change scenario in Madhya Pradesh

Madhya Pradesh is located in central India between 21°04' N and 26°54' N latitudes and 74°02'E and 82°49'E longitudes. The state has a subtropical climate with three distinct seasons: summer (April to June), monsoon (July to September) and winter (November to February) (GIZ,2014). The southeastern districts of the state receive high rainfall of around 2150 mm, whereas it decreases in western and northwestern districts to around 1000 mm or less (GIZ,2014). The mean maximum temperature in the summer season ranges from 40°C to 42.5°C in northern parts of the state. In winter, it is as low as 10°C in northern Madhya Pradesh and varies from 10°C to 15°C in Southern Madhya Pradesh. (GIZ,2014).

The long-term trend of rainfall is reported to be decreasing in the state, along with a decrease in the frequency of rainy days. (Naidu et al.2009; Das et al.,2014). While moderate rain events are reported to have decreased, extreme rain events have increased (Dash et al.,2009; Dash et al.,2011). While Eastern and western Madhya Pradesh experienced a significant annual mean maximum temperature increase, central parts have experienced an increase in annual mean minimum temperature from 1951-2013 (Mishra et al., 2016). The frequency of heatwaves, hot days and extreme and severe droughts have also been increasing in recent decades (Mishra et al., 2016).

Table 1.1 shows the result of the trend analysis (Mann-Kendall test) conducted for annual mean maximum and annual mean minimum temperature (for the period 1958-2015) and monsoon rainfall (for the period 1901-2021) at the district level. The annual mean maximum temperature increased significantly in 17 districts, while the 31 districts experienced a non-significant increase. Only two districts, viz. Bhind and Morena possess a decreasing trend in annual mean maximum temperature. The annual mean minimum temperature has increased significantly in all the districts of Madhya Pradesh. Long-term average monsoon rainfall shows a mixed trend. While 6 districts showed a significant increase in monsoon rainfall, 12 had a significant decrease.

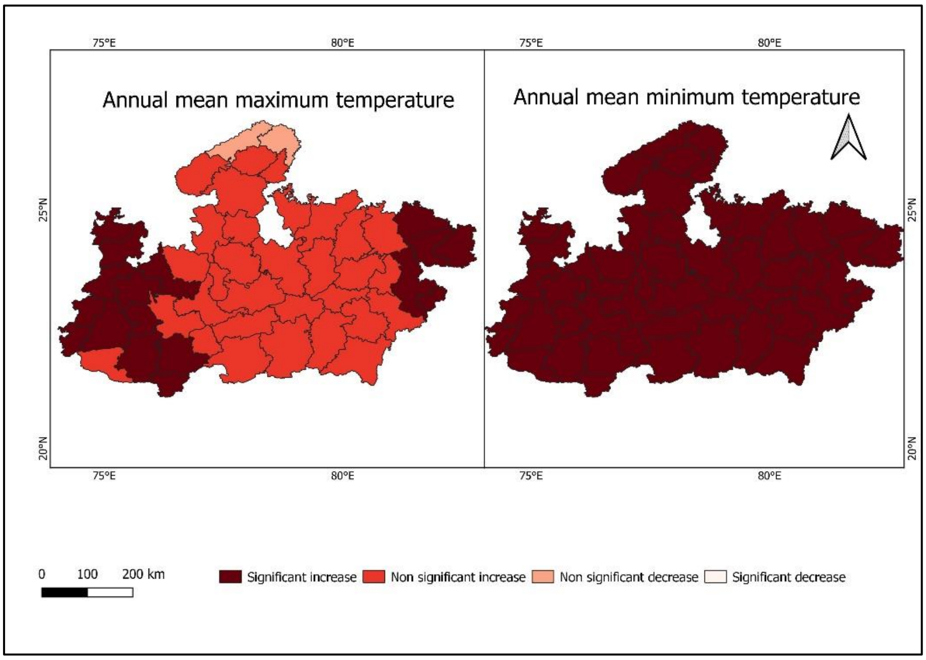
Monsoon rainfall in 17 districts decreased, though not significantly, while 15 had a non-significant increase.

Table 1.1 Results of Trend analysis

District	Annual mean maximum temperature		Annual mean minimum temperature		Monsoon rainfall	
	Z value	Sen's Slope	Z-Value	Sen's Slope	Z-Value	Sen's Slope
Alirajpur	**2.031**	**0.0060**	**4.578**	**0.016**	0.379	0.265
Anuppur	**2.279**	**0.0075**	**4.647**	**0.013**	-1.582	-0.930
Ashoknagar	1.717	0.0065	**4.826**	**0.021**	-0.630	-0.361
Balaghat	1.893	0.0055	**5.046**	**0.017**	**-3.752**	**-2.756**
Barwani	1.948	0.0060	**4.468**	**0.015**	**2.467**	**1.230**
Betul	1.576	0.0047	**4.165**	**0.016**	0.867	0.547
Bhind	-1.060	-0.0039	**6.147**	**0.021**	-1.275	-0.707
Bhopal	1.535	0.0055	**4.867**	**0.020**	0.309	0.214
Burhanpur	**2.485**	**0.0072**	**4.426**	**0.016**	1.230	0.629
Chhatarpur	1.246	0.0048	**4.592**	**0.016**	**-2.153**	**-1.451**
Chhindwara	1.744	0.0058	**4.592**	**0.017**	-1.559	-0.956
Damoh	1.107	0.0047	**4.853**	**0.019**	-1.597	-1.212
Datia	1.163	0.0042	**4.826**	**0.015**	-0.925	-0.509
Dewas	1.921	0.0062	**4.826**	**0.019**	0.880	0.643
Dhar	**2.155**	**0.0065**	**4.743**	**0.018**	1.342	0.722
Dindori	1.563	0.0051	**5.239**	**0.017**	**-2.372**	**-1.474**
Guna	1.563	0.0060	**5.087**	**0.022**	-0.278	-0.210
Gwalior	0.604	0.0021	**5.817**	**0.019**	0.177	0.098
Harda	1.728	0.0053	**4.413**	**0.016**	0.240	0.207
Hoshangabad	1.301	0.0049	**4.413**	**0.016**	-1.678	-1.400
Indore	**2.155**	**0.0065**	**4.963**	**0.019**	1.335	0.749
Jabalpur	1.181	0.0045	**4.991**	**0.019**	-1.835	-1.468
Jhabua	**2.168**	**0.0067**	**4.949**	**0.020**	**1.983**	**1.535**
Katni	1.315	0.0043	**5.032**	**0.019**	**-2.520**	**-1.685**
Khandwa	**2.223**	**0.0061**	**4.481**	**0.016**	-0.392	-0.278
Khargone	**2.182**	**0.0067**	**4.592**	**0.016**	1.069	0.559
Mandla	1.150	0.0036	**5.170**	**0.019**	**-2.162**	**-1.514**
Mandsaur	**2.292**	**0.0090**	**5.555**	**0.025**	**2.106**	**1.189**
Morena	-1.006	-0.0032	**6.189**	**0.022**	-0.603	-0.315
Narsimhapur	1.449	0.0048	**4.702**	**0.019**	**-2.216**	**-1.310**
Neemuch	**2.237**	**0.0088**	**5.597**	**0.026**	**2.180**	**1.228**
Panna	1.329	0.0045	**4.784**	**0.017**	-1.508	-1.068
Raisen	1.805	0.0060	**4.702**	**0.019**	-0.289	-0.174
Rajgarh	1.755	0.0066	**5.225**	**0.022**	-0.683	-0.411
Ratlam	**2.430**	**0.0079**	**5.431**	**0.023**	**2.713**	**1.874**
Rewa	**2.072**	**0.0077**	**4.275**	**0.012**	**-2.910**	**-1.674**
Sagar	1.422	0.0050	**4.757**	**0.020**	-0.419	-0.315

Satna	1.631	0.0053	**4.206**	**0.014**	-1.682	-0.927
Sehore	1.535	0.0058	**4.798**	**0.019**	0.199	0.137
Seoni	1.218	0.0041	**4.908**	**0.019**	**-3.322**	**-1.958**
Shahdol	**1.989**	**0.0068**	**4.660**	**0.014**	**-2.946**	**-1.705**
Shajapur	**2.003**	**0.0077**	**5.184**	**0.021**	0.925	0.629
Sheopur	1.452	0.0056	**4.839**	**0.018**	0.992	0.661
Shivpuri	1.315	0.0053	**4.881**	**0.018**	0.420	0.218
Sidhi	**2.155**	**0.0073**	**4.440**	**0.013**	**-3.287**	**-2.124**
Singrauli	**2.677**	**0.0072**	**4.041**	**0.011**	**-3.232**	**-1.648**
Tikamgarh	1.114	0.0041	**4.371**	**0.018**	-1.481	-0.915
Ujjain	**2.196**	**0.0069**	**5.252**	**0.022**	**2.207**	**1.378**
Umaria	1.576	0.0055	**5.239**	**0.017**	**-4.581**	**-2.832**
Vidisha	1.684	0.0069	**4.949**	**0.020**	0.692	0.429

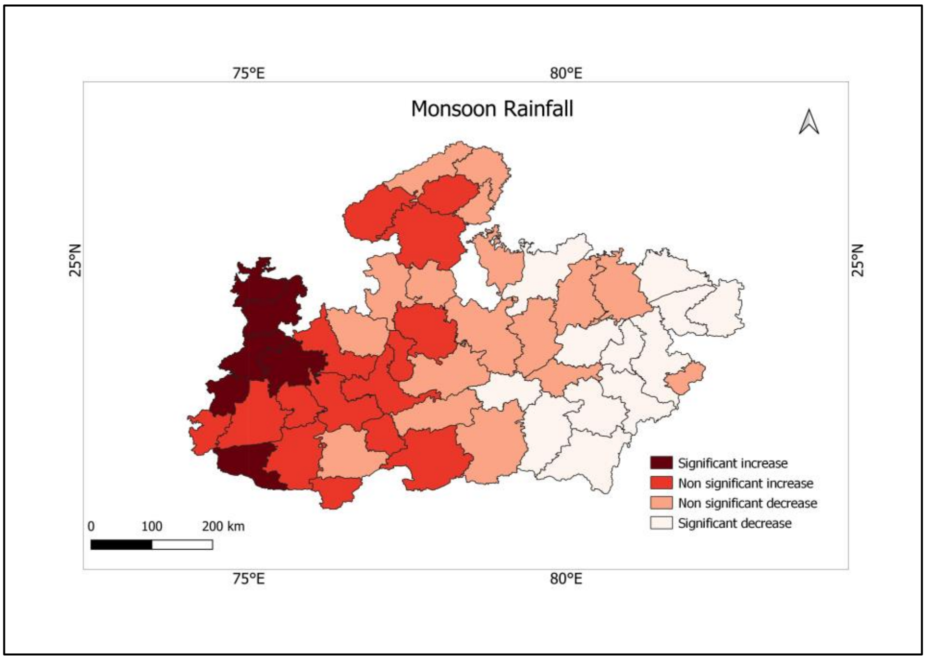
Source: Author's calculation



Source: Prepared by author using QGIS

Figure 1.1 District level trends in maximum and minimum temperature (1958-2015)

Figures 1.1 and 1.2 plot the districts showing significant and non-significant trends in temperature and rainfall. The annual mean maximum temperature is found to be significantly increasing in the western and eastern districts of the state, while the central districts possess an increasing trend, though not significant (Figure 1.1). Eastern districts are found to possess a significant decrease in rainfall (Figure 1.2).



Source: Prepared by author using QGIS

Figure 1.2 District level trends in monsoon rainfall (1901-2021)

1.4 Impacts of climate change

Climate change can adversely affect both biophysical and socioeconomic systems (DST,2020). It disproportionately affects developing countries like India due to high exposure to their geography, reliance on climate-sensitive sectors and low adaptive capacity (Heltberg et al.,2008).

1.4.1 Impacts on key sectors

Climate change significantly impacts four key sectors in India: agriculture, natural ecosystems and forests, human health, and water (GoI,2010). The agriculture sector is highly dependent on climatic variables and natural resources. An increase in temperature can affect the duration of crops, photosynthesis, pollination, evapotranspiration, and heat stress and may lead to a decline in the yield of crops (Gupta & Pathak,2016; Ranuzzi & Srivastava,2012; Mall et al., 2016; Kumar et al., 2014; Nageswararao et al.,2018; Saravanakumar,2015; Praveen & Sharma, 2020). Extreme events like droughts, floods, heatwaves and frost can also affect crop production through heat stress, reduced availability of water and loss in its quality through saline water intrusion, soil quality loss through erosion, etc. (FAO, 2018; Gupta & Pathak, 2016; Ranuzzi & Srivastava,2012). The higher incidence of pests and diseases and the shift in the areas suitable for the cultivation of crops are the other impacts caused by climate change. (Rao et al.,2019, Mall et al., 2016, Kim,2012). These impacts of climate change will lead to a reduction in income from the sector (Kumar, 2009; Kumar & Parikh, 2001; Mendelsohn, 2014; Saravanakumar,2015), which is a significant source of livelihood of around 700 million rural people in India (GIZ, 2011).

Indian forests will likely experience a shift in types and an increase in net primary productivity under different carbon dioxide emission scenarios (Ravindranath et al.,2006; Ravindranath et al., 2018). Forests in northern and southwestern parts of Madhya Pradesh are likely to be impacted in the short term, whereas forests in southern and eastern parts will also be affected in the long term (GIZ,2014). Nearly half of the 54,903 villages in Madhya Pradesh depend on forests for livelihood, including timber and non-timber forest products (NTFP) (Gupta,2013). Vegetation or species composition changes can impact their livelihoods (Ranuzzi & Srivastava, 2012).

Extreme events like floods, droughts, and high-intensity rainfall can impact groundwater recharge and water availability (GoI,2018). Rising sea levels can submerge coastal areas, saline intrusion into freshwater, and contamination (GoI, 2018). Increased water temperature can increase solubility and inorganic components, harming human health (GoI, 2018). Climate change can cause extreme weather-related health effects, including heat stress, cardiovascular failure, water and food-borne diseases, vector-borne diseases, malnutrition, and psycho-social impacts due to displacement (Bhattacharya et al.,2006; Joon & Jaiswal,2012).

1.4.2 Increased losses due to climate extremes

Climate change can increase the severity and frequency of extreme events, which may turn out to be disasters. Around 6691 climate-related disasters were reported globally between 2000 and 2019, causing 510837 deaths and affecting 3.9 billion people (CRED, 2020). Low and middle-income countries face a disproportionate burden due to these disasters. These countries have experienced 43 % of all major climate-related and geophysical disasters from 1998 to 2017 (Wallemacq, 2018). They faced around 68% of fatalities and have lost around 1.1 to 1.7 % of their GDP due to these disasters.

While India lost around 13 billion US$ due to Cyclone Amphan in 2020, 7.5 billion US$ was lost due to floods in the same year (CRED& UNDRR, 2020). The economic losses due to floods and the growth rate of per capita income possess a negative correlation (Parida et al.,2020). Panwar & Sen (2019) found that while GDP growth may take 5 to 6 years to recover from the impacts of a moderate flood, more than 10 years is required for severe floods.

1.4.3 Impacts on poor

The poor are highly affected by climate change owing to their higher exposure, high vulnerability and lack of access to coping measures. Their settlement in hazard-prone areas, excessive dependence on the primary sector, lower quality assets (e.g., housing quality) and the tendency to invest more in material assets than financial assets add to their vulnerability (Hallegatte et al., 2017). Less preparedness for disaster, less insurance penetration, and low access to early warning messages decrease their coping capacity (Hallegatte et al., 2017). The post-disaster recovery is also challenging for them (Hallegatte et al., 2017). Studies like Tripathi (2019) and Mani et al. (2018) observed that a change in climatic variables could change the poverty levels and the living standards of the Indian population. The living standard of Chhattisgarh and Madhya Pradesh would reduce by 9% when the temperature increases by 1° (Mani et al.,2018).

1.4.4 Impacts on vulnerable sections of population

Climate change impacts within the population of a particular region vary by age, gender, social or political identities, and resource access (Kuchimanchi et al., 2019; Ribot, 2010). Women, children, elderly, and marginalized populations are disproportionately affected.

Gender is an important factor shaping the differentiated impacts of climate change. Women play productive and reproductive societal roles (Ashraf & Azad,2015). The unpaid productive work at home and responsibilities for caring for children and the elderly result in less time and resources for a livelihood (Holmes et al.,2010). This leads to low decision-making and bargaining power within a household and more probability of being employed in insecure jobs (Holmes et al.,2010). Indian agriculture is becoming increasingly dependent on women due to the climate-induced migration of men. Though they represent a major share of the workforce in agriculture, their land rights are limited, leading to less access to credit, improved technologies and extension services, which hinders their coping capacity with climate change impacts (Holmes et al.,2010). As the activities carried out by women to meet family needs depend on natural resources like land, water and forest, the erosion of natural resources due to climate change hits them badly.

Increases in temperature, extreme rainfall, floods and droughts can affect the health of children. Low availability of water and its contamination due to drought or excess rainfall can lead to waterborne diseases like cholera, diarrhoea, malaria, dengue, hepatitis, etc., to which children are more susceptible due to their low immunity (Lawler,2011; Chatterjee,2015). Heatwaves can lead to heatstroke, asthma, and other allergic diseases among children, and extreme events like cyclones, floods, and droughts can result in malnutrition (Kabir et al.,2016; Rodriguez-Llanes et al.,2016). Income loss, forced displacements or migration resulting from climate change results in the loss of social networks and school dropouts and may induce psychological stress among children (Lawler,2011; Chatterjee,2015).

Indigenous communities generally contribute very little to greenhouse gas emissions but bear the disproportionate burden of climate change (Abate & Kronk, 2013). Tribal communities in India are characterized by a high concentration of poverty, low educational attainments, low infrastructural access and primitive modes of agriculture. Their higher dependence on agriculture and forestry, increasing landlessness and lack of access to development programmes, when compounded with adverse climate, may result in acute poverty, food insecurity, high proneness to diseases, unemployment, the shift from agriculture to wage labour and distress migration (Chakraborty &Dand, 2005; Bhawan & Marg, 2010; Karat & Rawal, 2014; GoI,2011; GoI,2020).

1.5 Measures to reduce impacts of climate change

Mitigation and adaptation are the two fundamental measures to reduce the impacts of climate change. Mitigation involves the implementation of policies to reduce GHG emissions through the management of emission sources and the enhancement of sinks (IPCC, 2007 & 2012). Adaptation in human systems involves "the process of adjustment to actual or expected climate and its effects, in order to moderate harm or exploit beneficial opportunities" (IPCC,2012). Though mitigation can reduce the further emission of GHG, the effect of already emitted GHG in the atmosphere and its resultant warming will continue for several decades. Therefore, adaptation to the impacts of warming and associated changes in climate is necessary. (Kim,2012). Also, mitigation is possible only up to an extent and can be practised only at the global level. Adaptation can be practised even at local scales. Reducing existing vulnerability in a system helps build better adaptation and resilience, i.e. the ability to bounce back. To adapt to future climate change, a better understanding of the current vulnerability of the exposed system is necessary, which involves "identification, quantification, and prioritisation of vulnerabilities" (Sarun et al.,2018).

Section 1.4 shows that climate change impacts are not equal for the whole population in a region experiencing the exact characteristics of climate change. The climate change impacts need not be felt most strongly in the most fragile biophysical environments; rather, the impacts will be higher even on the poor and marginalised residing in resilient biophysical environments (Vincent & Cull, 2010). Though a physical phenomenon is necessary for an extreme climate event, its translation to a disaster is determined by the differential vulnerability shaped by the demographic, socioeconomic and political characteristics of a region (Vincent & Cull, 2010; Sarun et al.,2018).

1.6 Vulnerability to climate change

Vulnerability to climate change is "the degree to which a system is susceptible to or unable to cope with adverse effects of climate change, including climate variability and extremes" (McCarthy et al.,2001). It is a function of exposure, sensitivity and adaptive capacity. Exposure is the degree to which an entity or system is exposed to the changes in mean and variation of climate change. It includes changes in climatic variables such as temperature, rainfall, wind speed, sea level change, and changes in intensity and frequency of extreme events such as droughts, floods, cyclones, etc. Sensitivity is the degree to which climate change affects the system either adversely or beneficially. Adaptive capacity is defined as the "ability of the system to adjust to potential damage, to take advantage of opportunities, or to respond to consequences" (IPCC, 2014, p118). Both exposure and sensitivity combined indicate the potential impacts of climate change; hence, the adaptive capacity is deducted from it while assessing the vulnerability.

According to Sarun et al. (2018), climate change vulnerability assessments play an important role in

1. Understanding of the current vulnerability of an entity, viz., a population, a system or an economic sector
2. Identification of factors that contribute to the higher vulnerability of some entities
3. Informing and facilitating the decision-making process through transparent and replicable ways
4. Targeting appropriate intervention measures to the most vulnerable entities.

Vulnerability to climate change is assessed mainly by biophysical and social vulnerability approaches. Biophysical approaches, which focus on endpoint interpretation or outcome vulnerability, conceptualise vulnerability as what is left behind after adaptation (O'Brien et al., 2004a). It considers humans as passive recipients of the impacts of climate change and ignores the possibilities of their capacities to mediate the impacts of climate change (Vincent,2004). Social vulnerability approaches, which focus on starting point interpretation or social or contextual vulnerability ((Fussel, 2005; Nguyen et al., 2016), conceptualise vulnerability as an apriori condition, which is inherent among the people and the communities and determined by the underlying socioeconomic, political and institutional factors which shape the allocation and access to resources (Fussel, 2007; Vincent & Cull, 2010; Ge et al., 2017). This approach suffers from the limitations of not considering the climatic features in an area.

Integrated vulnerability approaches try to overcome pitfalls in both approaches by combining the characteristics of a vulnerable social unit with its exposure to external stressors (Fussel, 2005). The IPCC vulnerability framework, Sustainable Livelihoods Framework and Hazard of Place model are the common integrated approaches for vulnerability assessment. The Hazard of Place model, one of the popular integrated approaches to vulnerability to hazards, was developed by Susan Cutter in 1996. The advantage of a place-based vulnerability index is that it facilitates the identification of integrated vulnerability to hazards and the separate assessment of two dimensions. As climate change is an external stressor and social vulnerability is an internal property, a separate assessment of changes in climatic parameters and social vulnerability will enable the identification of the most vulnerable dimension and, thus, targeted policymaking.

1.7 Vulnerability to climate change in Madhya Pradesh

Madhya Pradesh has higher exposure to changes in climatic variables, as discussed in section 1.3. National-level studies on vulnerability to climate change in India have identified Madhya Pradesh, as well as its districts, as highly vulnerable to climate change due to several factors like high climate sensitivity, high population growth rate, a higher share of marginalised communities and marginal workers, high dependence on agriculture, high unemployment rate, high poverty, lack of education and low access to basic civic amenities (O' Brien et al., 2004b; Sharma et al., 2015a; Chakraborty & Joshi, 2016; Sendhil et al., 2018). Das (2013) and Yenneti et al. (2016) identified very high socioeconomic vulnerability in the state. The districts like Alirajpur, Jhabua, Barwani, Sidhi, Singrauli, Panna and Rewa are identified as highly vulnerable to heat stress and climate change (Azhar et al.,2017; MPSKMCCC,2018). MPSKMCCC (2018) pointed out an increase in vulnerability in the state towards the mid-century (2050). The projected changes in climatic conditions in the next couple of decades and the higher vulnerability condition identified in Madhya Pradesh in the literature make a detailed study of vulnerability to climate change a necessity in this state.

1.8 Gaps in vulnerability literature

Studies that assess generic social vulnerability at the district level for the whole of India are limited. Though Vittal et al. (2020) prepared a social vulnerability index at the district level using the inductive approach of Cutter et al. (2003), it suffers from limited coverage of variables. The social vulnerability assessments are generally done by constructing a single vulnerability index (Das et al., 2021; Vittal et al.,2020). Social vulnerability is a multidimensional concept; hence, the aggregation of all its dimensions may mask the areas where the actual focus is required, which may lead to improper targeting of interventions. Borden et al. (2007) overcame this issue by segregating social vulnerability into the Socioeconomic and Built Environment Vulnerability Index. Holand et al. (2011) and Huang et al. (2015) adapted this segregated index in Norway and China respectively. Mazumdar & Paul (2016) first attempted this classification in the Indian context and segregated the social vulnerability index into socioeconomic and infrastructural vulnerability indices. However, the study is confined to eastern coastal states, and a nationwide application is not attempted.

The studies on vulnerability to climate change in India mainly follow the IPCC Third Assessment definition, i.e., vulnerability as the function of exposure, sensitivity and adaptive capacity (Bahinipati, 2011; Mohanty & Wadhawan, 2021; Tripathi,2014; Jeganathan et al.,2021;

Maiti et al.,2017; Maiti et al.,2015, MPSKMCCC, 2018). This model suffers from the segregation of variables into different subindices. Though it is generally considered an integrated approach, some authors consider it as biophysical. Also, IPCC has modified this definition in the recent assessment reports (sixth assessment report), conceptualising vulnerability as consisting of sensitivity and adaptive capacity only. Climate *change risk* is conceptualised as the interaction of Hazard, Exposure and Vulnerability (Begum et al., 2022). By following this definition, DST (2022) used only sensitivity and adaptive capacity components to assess vulnerability to climate change. The differences in the definition of vulnerability in the IPCC report constrain the usage of this framework in vulnerability assessment. Also, this approach will not identify the major drivers of vulnerability.

Studies that assess the climate change vulnerability at community level based on primary surveys (Antwi-Agyei et al., 2013; Singh Jatav,2020; Toufique & Islam,2014) mainly follow the Livelihood Vulnerability Index of Hahn et al. (2009). The lack of secondary data for the variables used in it constrains its usage at district or state level. At the same time, the place-based vulnerability assessments based on the Hazard of Place model have the advantage of applying to any scale of analysis. Place-based vulnerability models integrate biophysical and social vulnerability and create subindices for both vulnerabilities, along with the composite vulnerability index. Though this model is used in vulnerability studies in other countries, it is not applied in the Indian context.

The concept of vulnerability is dynamic and context-specific, i.e., the condition of vulnerability can vary from time to time and from place to place. However, the studies on vulnerability to climate change generally consider vulnerability at a particular point in time only (Maiti et al., 2015; Jeganathan et al.,2021; Menezes et al.,2018). A temporal assessment of vulnerability can capture the dynamics of the community over time and can track the progress in reducing social inequalities that cause vulnerability (Mavhura et al., 2017). Spatiotemporal assessments of social vulnerability to different hazards have been attempted in different countries (Cutter & Finch,2008; Frigerio et al.,2018; Santos et al.,2022). Yenneti et al. (2016) and Das et al. (2021) also attempted this assessment in India. However, all these studies assess generic social vulnerability only, and climatic variables are not included. While assessing the pattern of vulnerability to climate change, changes in biophysical vulnerability patterns have to be assessed along with changes in social vulnerability patterns. However, the climate change vulnerability literature lacks this aspect.

Scholars in countries like China and Australia (Ge et al.,2021; Wang et al.,2022) have attempted a comparison of rural-urban vulnerability to climate change, as the access to basic amenities and pattern of livelihood differs among these areas. Emphasis on urban development during economic reforms resulted in huge rural-urban disparities in Indian states, including Madhya Pradesh, in the patterns of livelihood and access to basic amenities like education, health, energy, infrastructure, etc. (IIPS & ICF,2017; Chaudhuri & Roy,2017; Sharma et al.,2015a; Das & Pathak,2012). This might lead to considerable disparities in coping capacities and vulnerability to stressors like climate change. Though attempts are made to assess the climate change vulnerability of either rural (Rao et al.,2016) or urban areas (Yenneti et al.,2016) in India, there is a gap in the literature on climate change vulnerability comparing rural and urban areas at each spatial unit of analysis. Also, the existing studies (Ge et al.,2021; Wang et al.,2022) focused on social vulnerability only and ignored biophysical or climatic variables.

The agriculture sector in India is highly vulnerable to climate change due to the high share of rainfed cultivation, fragmentation of land and increasing share of small and marginal landholders who possess low access to inputs and technologies. Most of the studies on the agriculture sector of India and other countries are static (Das,2013; Rao et al.,2013; Sehgal et al.,2013; Raju et al., 2017; MPSKMCCC,2018). Very few studies, like Varadan & Kumar (2015), used instability and change over a period as a variable to detect the change over time. Palanisami et al. (2008) attempted to assess the vulnerability of agroclimatic regions for three decades, but the index was constructed separately for each decade, and no comparison was attempted. As the index is constructed by simple averaging, there is no attempt to identify the significant contributors of vulnerability. Jha & Gundimeda (2019) used principal component analysis (PCA) to identify the major factors contributing to exposure, sensitivity, and adaptive capacity. However, the assessment was conducted for only one point of time. If the spatiotemporal pattern of the three subcomponents of vulnerability is assessed, it will identify the changes in each subcomponent over time and how far change in each contributes to change in the vulnerability of the agriculture sector. However, it has not been attempted in vulnerability studies in India and other countries.

Marginalised sections of an economy are generally more vulnerable to climate change due to their political and social identities, excessive dependence on natural resource-dependent sectors and limited access to basic facilities. The higher dependence on agriculture, forestry, increasing landlessness and lack of access to development programmes among these sections, when compounded with adverse climate, may result in acute poverty, food insecurity, high proneness to diseases, unemployment, the shift from agriculture to wage labour and distress migration (Chakravarty &Dand, 2005; Bhawan & Marg, 2010; Karat & Rawal, 2014; GoI,2011; GoI,2020). Though studies on vulnerability in India have identified districts with more marginalised sections as highly vulnerable to climate change (Azhar et al.,2017; Mishra,2015; Bahinipati,2014), a study specifically on these social groups has not been conducted in India. In global vulnerability literature and Indian literature, the vulnerability of specific communities, like farmers, fishing communities, etc., are addressed (Sahana et al.,2021; Huynh& Stringer,2018; Morzaria-Luna et al.,2014). However, differentiated vulnerability among social groups has not been attempted, as evident from the review of earlier studies. This comparison is necessary in states like Madhya Pradesh, where disparities among social groups are very high.

1.9 Statement of the problem

Madhya Pradesh is the second largest state in India in terms of geographic size, and it is the fifth largest populous state (6 % of the total Indian population) according to Census, 2011. The state stands fourth in decadal population growth rate (20.3%) and hence is included in the category of Empowered Action Group states[2]. Over the past decade, Madhya Pradesh became the 10th largest state in terms of Gross State Domestic Product (Rs.11.69 trillion) as per 2021-2022 financial year records; however, the performance of the state in terms of demographic and socioeconomic indicators is still far below the national average, making it 33rd in Human Development Index (HDI),2019.

Most national-level vulnerability assessments have attributed social vulnerability as the major reason for vulnerability to different stressors in Madhya Pradesh. However, there is no consensus regarding drivers of vulnerability, as the context differs in each study. As social vulnerability or contextual vulnerability is the internal property of a population, irrespective of the stressor, a detailed analysis of the factors contributing to their vulnerability needs to be understood. This requires comparing the social vulnerability of the Madhya Pradesh population with the population of other states and identification of factors which makes the state population more vulnerable than other states of India.

The projected changes in climatic conditions in the next few decades and the higher social vulnerability condition identified in Madhya Pradesh in the literature make an integrated assessment of vulnerability to climate change necessary in this state. As biophysical and social vulnerability have dynamic properties, evaluating their spatiotemporal pattern is necessary to understand whether climate change vulnerability increases or decreases over time. The factors contributing to the change

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[2] *Empowered Action Group states are specially designated group of states constituted by the Ministry of Health and Family Welfare to stabilize population growth. These states together constitute 45% of the population of India.*

must be identified to facilitate targeted interventions to reduce vulnerability.

The benefits of economic growth of Madhya Pradesh remain concentrated in certain pockets of the state, as is evident from the higher rural-urban disparities prevailing in the state in access to basic facilities, poverty, literacy rate, etc. In the context of the increasing impacts of climate change, the disparities can accentuate vulnerabilities in some areas. Moreover, earlier studies identified rural and urban Madhya Pradesh as highly vulnerable to climate change. Due to the high disparities and identification of both areas as highly vulnerable, an assessment of the spatiotemporal pattern of vulnerability is essential in rural as well as urban areas of Madhya Pradesh.

Though the agriculture sector of Madhya Pradesh performs better than many other Indian states due to an increase in irrigated area, increased power supply for agriculture, increased agricultural mechanization, development of road network, effective procurement mechanism, and Minimum Support Price for wheat, the performance is not even across the state. Regional disparities in land distribution, land use patterns, cropping patterns, access to inputs like fertilizers, irrigation, and mechanization, as well as increased government support towards commercialization, have resulted in the uneven development of this sector (Singh et al.,2018; Dutta et al.,2020; Shevalkar,2020). The high share of rainfed cultivation, high fragmentation of landholding, lower access to credit, low investment capacity and lack of reach of extension services among tribal farmers, who constitute a major share of farmers in Madhya Pradesh, also add to the issues in the agricultural sector in the state. These existing issues compound with changes in climatic parameters and their extremes, resulting in adverse impacts. Hence, identifying major factors contributing to climate change vulnerability in this sector is necessary to reduce the overall vulnerability of the state to climate change. Also, identifying the pattern of vulnerability and its subcomponents is essential to understand the changes in vulnerability over time.

Madhya Pradesh state has a higher concentration of Scheduled Tribes (ST) and Scheduled Castes (SC) in its population. These social groups are characterized by a high concentration of poverty, low educational attainments, low infrastructural access and primitive modes of agriculture. 73% of SC and 93% of ST live in rural areas, and their basic social, institutional and infrastructural facilities are very low. If the historical and projected changes in climate in the state are compounded by the poorest socioeconomic characteristics, lower infrastructural facilities, low asset base, and primitive mode of agriculture of these social groups, it can lead to loss of livelihood and income and may result in acute poverty. This necessitates the identification of the vulnerability of these social groups to climate change and the formulation of policy measures to reduce it.

1.10 Research questions

This study tries to answer the following research questions:

1. How far population in Madhya Pradesh is socially vulnerable when compared to other states of India?

2. a) Is the vulnerability to climate change in Madhya Pradesh increasing or decreasing?

   b) Is rural and urban vulnerability to climate change decreasing simultaneously?

3. Whether the vulnerability of the agriculture sector to climate change is increasing or decreasing, and what contributes to its vulnerability?

4. Why are marginalised sections of the population more vulnerable to climate change?

1.11 Research objectives

The following objectives are set for this thesis to address the questions posed in section 1.10.

1. To assess the social vulnerability of districts of Madhya Pradesh in comparison to other districts of India.

2. To identify the spatiotemporal pattern of the vulnerability of districts of Madhya Pradesh to climate change and to identify the role of rural-urban disparities in vulnerability to climate change.
3. To assess the spatiotemporal vulnerability of the agriculture sector in Madhya Pradesh to climate change.
4. To compare the vulnerability to climate change among social groups in Madhya Pradesh districts (SC, ST and Non-SC/ST)

1.12 Research Method

The study involves quantifying the vulnerability of Madhya Pradesh districts by preparing vulnerability indices. The study is conducted at the district level, as it is the smallest unit for administrative purposes and implementation of any targeted interventions. As three out of four objectives assess the vulnerability of the district population, the Census of India is used as the primary data source. Agricultural Census and ICRISAT district-level database, and IWRIS database are also used as data sources in the study. The study mainly uses Principal Component Analysis during the construction of vulnerability indices. Spatial autocorrelation techniques like Moran's I and LISA (Local Indicators of Spatial Autocorrelation) are also used in two objectives to identify the spatial clustering of vulnerability. The details of the conceptual framework, main tools used, main variables, data sources and steps involved in constructing vulnerability indices are provided in Chapter 3.

1.13 Chapterization

The chapters included in this thesis are detailed below:

Chapter 1: Introduction

Chapter 2: The Concept of Vulnerability to climate change and Review of earlier studies

Chapter 3: Description of study area, methodology, data sources, and variables used

Chapter 4: Assessment of the social vulnerability of the Madhya Pradesh population in comparison to the population in other states of India

Chapter5: Spatiotemporal Assessment of Vulnerability of Madhya Pradesh Population to climate change

Chapter 6: Spatiotemporal Assessment of the Vulnerability of the agriculture sector to climate change

Chapter 7: Spatial Assessment of the Vulnerability of social groups to climate change

Chapter 8: Major Findings, conclusion and policy suggestions

1.14 Limitations and further scope of thesis

The study uses an indicator approach, which gives an aggregated picture, i.e., the vulnerability at the meso-level. It provides a clearer picture of vulnerability than state-level aggregated data and discusses the vulnerabilities within rural and urban areas of districts and social groups within districts. These levels also could not accurately represent the ground-level reality at the community or household levels. Antwi-Agyei et al. (2013) opined that national-level assessments could mask local-level variability, i.e., regions that seem less vulnerable may not be so. It necessitates ground-level studies in hotspots to assess vulnerability to climate change, which can be attempted later. Also, the lack of secondary data for all the required dimensions of vulnerability has constrained the selection of indicators.

Though the second objective could assess the spatiotemporal pattern of climate change vulnerability over three decades, the lack of data for certain indicators in the 1991 population census limited the number of indicators used in the study. The enumeration of the population census in 2021 was delayed due to COVID, so the current socioeconomic and demographic situation could not be accurately represented in the study. The government of India has initiated efforts to conduct the population census for this decade. This study can be updated after the release of new data. The lack of recent data for certain variables related to the agriculture sector has constrained the indicator selection while assessing the vulnerability of the agriculture sector in the third objective.

In the fourth objective, the Non SC/ST groups include information about several population groups, including the social groups other than SC and

ST and religious minorities in India. As the data on Other Backward Castes (OBC) is not available separately in the Census of India (2011), this study could not identify whether the vulnerability of OBCs to climate change differs from other social groups. The study can be advanced further if a data source with separate data for SC, ST, OBC, and others is used. Though the Bhind district is classified as very high in the climate change index, its CVI of ST could not be calculated due to the lack of data for AVI variables. The CVI of this social group can be calculated once the data becomes available.

This chapter discussed climate change, its impacts, and the need for vulnerability assessment in Madhya Pradesh. The next chapter will discuss the concept of vulnerability and the earlier attempts to assess vulnerability to climate change and related hazards.

Chapter 2

The Concept of Vulnerability to Climate Change

The introduction chapter explained the climate change scenario globally, nationally, and in Madhya Pradesh. It also explained the impacts of climate change on key sectors and poor and vulnerable sections of the population. The relevance of assessing vulnerability to climate change in Madhya Pradesh is also discussed. This chapter explains the concept of vulnerability, its varying definitions and characteristics, the evolution of different models, the use of the concept in climate change discipline and its assessment. Another section of the chapter details the earlier attempts to assess vulnerability and identify the gaps in the literature.

The word 'Vulnerability' is originated from the Latin words *vulnus* (a wound) and *vulnerare* (to wound) (Kelly & Adger,2000). It is "the degree to which a system, subsystem, or system component is likely to experience harm due to exposure to a hazard, either a perturbation or stressor" (Turner et al.,2003). The degree of vulnerability may vary from time to time, depending on the changes in the magnitude of exposure and resilience of a system to a particular stressor (Mazumdar & Paul, 2016).

This concept originated in natural hazard research (Schelhas et al.,2012; Vincent,2004) as they started emphasizing bottom-up approaches rather than top-down approaches. Later, it found wide applications in poverty, development and environmental issue-related studies. As global environmental change became a prominent issue, it is also increasingly used in climate change studies (Schelhas et al.,2012). The definitions of vulnerability vary depending on its source of origin and the discipline of usage. This chapter explains the evolution of theoretical vulnerability models, the use of this concept in climate change, and standard approaches for assessing vulnerability and its quantification. The chapter also looks into the models, tools, and techniques used in earlier studies of climate change vulnerability.

2.1 Definitions of vulnerability

Definitions of vulnerability may vary depending on the context in which it is applied. Economics literature conceptualises vulnerability as the outcome of household responses to risk (Alwang et al., 2001). Poverty literature considers it as an expost concept defined as “the likelihood of falling below a consumption threshold” (Luers et al.,2003). In livelihoods literature, it is a forward-looking and ongoing state, defined as the probability of occurrence of livelihood stress (Alwang et al.,2001). Natural hazards or environmental sciences discipline defines vulnerability as the susceptibility or defencelessness of an individual to a particular stressor (flood, drought, epidemics). In the climate change discipline, social scientists view vulnerability as a set of socioeconomic factors determining the capacity to cope with the change. In contrast, climate scientists view it in terms of the likelihood of weather and climate-related events and their impacts (Garg et al.,2007). In the impacts literature on climate change discipline, the term vulnerability “incorporates the idea of the potential for negative consequences which are difficult to ameliorate through adaptive measures given the range of possible climate changes that might reasonably occur” (Reilly & Schimmelpfennig,1999). Table 2.1 shows the definitions of vulnerability by different authors.

Table 2.1. Definitions of vulnerability

Author	Definition
UNDRO (1979)	“The degree of loss to a given element at risk or set of such elements resulting from the occurrence of a natural phenomenon of a given magnitude and expressed on a scale from 0 (no damage) to 1 (total damage)”
Timmerman (1981)	“The degree to which a system acts adversely to the occurrence of a hazardous event. The degree and quality of the adverse reaction are conditioned by a system’s resilience (a measure of the system’s capacity to absorb and recover from the event)”

Susman et al (1983)	"The degree to which different classes of society are differentially at risk, both in terms of the probability of occurrence of an extreme physical event and the degree to which the community absorbs the effects of extreme physical events and helps different classes to recover"
Kates (1985)	"The capacity of the societies impacted by climatic or social perturbation, to suffer harm or to react adversely"
Chambers (1989)	"The exposure to contingencies and stress, and the difficulty in coping with them. It has two sides: external side of risk, shocks and stress to which an individual or household is a subject and internal side, defencelessness, lack of capacity to cope without damaging loss"
Dow (1992)	"The differential capacity of groups and individuals to deal with hazards, based on their positions within physical and social worlds"
Cutter (1993)	"The likelihood that an individual or group will be exposed to and adversely affected by a hazard. It is the interaction of the hazards of place (risk &mitigation) with the social profile of communities"
Blaikie et al (1994), Wisner et al (2004)	"The characteristics of a person or group in terms of their capacity to anticipate, cope with, resist and recover from impacts of a hazard"
Adger & Kelly (1999)	"The state of individuals, groups, or communities defined in terms of their ability to cope with and adapt to any external stress placed on their livelihoods and well-being. The vulnerability of any group is determined by the availability of resources and, crucially, by the entitlement of individuals and groups to call on these resources"
McCarthy et al (2001)	"The degree to which a system is susceptible to or unable to cope with the adverse effects of climate change, including climate variability and extremes, and it is the function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity and its adaptive capacity"
UNISDR (2004)	"The conditions determined by physical, social, economic, and environmental factors or processes, which increase the susceptibility of a community to the impact of hazards"
Birkmann (2006)	"The intrinsic and dynamic feature of an element at risk that determines the expected damage/ harm resulting from a given hazardous event and

	is often even affected by the harmful event itself. Vulnerability changes continuously over time and is driven by physical, social, economic and environmental factors”
Adger (2006)	“The state of susceptibility to harm from exposure to stresses associated with environmental and social change and from the absence of capacity to adapt”

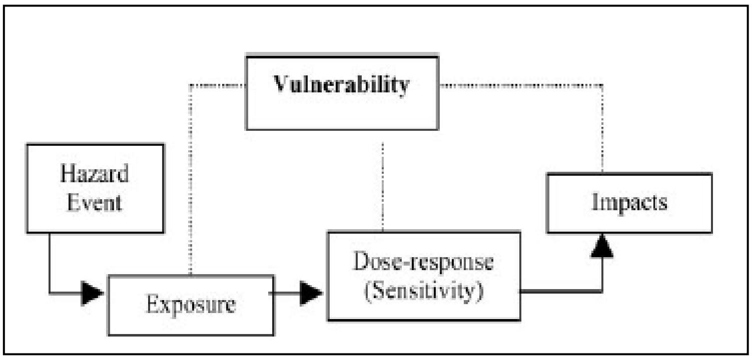
Compiled from different sources: Ciurean et al.,2013; Fussel (2005), Paul (2013).

From the definitions provided in Table 1, it is clear that the vulnerability of any system is reflective of the rate to which it is exposed to a stressor, susceptibility to harm from the stressor, and the capacity to cope, adapt or recover from the effects of that stressor (Paul,2013). It is relative and varies over space, time and among entities exposed (Cutter et al., 2003).

2.2 Evolution of different models of vulnerability

During the Cold War period, disasters and hazards were considered synonymous. Disasters were believed to be caused by natural forces, and human intervention was limited to predict, warn, and prepare for them (Wisner, 2016). White (1945) argued that "floods are acts of God, but flood losses are largely acts of man". His "School of Natural Hazards Studies" propounded the basic idea of risk perception and suggested measures like evacuation, zoning, and insurance as an alternative to traditional flood control methods like dams and levees (Burton et al.,2018).

2.2.1 Risk/hazard perspective



Source: Turner et al. (2003)

Figure 2.1 Risk Hazard Framework

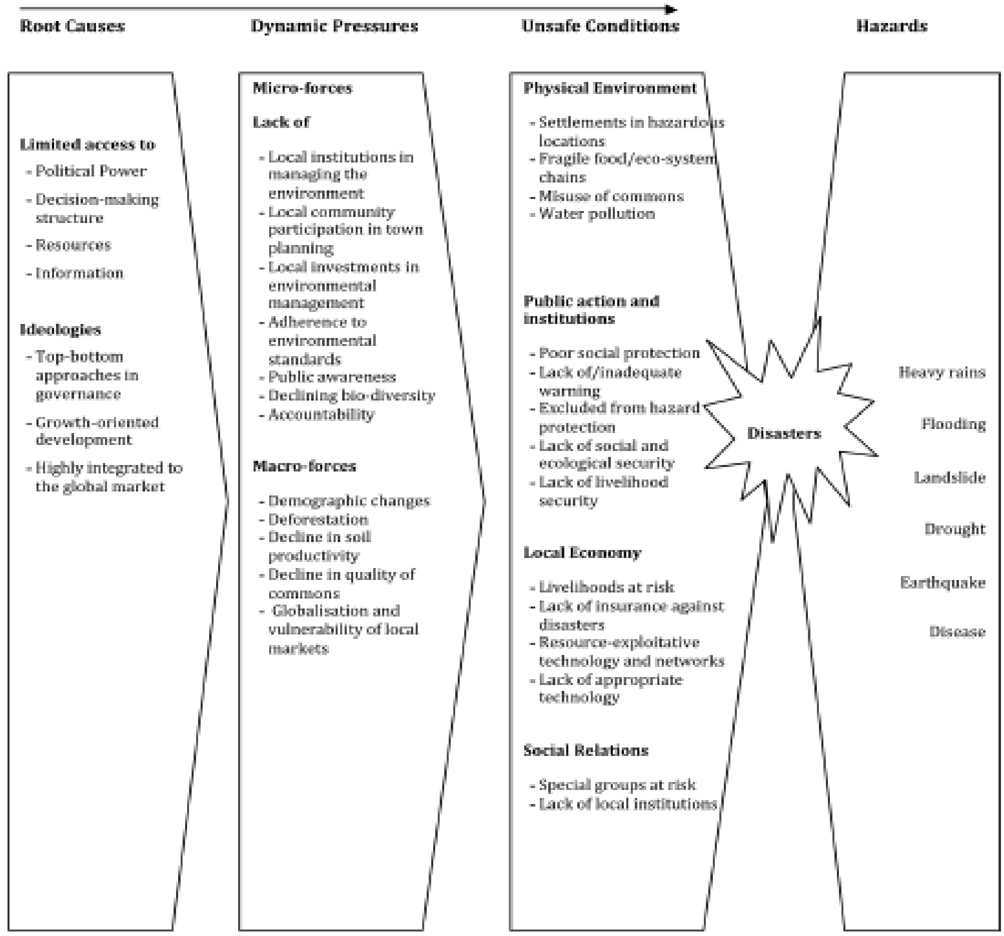
The risk/hazard model of vulnerability was developed from the school of natural hazards (Cutter et al.,2009). It considers "impacts of a hazard as a function of exposure to the hazard event and dose-response (sensitivity) of the entity exposed" (Srivastava,2015). This model is used by IPCC climate change impacts researchers (Eakin& Luers, 2006). It overemphasized biophysical elements and neglected the role of structural and human factors in producing vulnerability (Tesso et al., 2012).

2.2.2 Political economy/ecology perspective

Political economy/ political ecology researchers consider vulnerability as an intrinsic property of human systems. Natural hazards are regarded as the only one among the multiple stressors faced by the exposed population (Burton et al.,2018). They focused on human vulnerability and emphasized "how political, economic, social, historical, and institutional factors produce differential exposure and susceptibility" (Burton et al.,2018). This approach neglected the role of interactions between natural and human systems and the importance of system feedback (Turner et al.,2003). The concept of 'social vulnerability' has evolved from the political economy/ecology perspective.

2.2.3 Pressure and Release Model

The Pressure and Release Model developed by Wisner et al. (2004) combined the elements from the political ecology approach and risk hazard approach (Bahinipati, 2011; Paul,2013). This model conceptualises risk as the product of hazard and vulnerability. According to this model, vulnerability depends on three social factors: root causes (economic, demographic and political processes determining the power distribution), dynamic pressures (spatial or temporal changes in society or population) and unsafe conditions (posed by the physical environment or socioeconomic context)" (Wisner et al.,2004; Bahinipati,2011). The dynamic pressures convert the root causes into unsafe conditions, which, combined with the pressure created by physical and biological hazards, results in disaster (Cutter et al.,2009; Paul,2013; Ciueran et al.,2013).



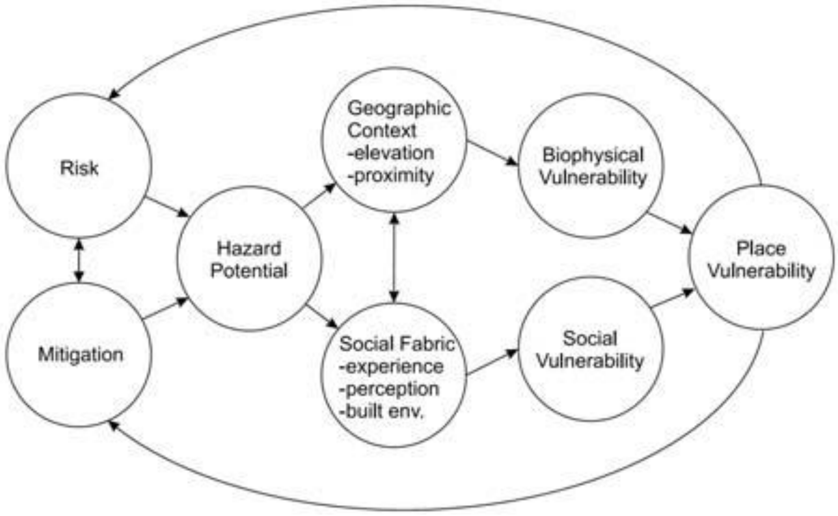
Source: Wisner et al.,2004

Figure 2.2 Pressure and Release model

This model is well suited for descriptive analysis of chronic, slow onset, and spatially diffuse hazards (Tsasis & Nirupama, 2008; Santha & Bhuvaneswari,2009; Santha & Sreedharan,2010; Barnes,2014). However, it failed to address the role of proximity to the source of threat and the interaction between social and natural systems in hazard creation" ((Burton et al., 2018; Cutter,2009).

2.2.4 Hazard of Place model

The system-level vulnerability analysis by the Risk/Hazard approach and the Pressure and Release model aided an in-depth understanding of physical and social determinants of vulnerability. However, they failed to explain how vulnerability varies spatially and manifests at local scales (Burton et al., 2018). The questions "vulnerability of whom" and "vulnerability to what" are effectively addressed in the Hazard of Place model developed by Susan Cutter in 1996. It incorporates spatial information of multiple hazards in a place and population information at the unit of analysis in a Geographic Information System platform (Cutter et al.,2009).



Source: Cutter et.al,2003

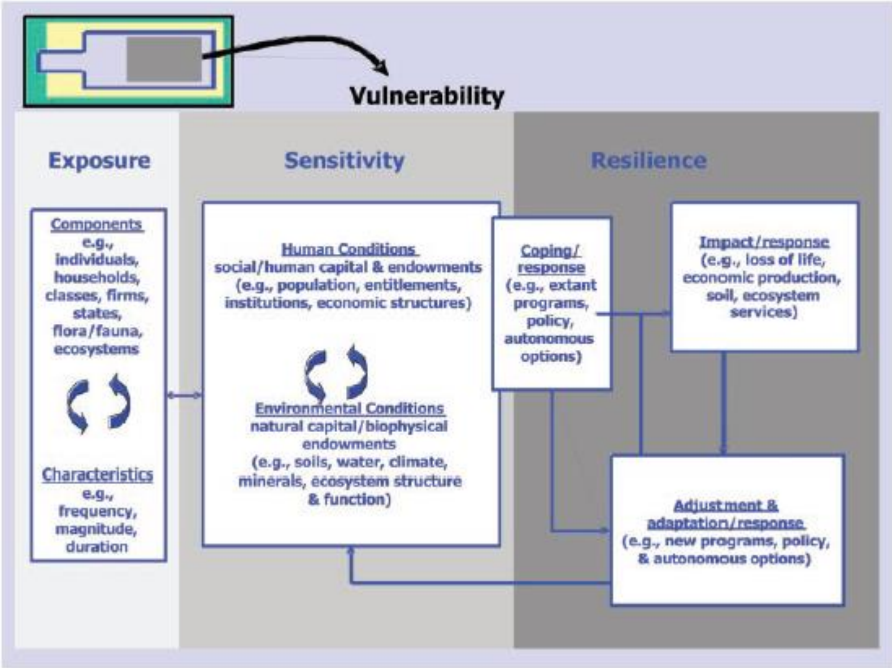
Figure 2.3 Hazard of Place Model

In this model, *Risk* is defined as “the likelihood of the event occurring” and includes three sub-elements: the potential source of the risk, the impact of the risk and an estimate of its frequency of occurrence” (Cutter et al.,2000). The interaction of risk and mitigation creates the hazard potential, which, when combined with the geographic context of an area, produces biophysical vulnerability (Cutter et al.,2000). At the same time, social vulnerability is formed by the interaction of hazard potential with the social fabric of a place (Burton et al.,2018). Biophysical and social vulnerabilities interact to produce vulnerability specific to a particular location and period. Place-based vulnerability provides feedback to enhance or reduce risk and mitigation, which can increase or decrease vulnerability (Cutter et al.,2000). This model failed to examine the underlying causes of social vulnerability (Cutter et al.,2009) and failed to include variables like social capital and governance, which are nonquantifiable and have limited spatial variation (Burton et al.,2018). Despite these disadvantages, its suitability for application at any spatial scale and the possibility of quantifying vulnerability made this model famous.

As the model could not fully explore the drivers of social vulnerability, Cutter et al. (2003) developed social vulnerability indices through an inductive approach. The social vulnerability index and its construction gained popularity as it allowed quantification of the generalized vulnerability of a population. The potential of population census to provide data at lower scales, even up to the village level, has inspired researchers in different countries to adapt this index and assess the generalized vulnerability of the population to any environmental hazard (Wisner, 2016). Cutter also tried to identify the dynamic nature of vulnerability by assessing the spatial and temporal changes in the social vulnerability of populations exposed to natural hazards (Cutter & Finch, 2007). The original Hazard of Place model was the spatial integration of biophysical and social vulnerabilities, and Borden et al. (2007) tried to quantify this model.

2.2.5 Vulnerability in sustainability science framework

This framework was developed by Turner et al. in 2003. This model defines *vulnerability* as “the degree to which a system, subsystem, or system component is likely to experience harm due to exposure to a hazard, either a perturbation or stress or stressor” (Turner et al.,2003). It aims to address the fundamental questions: “Who and what is vulnerable to environmental change, how to identify thresholds that signal change, how changes are attenuated or amplified by human and environmental conditions, and the degree to which resilience is a useful concept for developing proactive strategies for vulnerability reduction*”* (Burton et al.,2018). Cutter et al. (2009) criticized this approach as more appropriate in qualitative assessments than in empirical investigations since it does not distinguish between exposure and sensitivity and does not specify where vulnerability begins and ends.



Source: Turner et al. (2003)

Fig 2.4. Vulnerability in Sustainability Science Framework

Though more frameworks like Bogardi/Birkmann/Cardona (BBC) conceptual framework, Methods for the Improvement of Vulnerability Assessment in Europe (MOVE) framework etc., are developed after these models, they are not explained here due to the limited application of these frameworks in vulnerability assessment.

2.3 Vulnerability to climate change

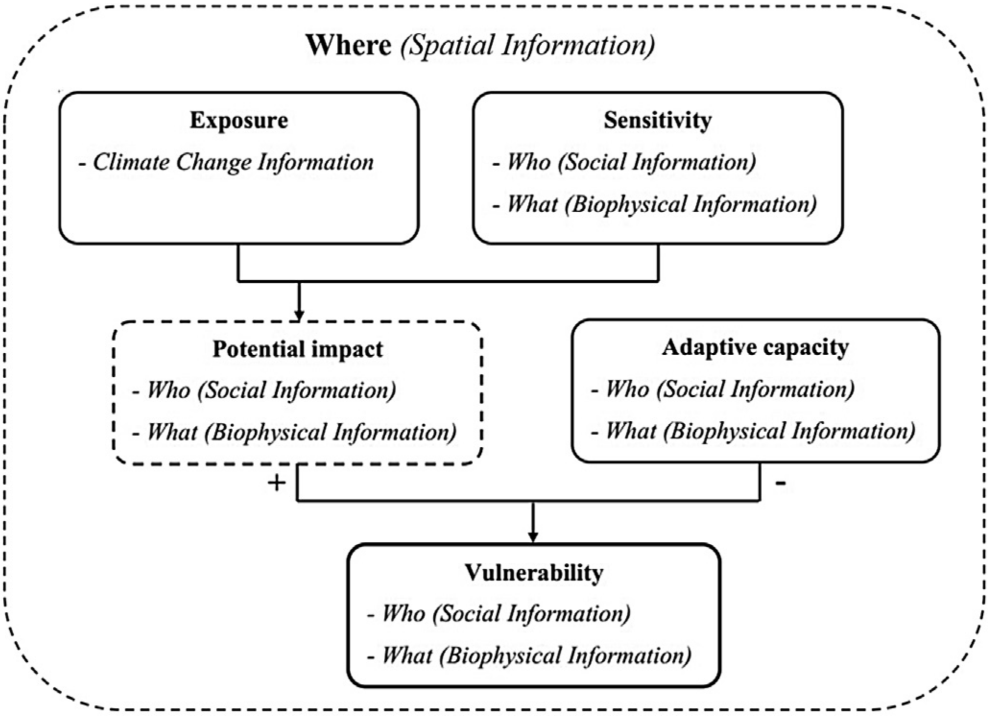
Generally, two strands of approaches are used for assessing vulnerability to climate change: Biophysical approaches, which focus on endpoint interpretation or outcome vulnerability, and social vulnerability approaches, which focus on starting point interpretation or social or contextual vulnerability (Fussel, 2005; Nguyen et al., 2016). The biophysical approach, which originates in risk hazard models, begins with the projection of future emission trends, development of climate scenarios, biophysical impact studies and identification of options for adaptation. (Kelly & Adger, 2000; O'Brien et al., 2004a). Vulnerability is conceptualised as the adverse consequences that remain after the adaptation process (Adger et al.,2004), which may be represented as monetary cost or change in yield, human mortality, damage to the ecosystem etc. (O'Brien et al., 2004a). This approach considers humans as passive recipients of the impacts of climate change and ignores the possibilities of their capacities to mediate the impacts of climate change (Vincent,2004).

The social vulnerability approach, rooted in political economy or (and) ecology models of vulnerability, puts the human system at a central stage and considers vulnerability as a state that exists in a system even before encountering a hazard (a priori) (Cutter & Finch,2008). It conceptualises vulnerability as determined by the underlying socioeconomic, political and institutional factors that shape resource allocation and access (Fussel, 2007; Vincent & Cull, 2010; Ge et al., 2017). It also realises that the susceptibility to climate change depends mainly on the current responding capacity of the population rather than the probabilistic future events (Kelly & Adger, 2000). This approach suffers from the limitations of not considering the climatic or biophysical features in an area. Biophysical approaches focus on technological adaptation to minimise the impacts of climate change. In contrast, social vulnerability approaches focus on sustainable development strategies that focus on increasing the response capacity of human populations to hazards (Fussel,2009).

Integrated vulnerability approaches try to overcome pitfalls in both approaches by integrating biophysical and socioeconomic concepts with indicators. These approaches combine the traits of a vulnerable social unit with their exposure to external stressors (Fussel, 2005). The IPCC vulnerability framework, Livelihood Vulnerability Index, Hazard of Place model, etc., are some common integrated approaches for vulnerability assessment.

2.3.1. IPCC Framework of vulnerability

The third assessment report of IPCC defines *vulnerability* as “the degree to which a system is susceptible to and unable to cope with adverse effects of climate change, including climate variability and extremes” (McCarthy et al., 2001). This definition identifies three elements that make up the vulnerability to climate change: exposure: “the character, magnitude and rate of climatic variation to which a system is exposed"; sensitivity: "the degree to which a system or species is affected, either adversely or beneficially by climate variability or change" and adaptive capacity: "the ability of systems, institutions, humans and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences" (McCarthy et al., 2001).



Source: Nguyen et al. (2016)

Figure 2.5 IPCC framework of vulnerability

Figure 2.5 shows the combination of three components in assessing climate change vulnerability provided by Nguyen et al. (2016). Exposure (climate change information) is combined with sensitivity (social information about "who is sensitive" and biophysical information about "what is sensitive and what could be affected") to determine primarily where the potential impacts will be felt (e.g., the area most likely to be affected by climate change). This potential impact, combined with social and biophysical information on adaptive capacity, indicates vulnerability.

This approach has undergone some modifications in the sixth assessment report (AR6), which considers vulnerability a risk component. *Risk* is "the potential for adverse consequences for human or ecological systems, recognizing the diversity of values and objectives associated with such systems. In the context of climate change, risks can arise from potential impacts of climate change as well as human responses to climate change" (Reisinger et al.,2020). In the new framework, *vulnerability* is defined as "the propensity or predisposition to be adversely affected and encompasses a variety of concepts and elements, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt". Here, 'exposure' element is considered as separate from vulnerability and its definition is changed to "the presence of people; livelihoods; species or ecosystems; environmental functions, services, and resources; infrastructure; or economic, social, or cultural assets in places and settings that could be adversely affected" (Begum et al.,2022). IPCC argues that the new conceptualization of vulnerability has changed from top-down to bottom-up and from endpoint to starting point interpretation (Begum et al.,2022). The new framework cannot be considered an integrated approach as it lacks climate information for an area. Hence, the first definition is still used in most vulnerability assessments worldwide, even after the publication of AR6.

2.3.2 Livelihood Vulnerability Index

Hahn et al. (2009) developed the Livelihood Vulnerability Index (LVI) from the Sustainable Livelihoods Approach. The sustainable livelihoods framework shows "how, in different contexts, sustainable livelihoods are achieved through access to a range of livelihood resources which are combined in the pursuit of different livelihood strategies" (Scoones,1998). The approach considers five categories of household assets: "natural, social, financial, physical and human capital" to assess the ability of households to survive external shocks (Hahn et al.,2009). As climate change complicates the livelihood security of households, LVI is created by incorporating climate exposure with the sustainable livelihoods approach (Hahn et al.,2009). The LVI comprises seven components: "Natural disasters and climate variability, Socio-demographic profile, Livelihood Strategies, Health, Social networks, Food and Water" (Hahn et al.,2009). They also created LVI-IPCC by segregating the seven components under exposure, sensitivity and adaptive capacity. This index is widely applied in climate change vulnerability assessments using primary surveys (Antwi-Agyei et al., 2013; Singh Jatav,2020; Toufique & Islam,2014). The lack of secondary data for all the components of this framework reduces its utility in studies using secondary data.

2.3.3 Other frameworks

Place-based vulnerability assessments based on the Hazard of Place model are popular among assessments of vulnerability to natural hazards. This model also finds application in climate change vulnerability studies (O'Brien et al.,2004b).

2.4 Assessment of vulnerability to climate change

The vulnerability assessment tries to answer the question: Who is vulnerable? Where are they located, and what drives their vulnerability? (Parker et al.,2019). Though the conceptual models of vulnerability were developed in the 1970s or 80s, their empirical assessment began only in recent decades. The lack of data availability at particular scales of analysis, differences in methodological approaches, disagreements on the indicators and drivers of vulnerability, etc., constrained the quantification of vulnerability (Birkmann,2007). The vulnerability assessments differ in the approaches used (qualitative/quantitative), scales of analysis (global, state, district, tehsil, village, household, etc.), frameworks used (IPCC, PAR, LVI, etc.), and the constituent components of vulnerability. While the qualitative approaches employ interviews, focus group discussions, and cognitive mapping to explain how local communities perceive vulnerability, Indicator approaches and GIS-based methods are used to assess it quantitatively (Venus et al.,2022).

2.4.1 Indicator approach

The indicator approach facilitates quantifying qualitative data by using proxies (Nguyen et al., 2016). It helps identify the most vulnerable entities and aids in monitoring changes over time and space (Parsons et al., 2016; Vincent,2004). The usage of indices also aids policymakers in devising adaptation strategies (Satapathy et al.,2014). An index might have a top-down or bottom-up approach, be qualitative or quantitative, be based on secondary or field-based data, and be monitored locally or nationally. (Parsons et al.,2016).

The construction of vulnerability indices involves the following steps:

1. *Selection of indicators*

Indicators for constructing vulnerability indices are selected using theory-driven, data-driven, and normative techniques (Harvey et al.,2009; Hinkel,2011). Theory-driven procedures, also known as deductive approaches, use conceptual frameworks, theories or models about the system to identify the variables. IPCC vulnerability framework and LVI use theory-driven procedures. Data-driven techniques, also known as inductive approaches, choose variables based on data availability and the statistical association of variables with documented vulnerability outcomes (for example, mortality due to natural disasters). This approach collects the maximum possible variables, and data reduction techniques such as factor analysis are used to construct the index. In normative approaches, indicators are identified through participatory approach, key informant interviews or expert opinion (Asare- Kyei et al.,2017; Mavhura et al., 2017).

2. *Quantification of indicators*

The indicators are quantified by collecting data from secondary sources or primary surveys.

3. *Normalisation or standardisation of indicators*

Each indicator has to be normalised or standardised to render it as a dimensionless measure or number for aggregation. Standardisation involves the conversion of each indicator to Z scores with zero mean and unit variance. Normalisation involves the conversion of each indicator to the range of 0 to 1.

4. *Aggregation of indicators*

The deductive approach aggregates the normalised or standardised indicators into a single index or subindices using the arithmetic mean or geometric mean (Chakraborty & Jsohi,2014). Unweighted indices are constructed when all the indicators are assumed to contribute equally to vulnerability (Malik et al.,2012). In the case of weighted indices, weights are assigned based on expert ranking, stakeholder perception or

PCA (Asare-Kyei et al.,2017; Jamir et al.,2013; Ravindranath et al., 2011; Mavhura et al.,2017). In the inductive approach, PCA is used to identify the latent factors that explain the high variation among the indicators (Borden et al., 2007). These latent factors or principal components are aggregated with or without weightage to form the indices.

5. *Categorisation of indices and plotting*

Vulnerability indices are segregated into different categories to identify the most vulnerable units. The categorisation is done by using classification methods or cluster analysis. Classification is generally based on quantiles, equal intervals (Jha & Gundimeda, 2019), natural breaks, mean and standard deviation, etc. Studies also use k-means cluster analysis for the categorisation of indices. GIS software is used to plot the spatial pattern of indices.

6. *Validation of indices*

Correlation of indices with other indices like HDI (Mishra,2015) with its subindices (Yenneti et al., 2016; Doyle et al., 2017), matching results with previous studies or correlating with disaster outcomes are the popular methods used for validating the results.

Though the indicator approach is the most popular technique for assessing vulnerability to climate change or natural hazards, it is also not free from limitations. Identification of indicators and their classification under different components of vulnerability is subject to spatial context and data availability. As some aspects of vulnerability (e.g., social and mental states of the population) are not quantifiable, this approach may fail to comprehensively assess vulnerability conditions at a place (Tate,2012). The lack of data may lead to reliance on easily measurable variables, which may result in the misrepresentation of people and the complex physical and politico-economic contexts in which they reside (Aksha et al.,2019). Also, the macro level aggregation may result in ignoring the context and specificity of different vulnerable regions.

2.5 Review of earlier attempts to assess vulnerability

This section deals with the earlier attempts in the literature to assess vulnerability to climate change. The natural hazard vulnerability assessments are also added in this section, as the methodology is similar for both. It also identifies the reasons for assessing rural-urban and social group-wise disparities in vulnerability to climate change.

2.5.1 Methodological differences in the assessment of vulnerability to climate change

The literature available on vulnerability assessment is diverse. The studies differ in the type of stressor to which vulnerability is assessed, approaches used for selection of indicators and construction of index (deductive/inductive), the scale at which analysis is conducted (micro/ macro/ meso), type of data (primary/ secondary), time dimension (spatial/ spatiotemporal/ simulation of future), dimensions of vulnerability assessed (biophysical only/ social vulnerability only/ integrated approaches), frameworks used and components of the vulnerability index.

The review of existing studies found that most studies in India and other countries use an integrated approach to assess vulnerability to climate change. The meso-level or national-level analysis in India and other countries mainly use the IPCC approach (Heltberg & Bonch-Osmolovsky,2011; Malik et al.,2012; Tripathi,2014; Bahinipati,2014; Chakraborty & Joshi,2014; Jha & Gundimeda,2019), while micro-level studies use LVI (Hahn et al.,2009; Antwi-Agyei et al.,2013; Botero & Salinas,2013; Madhuri et al.,2014; Dubey & Chaturvedi,2022; Panthi et al.,2016; Radhakrishnan & Gupta,2017; Sewando et al.,2016; Singh Jatav,2020; Toufique & Islam,2014; Venus et al.,2022).

Studies that assess only the social vulnerability dimension to climate change also vary in the approaches used. While Maiti et al. (2017) and Maiti et al. (2015) integrated climatic variables with social vulnerability indicators using the IPCC framework, Sahana et al. (2021) integrated biophysical characteristics into LVI. At the same time, studies like Yenneti et al. (2016) and Ge et al. (2017) omitted climatic or biophysical variables while using the IPCC approach to assess social vulnerability to climate change. Scholars like Malakar and Mishra (2017), Wu et al. (2016), and Jhan et al. (2020), who prepared frameworks to assess social vulnerability to climate change, have generally omitted climatic or biophysical variables.

Though most integrated vulnerability assessments use the IPCC framework, the equations used for combining exposure, sensitivity and adaptive capacity differ among these studies. While some authors followed the simple aggregation by IPCC (Jamir et al.,2013; Cinner et al.,2013; Pandey & Jha,2012; Bahinipati,2014), some authors tried to average them (Chakraborty & Joshi,2014; Adeloye et al.,2015; Heltberg & Bonch-Osmolovskiy,2011; Malik et al.,2012). Certain scholars (Mohanty & Wadhawan,2021; Singh & Nair,2013; Pandey & Bardsley,2015) used products of components instead of aggregation. The studies using this approach also differ in vulnerability components (Bahinipati,2014; Young et al.,2010; Menezes et al., 2018). Moreover, the revision of the framework in the recent assessment report constrains the usage of the old framework of the IPCC. Although LVI is widely used by studies assessing vulnerability to climate change, the assessment is conducted at the community level, and meso or macro analyses are limited due to the constraints on data availability.

2.5.2 Advantages of place-based vulnerability approaches

Place-based vulnerability assessments use an integrated approach, and social vulnerability assessments for natural hazards follow an inductive approach. The inductive approach selects the indicators based on statistical relations with vulnerability or disaster outcomes and avoids biases in selecting indicators or weights. This approach is based initially on the Hazard of Place (HoP) model, which integrates biophysical and social vulnerability at a particular place. Cutter et al. (2000) applied this model in Georgetown, but the vulnerability was not quantified, and an in-depth study of the social vulnerability dimension was lacking. Borden et al. (2007) quantified place-based vulnerability by an indicator approach. He prepared a Place Vulnerability Index (PVI) as an aggregate of the "Social Vulnerability Index (SoVI), Built Environment Vulnerability Index (BEVI), and Hazard Vulnerability Index (HazVI)."

Cutter et al. (2003) overcame the limitations of the social vulnerability dimension in the earlier model by developing an inductive approach for a separate assessment of social vulnerability. While certain scholars (O'Brien et al.,2004b; Sherbinin & Bardy,2015; Klienosky et al.,2007) follow original HoP model by overlaying exposure maps to social vulnerability maps, certain other scholars (Siagian et al.,2013; Mavhura et al.,2017; Aksha et al.,2019; Armas & Gavris,2016) used SoVI to assess the generic social vulnerability of population. The SoVI of Cutter (2003) was a composite index that suffered from masking different vulnerability dimensions.

Borden et al. (2007) segregated the social vulnerability index while preparing PVI. Holand et al. (2011), Huang et al. (2015) and Mazumdar & Paul (2016) adapted SoVI and BeVI from Borden's index, but omitted the HazVI. Torok et al. (2021) initiated applying the place-based vulnerability model in the climate change discipline by indicating biophysical vulnerability with climate impact vulnerability index and social vulnerability segregated into the built environment, demographic and socioeconomic vulnerability indices. This assessment facilitates the identification of dimensions of vulnerability to which each study unit is vulnerable and thus aids targeted interventions.

2.5.3 Spatiotemporal assessments of vulnerability to climate change

A dynamic vulnerability assessment is beneficial for understanding the changes in vulnerability conditions of the study units over time. However, data limitations have constrained the vulnerability assessments to one particular point. Cutter & Finch (2008) attempted a spatiotemporal assessment of the social vulnerability of US counties in 5 decades (1960 to 2000), and Frigerio et al. (2018) followed it in Italy for three decades (1991 to 2011). Das et al. (2021) and Vittal et al. (2020) followed this for Indian districts using data from the 2001 and 2011 censuses. However, all these studies focused only on the social vulnerability dimension, and changes in biophysical characteristics or climatic indices were not attempted.

2.5.4 Rural -urban disparity in vulnerability to climate change

Ge et al. (2017), Wang et al. (2022), and Ge et al. (2021) identified significant differences in the social vulnerability of rural and urban areas in China and Australia. These studies considered only the social vulnerability dimension and omitted biophysical elements from their analysis. Though Indian scholars have attempted to assess rural (Rao et al.,2016) or urban (Yenneti et al.,2016) vulnerability, a comparison of both has not been attempted in India. Indian states like Madhya Pradesh possess higher rural-urban divide in access to basic facilities, education, employment, demographic characteristics etc. (Chaudhuri & Roy, 2017; IIPS & ICF,2017; GoMP,2015; Chaurasia,2011; Chaubey & Chaubey,1998), which might affect their urban vulnerability to climate change as well. Studies have even found that urbanization can reduce the disaster losses in India (Patri et al.,2022). However, a comparison of vulnerability between rural and urban areas is not attempted in India.

2.5.5 Vulnerability of agriculture sector to climate change

The vulnerability assessments in the agriculture sector have identified changes in maximum and minimum temperature and high intensity and variability of rainfall as significant contributors to exposure (Sehgal et al., 2013; Srivastava,2015). Whereas landholding size, yield of crops, cropping intensity, commercialization and diversification, and access to inputs contributed to the sensitivity and adaptive capacity of the agriculture sector (Raju et al., 2017; Sehgal et al.,2013; Srivastava, 2015; Antwi-Agyei et al., 2012; Das,2013; Choudhary & Sirohi,2022). While Das (2013) identified higher socioeconomic vulnerability as a leading contributor to its highest vulnerability to climate change, O’Brien et al. (2004b) identified high climate sensitivity, import sensitivity and low adaptive capacity as significant contributors to its vulnerability to climate change and globalization. 14 out of the 115 very high agriculturally vulnerable districts of India belong to Madhya Pradesh due to their high or very high exposure and sensitivity and low adaptive capacity (Rao et al.,2013). The studies on the vulnerability of the agriculture sector to climate change are generally static, as they discuss vulnerability at only one point in time (Das,2013; Rao et al.,2013; Sehgal et al.,2013; Raju et al., 2017). Varadan & Kumar (2015) used instability and change over a period as a variable to detect the change over time. Palanisami et al. (2008) attempted to assess the vulnerability of agroclimatic regions in Tamil Nadu for three decades. However, the index is constructed separately for each decade, and the results show only the ranking of each zone in each year of study. As the index is constructed by simple averaging, there is no attempt to identify the significant contributors of vulnerability.

2.5.6 Vulnerability of social groups to climate change

In Indian states like Madhya Pradesh, higher disparities exist among different social groups in terms of wealth status (Tagade et al.,2018), education (Thorat,2006), employment opportunities (Bango & Kashyap, 2018), access to land (Mohanty,2001; Thangaraj, 1994; Parida,2013), access to basic facilities (Bosher et al., 2007; Dutta et al.,2015; Kuchimanchi et al., 2019) and access to extension services (Krishna et al.,2018). Chaurasia (2013) identified ST in rural areas as the most disadvantaged population group in Madhya Pradesh and Non SC/ST in urban areas as the most advantaged population group in terms of the HDI. Chaurasia (2011) found that ST possesses the highest child deprivation index, highest human poverty index, lowest expectation of life at birth, low school participation rate, high child mortality, etc., compared to other social groups. School dropout rates are found to be high among children of SC and ST, and they lag behind others in access to basic assets (Ahuja,2014). The vulnerability assessments in India, like Azhar et al. (2017), Mishra (2015) and Bahinipati (2014), have identified districts with more marginalised sections as highly vulnerable to climate change. However, a study specifically on these social groups has not been conducted yet. In global and Indian vulnerability literature, the vulnerability of specific communities like farmers, fishing communities, agropastoralists, forest fringe villagers, etc., are addressed (Sahana et al.,2021; Huynh& Stringer,2018; Morzaria-Luna et al.,2014; Yadava & Sinha,2020). However, the differentiation of vulnerability among social groups is not attempted, as the review shows.

2.5.7 Research gap

The main gaps identified from the review can be summarized as follows:

1. A comprehensive assessment of the generic social vulnerability of the population is lacking in Indian literature.

2. Integrated vulnerability assessment to climate change using a place-based vulnerability model is more suitable than IPCC and LVI for meso-level analysis. However, no study has attempted this model in India.

3. Analysis of spatiotemporal patterns of vulnerability to climate change will help identify whether vulnerability is increasing or decreasing. Social vulnerability studies in other countries have attempted spatiotemporal assessments but have not been applied to integrated approaches.

4. Assessment of disparities among climate change vulnerability of rural and urban populations is necessary in India, especially Madhya Pradesh. However, it has yet to be attempted in India. Though this disparity is studied in other countries, they considered social vulnerability dimensions only.

5. Spatiotemporal assessments of agriculture sector vulnerability are not attempted.

6. Social group-wise vulnerability within a population is also not attempted.

This chapter has explained the concept of vulnerability, the definitions used, the evolution of different models, the relevance of assessing vulnerability to climate change and identified the gaps in existing studies. The next chapter deals with the profile of the study area, i.e., the state of Madhya Pradesh.

Chapter 3

Description of study area, methodology, data sources and variables used

The earlier chapter explained the concept of vulnerability, its origin and use in various disciplines, different models of vulnerability, usage of the concept in climate change discipline, etc. Before conducting the vulnerability assessment, detailed information on the study area and the methodology followed. This chapter presents the socioeconomic and agricultural background of the state of Madhya Pradesh, the theoretical models used in the study, the conceptual framework, major data sources used, variables used for constructing indices and the tools used in the thesis.

3.1 The location of study: Madhya Pradesh

Madhya Pradesh is located in central India between 21°04' N and 26°54' N latitudes and 74°02'E and 82°49'E longitudes. It was initially formed on 1st November 1956 by merging Madhya Bharat, Vindhya Pradesh, Bhopal and Madhya Pradesh, according to the States Reorganization Act of 1956. In 2000, Chhattisgarh state was carved out from Madhya Pradesh by enacting the Madhya Pradesh Reorganization Act. Madhya Pradesh is a landlocked state surrounded by Chhattisgarh, Rajasthan, Gujarat, Uttar Pradesh, Jharkhand and Maharashtra. It is the second largest state in geographical size (3 08,245 sq. km). It consists of 6 % of the total population in India (7,26,26,809) and ranks fourth in the decadal population growth rate (20.3%) in the last decade (2001-11) (GoI,2011). The state is currently divided into ten divisions and 53[3] districts for administrative purposes. The table 3.1 shows the demographic characteristics of 50[4] districts of Madhya Pradesh, according to the population census of 2011 in Madhya Pradesh.

[3] *Agar Malwa, Niwari and Mauganj districts are formed after the last population census (2011) in Madhya Pradesh. This study considers only 50 districts due to lack of data for new districts*

[4] *This study considers Agar Malwa as part of Shajapur, Niwari as part of Tikamgarh and Mauganj as part of Rewa, due to nonavailability of data.*

Table 3.1 Demographic characteristics of districts of Madhya Pradesh

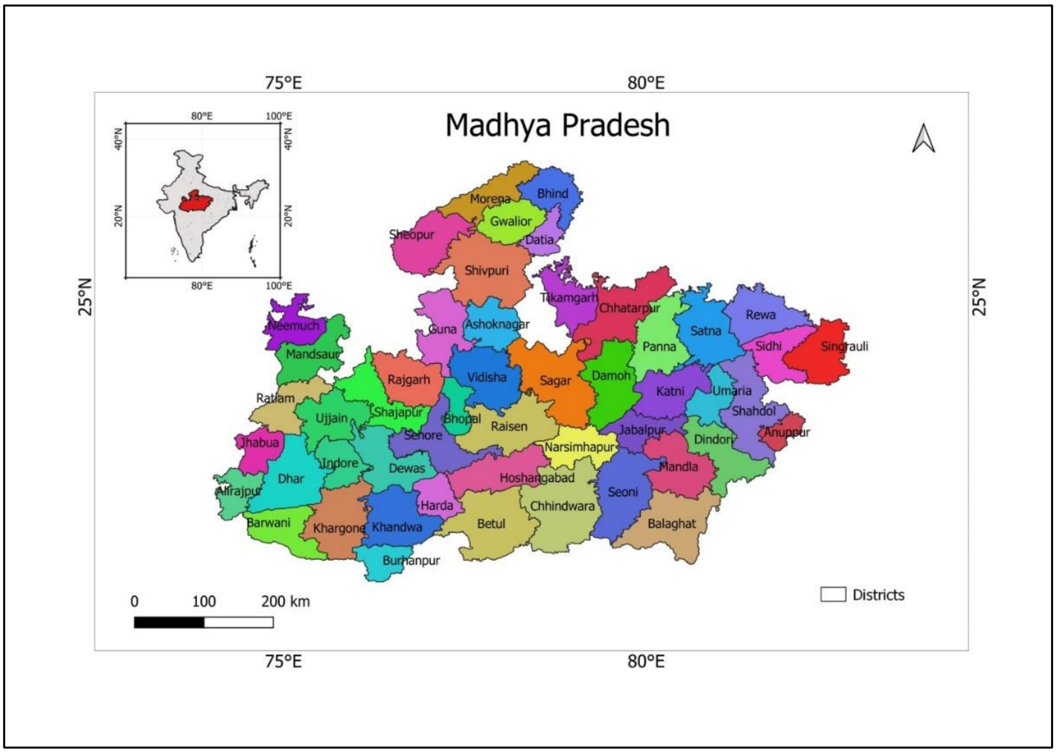
Sl. No.	District	Total Population	% of population	Geographical area (Sq.km)	% of Geographical area	Population density	Population growth rate	Percentage of urban population (2011)	% of SC	% of ST
1	Sheopur	687861	0.9	6606	2.1	104	22.9	15.6	15.8	23.5
2	Morena	1965970	2.7	4989	1.6	394	23.4	23.9	21.4	0.9
3	Bhind	1703005	2.3	4459	1.4	382	19.2	25.4	22	0.4
4	Gwalior	2032036	2.8	4560	1.5	445	24.5	62.7	19.3	3.5
5	Datia	786754	1.1	2902	0.9	292	18.5	23.1	25.5	1.9
6	Shivpuri	1726050	2.4	10066	3.3	168	22.8	17.1	18.6	13.2
7	Tikamgarh	1445166	2	5048	1.6	286	20.1	17.3	25	4.7
8	Chhatarpur	1762375	2.4	8687	2.8	203	19.5	22.6	23	4.2
9	Panna	1016520	1.4	7135	2.3	142	18.7	12.3	20.5	16.8
10	Sagar	2378458	3.3	10252	3.3	232	17.6	29.8	21.1	9.3
11	Damoh	1264219	1.7	7306	2.4	173	16.6	19.8	19.5	13.2
12	Satna	2228935	3.1	7502	2.4	297	19.2	21.3	17.9	14.4
13	Rewa	2365106	3.3	6314	2	374	19.9	16.7	16.2	13.2
14	Umaria	644758	0.9	4076	1.3	158	25	17.1	9	46.6
15	Neemuch	826067	1.1	4256	1.4	194	13.8	29.7	13.5	8.6
16	Mandsaur	1340411	1.8	5535	1.8	242	13.2	20.7	18.6	2.5
17	Ratlam	1455069	2	4861	1.6	299	19.7	29.9	13.6	28.2
18	Ujjain	1986864	2.7	6091	2	326	16.1	39.2	26.4	2.5

19	Shajapur	1512681	2.1	6195	2	244	17.2	19.4	23.4	2.5
20	Dewas	1563715	2.2	7020	2.3	223	19.5	28.9	18.7	17.4
21	Dhar	2185793	3	8153	2.6	268	25.6	18.9	6.7	55.9
22	Indore	3276697	4.5	3898	1.3	839	32.9	74.1	16.6	6.6
23	Khargone	1873046	2.6	8025	2.6	233	22.9	16	11.2	39
24	Barwani	1385881	1.9	5427	1.8	256	27.6	14.7	6.3	69.4
25	Rajgarh	1545814	2.1	6153	2	251	23.3	17.9	19.1	3.5
26	Vidisha	1458875	2	7371	2.4	198	20.1	23.3	20	4.6
27	Bhopal	2371061	3.3	2772	0.9	854	28.6	80.9	15.1	2.9
28	Sehore	1311332	1.8	6578	2.1	199	21.5	18.9	20.7	11.1
29	Raisen	1331597	1.8	8466	2.7	157	18.3	22.8	17	15.4
30	Betul	1575362	2.2	10043	3.3	157	12.9	19.6	10.1	42.3
31	Harda	570465	0.8	3334	1.1	171	20.2	20.9	16.3	28
32	Hoshangabad	1241350	1.7	6703	2.2	185	14.5	31.4	16.5	15.9
33	Katni	1292042	1.8	4950	1.6	261	21.4	20.4	12.1	24.6
34	Jabalpur	2463289	3.4	5211	1.7	472	14.5	58.5	14.1	15.2
35	Narsimhapur	1091854	1.5	5133	1.7	213	14	18.6	16.9	13.4
36	Dindori	704524	1	7470	2.4	94	21.3	4.6	5.6	64.7
37	Mandla	1054905	1.5	5800	1.9	182	18	12.3	4.6	57.9
38	Chhindwara	2090922	2.9	11815	3.8	177	13.1	24.2	11.1	36.8
39	Seoni	1379131	1.9	8758	2.8	157	18.2	11.9	9.5	37.7
40	Balaghat	1701698	2.3	9229	3	184	13.6	14.4	7.4	22.5
41	Guna	1241519	1.7	6390	2.1	194	27	25.2	15.6	15.4

42	Ashoknagar	845071	1.2	4674	1.5	181	22.7	18.2	20.8	9.7
43	Shahdol	1066063	1.5	6205	2	172	17.4	20.6	8.4	44.7
44	Anuppur	749237	1	3747	1.2	200	12.3	27.4	9.9	47.9
45	Sidhi	1127033	1.6	4851	1.6	232	23.7	8.3	11.6	27.8
46	Singrauli	1178273	1.6	5675	1.8	208	28	19.2	12.8	32.6
47	Jhabua	1025048	1.4	3600	1.2	285	30.7	9	1.7	87
48	Alirajpur	728999	1	3182	1	229	19.5	7.8	3.7	89
49	Khandwa	1310061	1.8	7352	2.4	178	21.5	19.8	12	35
50	Burhanpur	757847	1	3427	1.1	221	19.4	34.3	8.5	30.4
		72626809		308252					**15.6**	**21.1**

Source: GoI, 2011

The population of these districts ranges from 5,70,465 in Harda to 32,76,697 in Indore. Chhindwara is the largest district in terms of geographical area (11815 sq. km), and Bhopal is the smallest district (2772 sq. km.). Only four districts, viz. Indore, Bhopal, Gwalior, and Jabalpur have more than 50% of the urban population, and the rest of the districts are primarily rural and thus possess very low population density. Indore had the highest population growth rate from 2001 to 2011 (32.9), whereas Anuppur had the lowest growth rate (12.3). Figure 3.1 shows the districts of Madhya Pradesh as existing in 2011.



Source: Prepared using QGIS

Figure 3.1 Districts of Madhya Pradesh

The rural-urban population in the state is 72:28, with only four districts (Bhopal, Indore, Gwalior and Jabalpur) having over 50% urban population (GoI,2011). The rural and urban population shows higher disparities in socioeconomic characteristics (Table A.1 in appendix). Rural Madhya Pradesh possesses lower literacy rates, lower access to basic facilities and higher work participation rates than urban areas. The share of marginal workers (who work for less than 6 months) among total workers is high in rural areas. The rural areas have a better sex ratio but a higher gender gap in literacy than urban areas. However, the gender gap in work participation is small in rural areas, as more women work in the agricultural sector.

21% of the Madhya Pradesh population belongs to ST, and 16% to Scheduled Castes (SC). Alirajpur has the highest share of ST in its population (89%), and Ujjain has the highest share of SC in its population (26%). The access to basic facilities for the SC and ST populations is shallow, as 73% of SC and 93% of ST live in rural areas (Table A.2 in the appendix). The literacy rate and access to basic facilities remain the lowest for ST, as compared to other social groups. The work participation rate, share of marginal workers and dependence on agriculture are also highest among ST. The relatively better status of women in tribal culture resulted in a better sex ratio and lower gender gaps in literacy rate and work participation than other groups.

The agriculture sector acts as a major contributor to state gross value added (46.98 % in 2020-21[5])and as a major employer of the state population. The sector's performance is also significantly better than in other states of India (Gulati et al.,2021). Despite the remarkable growth, it suffers from increasing marginalisation of holdings, a high share of rainfed cultivation, lower access to credit, low investment capacity and lack of reach of extension services, especially among tribal farmers.

The population dependence on agricultural sector (70%) is higher than India's average of 55% (Gulati et al.,2021). 46 out of 50 districts possess more than 50% of the population that is agriculturally dependent, and Khandwa has the highest share (90%). The agricultural dependence of ST and SC is higher than that of other social groups. The agricultural dependence among ST is highest in Burhanpur (95%), among SC is highest in Shajapur (88%), and among Non SC/ST is highest in Rajgarh (82%) (Table A.3 in appendix). Though the dependence on the agriculture sector is higher among SC & ST, their ownership of holdings is very low. When Non SC/ST possess almost 72% of the operational holdings in the state, SC possesses only 8%, and ST only has 20% (GoI,2020). Marginalisation of landholdings is also higher among SC & ST than Non SC/ST (Table A.4 in appendix).

These prevailing socioeconomic situations and the climate change scenario discussed in section 1.3 make a climate change vulnerability assessment necessary in Madhya Pradesh.

[5] *https://www.ibef.org/uploads/states/infogrphics/large/Madhya-Pradesh-Infographic-September-2021.pdf*

3.2 Theoretical and conceptual frameworks used in the study

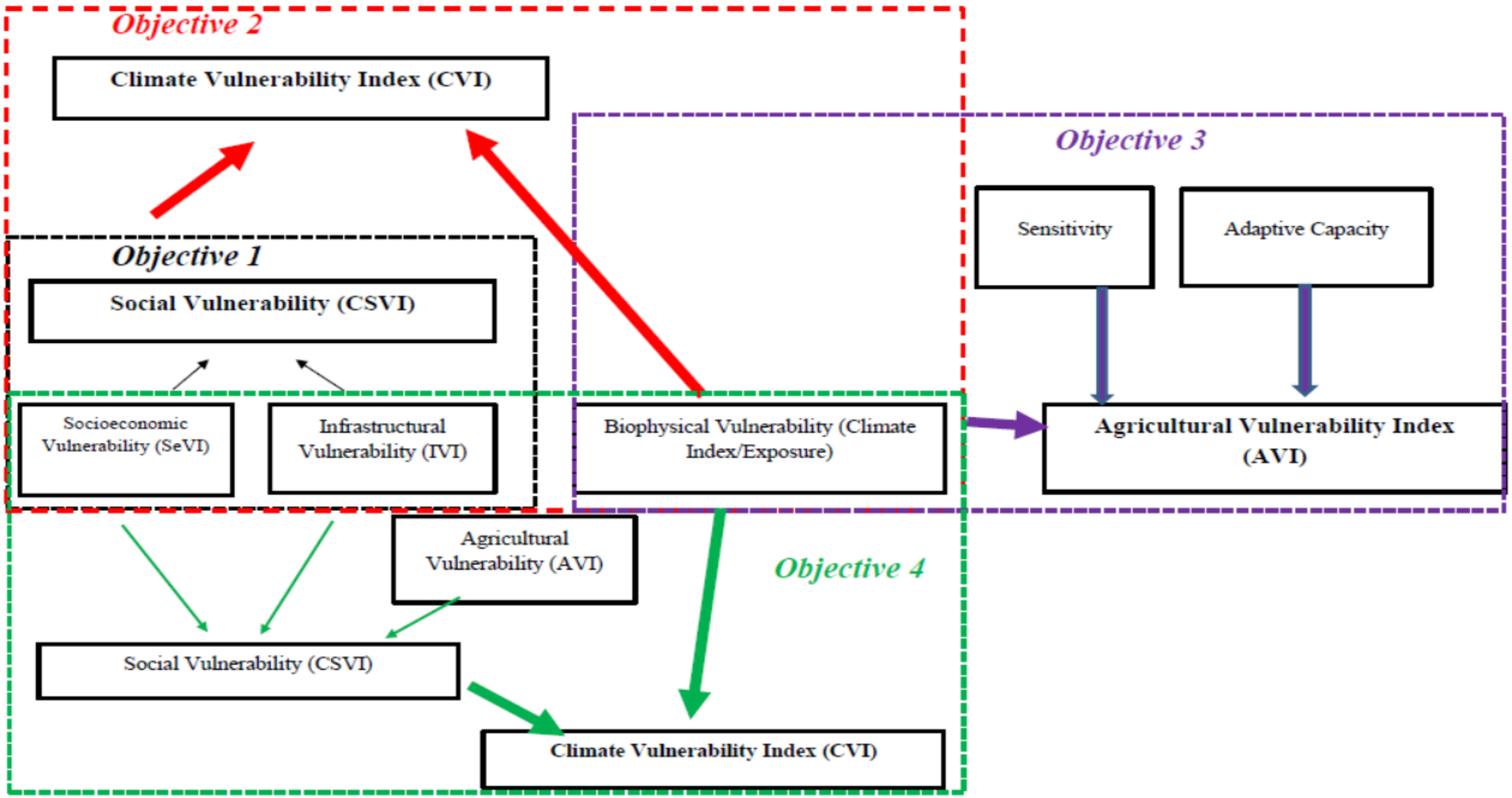
Table 3.2 Models used in the objectives of thesis

Sl. No.	Objective	Model used
1	To compare social vulnerability of Madhya Pradesh population with population of other states of India	SoVI
2	To assess the spatiotemporal pattern of climate change vulnerability in Madhya Pradesh at district level and rural and urban area of districts	HoP model
3	To assess spatiotemporal pattern of agriculture sector vulnerability to climate change in Madhya Pradesh	IPCC approach
4	To assess the vulnerability of social groups in Madhya Pradesh to climate change	HoP model

The vulnerability assessment involves four objectives as specified in table 3.2. Table 3.2 shows the theoretical models used for assessing the objectives of this thesis, and figure 3.2 depicts the conceptual framework of the study.

The first objective of this study deals with the generic social vulnerability of the population and does not consider indicators related to climate change exposure. Hence, it adapts the Social Vulnerability Index (SoVI) developed by Cutter et al. (2003). Holand et al. (2011) advanced this method by segregation of SoVI, and Mazumdar & Paul (2016) applied this in the Indian context. The first objective tries to apply this bifurcated social vulnerability index to the whole of India by identifying separate Socioeconomic Vulnerability Index (SeVI) and Infrastructural Vulnerability Index (IVI) for each district of India. Composite Social Vulnerability Index (CSVI) identifies whether the aggregation masks the vulnerability dimension where adaptation interventions are needed.

Here, ***Social Vulnerability = Socioeconomic Vulnerability +Infrastructural Vulnerability***



Source: Author's preparation

Figure 3.2 Conceptual framework of thesis

The second objective deals with the climate change vulnerability of the Madhya Pradesh population for three decades. Hence, it uses a place-based vulnerability approach, initially developed by Cutter et al. (1996) and later quantified by Borden et al. (2007). This approach allows for a separate assessment of changes in climatic parameters and social vulnerability, identifies the most vulnerable dimension, and, thus, facilitates targeted policymaking. The Climate Vulnerability Index (CVI) is constructed as a weighted average of the Climate Index and Composite Social Vulnerability Index. As in the first objective, the Composite Social Vulnerability Index (CSVI) is further segregated into the Socioeconomic and Infrastructural Vulnerability Indices. Hence, the first part of this objective aims to assess the spatiotemporal pattern of vulnerability to climate change by preparing CVI and its subindices for districts of Madhya Pradesh for three decades (1991,2001 and 2011). The second part of this objective tries to understand whether climate change vulnerability differs in rural and urban areas. Hence, the indices have been prepared for rural and urban areas for three decades (1991,2001 and 2011).

Here, ***Climate Vulnerability = Climate Index + Social Vulnerability Index***

Social Vulnerability = Socioeconomic Vulnerability + Infrastructural Vulnerability

In contrast to the first two objectives, which deal with the vulnerability of the population, the third objective deals with the vulnerability of a particular sector, viz., the agriculture sector. As vulnerability in the agriculture sector is conceptualised as what is left behind after adaptation, the IPCC framework in the third assessment report is used in this objective. Here, the Agricultural Vulnerability Index (AVI) is constructed from Exposure, Sensitivity, and Adaptive Capacity subindices. As this objective also deals with spatiotemporal assessment, AVI and subindices are prepared for five decades (1970-1979,1980-1989,1990-1999,2000-2009 and 2010-2015).

Here, ***Agricultural Vulnerability = Exposure + Sensitivity – Adaptive Capacity***

In the fourth objective, place-based vulnerability is used, and CVI is prepared for three social groups, viz. SC, ST and Non SC/ST in Madhya Pradesh. As agriculture is the primary source of livelihood for marginalised social groups such as SC & ST, the CSVI contains a subindex for agricultural vulnerability along with socioeconomic and infrastructural vulnerability indices.

Here, ***Climate Vulnerability = Climate Index + Social Vulnerability Index***

Social vulnerability = Socioeconomic Vulnerability + Infrastructural Vulnerability + Agricultural Vulnerability

3.3 Unit of study

The districts are considered the most effective units for planning and implementing development programmes in India (Prasad, 2016; Rao et al.,2016). Indian studies assessing vulnerability, poverty, and backwardness (Chaudhari & Gupta,2009) point out the limitations of state-level aggregation of results in practical policy implementations and hence suggest district as the most suitable level of analysis. The first objective of the thesis is to assess the vulnerability of the population among 640 districts of India. In the second objective, the population of 50 Madhya Pradesh districts and its rural and urban populations are considered. In the third objective, the agriculture sector at the district level, and in the fourth objective, social groups at the district level are considered as the unit of analysis.

3.4 Data sources used

The data for all the objectives are collected from secondary data sources. The socioeconomic and infrastructural variables are collected from the population census of India over different decades**.** Data related to the agriculture sector are collected from the district-level database of the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) and Agriculture Census.

The district-level temperature data is collected from the ICRISAT database, and rainfall is collected from the India Water Resources Information System database. The type of variables collected, units of study, reference period and link to the data source are provided in Table 3.3.

Table 3.3 Sources of data

Sl.No.	**Objective**	**Unit of study**	**Variables collected**	**Data source**	**Link to the data source**	**Reference period**
1	To compare social vulnerability of Madhya Pradesh population with population of other states of India	640 districts of India	Socioeconomic Variables	Primary Census Abstract tables	https://censusindia.gov.in/census.website/data/census-tables	2011
			Infrastructural variables	House listing and housing census tables		
2	To assess the spatiotemporal pattern of climate change vulnerability in Madhya Pradesh	50 districts of Madhya Pradesh and	Socioeconomic Variables	Primary Census Abstract tables	https://censusindia.gov.in/census.website/data/census-tables	1991,2001 &2011

	at district level and rural and urban area of districts	their rural and urban areas	Infrastructural variables	House listing and housing census tables		
			Monthly maximum and minimum temperature	ICRISAT district level database	http://data.icrisat.org/dld/src/environment.html	1962-2011
			Annual average rainfall	India-WRIS database	https://indiawris.gov.in/wris/#/DataDownload	1962-2011
3	To assess spatiotemporal pattern of agriculture sector vulnerability to climate change in Madhya Pradesh	Agriculture sector of 37 districts of Madhya Pradesh	Agriculture sector related variables	ICRISAT district level database	http://data.icrisat.org/dld/src/crops.html	1970-2015
			Monthly maximum and minimum temperature	ICRISAT district level database	http://data.icrisat.org/dld/src/environment.html	1970-2015
			Annual average rainfall	India-WRIS database	https://indiawris.gov.in/wris/#/DataDownload	1970-2015

4	To assess the vulnerability of social groups in Madhya Pradesh to climate change	SC, ST & Non SC/ST of 50 districts of Madhya Pradesh	Socioeconomic Variables	Primary Census Abstract tables	https://censusindia.gov.in/census.website/data/census-tables	2011
			Infrastructural variables	House listing and housing census tables		
			Operational holding characteristics of SC, ST and Non SC/ST in districts of Madhya Pradesh	Agriculture Census	https://agcensus.dacnet.nic.in/DatabaseHome.aspx	2010-11
			Monthly maximum and minimum temperature	ICRISAT district level database	http://data.icrisat.org/dld/src/environment.html	1982-2011
			Annual average rainfall	India-WRIS database	https://indiawris.gov.in/wris/#/DataDownload	1982-2011

3.5 Variables used in the study

Table 3.4 Variables used in the study

Sl. No.	Concept	Variable used	Relation with vulnerability	Used in objectives
Climatic Variables				
1	Rate of change in temperature	Rate of change in annual mean maximum temperature	Positive	2,3,4
		Rate of change in annual mean minimum temperature	Positive	2,3,4
2	Variation in rainfall	Coefficient of variation in annual rainfall	Positive	2,3,4
		Coefficient of variation in monsoon rainfall	Positive	3,4
Socioeconomic Variables				
1	Decadal growth in population	Decadal Population Growth rate	Positive	1,2,4
2	Population density	Population density	Positive	1,2
3	Age	% of children to total population	Positive	1,2,4
		% of elderly to total population	Positive	1,4
4	Gender	% of female to total population	Positive	1,2
5	Family structure	% of female headed households to total households	Positive	1
6	Socially dependent population	% of SC to total population	Positive	1,2
		% of ST to total population	Positive	1,2
7	Special needs population	% of disabled population to total population	Positive	4
8	Houseless population	% of houseless population to total populatio	Positive	1
9	Education	Literacy rate	Negative	2

		Literacy rate of male	Negative	1,4
		Literacy Rate of female	Negative	1,4
		Gender gap in literacy rate	Positive	2
10	Employment	Male Work Participation Rate	Negative	1
		Female Work Participation Rate	Negative	1,4
		Gender gap in work participation rate	Positive	2
		% of marginal workers to total population	Positive	2
11	Single sector dependence	% of main workers depending on primary sector	Positive	1
		% of main workers depending on agricultural sector	Positive	2
		% of marginal workers depending on primary sector	Positive	1
Infrastructural variables				
1	Infrastructure and lifelines	% of households having access to electricity as source of light	Negative	1,2,4
		% of households having access to drinking water within premises	Negative	1,2,4
		% of households having access to latrine within premises	Negative	1,2,4
		% of households having access to clean fuel	Negative	2,4
		% of households with dilapidated housing condition	Positive	4
		% of households with access to banking services	Negative	4
2	Socioeconomic status	% of households having access to radio	Negative	2,4
		% of households having access to television	Negative	2,4
		% of households having access to telephone	Negative	2,4

		% of households having access to two-wheeler	Negative	2,4
		Percentage of households having access to four-wheeler	Negative	2,4
		Agriculture sector related variables		
1	Demographic dependence	Number of agricultural dependents per ha of NCA	Positive	3
		Percentage of holdings of small and marginal farmers	Positive	3,4
2	Marginalisation	Average size of landholding	Negative	4
3	Rights to land	Percentage of holdings self-owned and operated to total holdings	Negative	4
		Percentage of female operated holdings to total holdings	Negative	4
4	Land use	Percentage of Net Cropped Area to total geographical area	Negative	3
		Cropping Intensity	Negative	3,4
5	Yield of major crops	Yield of Wheat	Negative	3
		Yield of Chickpea	Negative	3
		Yield of Oilseeds	Negative	3
6	Inputs	Irrigation Intensity (Net Irrigated Area/ Net Cropped Area *100)	Negative	3
		Percentage of net irrigated area to area under total holdings	Negative	4
		Total consumption of fertilizer per ha of GCA	Negative	3
		Livestock population per ha of GCA	Negative	3
		Poultry population per ha of GCA	Negative	3

3.5.1 Climatic variables

The Climate Index (CI) indicates the historical changes in climatic parameters such as temperature and rainfall. The rate of change in annual mean maximum temperature and annual mean minimum temperature and variation in annual and monsoon rainfall is used for climate index. The increase in maximum and minimum temperature and higher variability in rainfall is adversely affecting different sectors and the marginalised sections of the population (Sections 1.4 and 1.5).

3.5.2 Socioeconomic Variables

Socioeconomic vulnerability indicates how the disparities in demographic characteristics, employment characteristics, access to education, etc., contribute to their vulnerability to climate change. It consists of demographic indicators like the decadal growth rate, the share of the economically dependent population, people with special needs etc. It also measures access to education and employment among male and female. The districts with higher population growth rates, economically dependent or special needs populations, are assumed to be highly socioeconomically vulnerable. Access to education is found to improve skills, increase income, and may lead to the overall development of an individual (Thorat, 2006).

3.5.3 Infrastructural Variables

Infrastructural vulnerability measures how limited access to infrastructure and lifelines and low socioeconomic status, as indicated by assets in a household, can contribute to vulnerability to climate change. It consists of access to infrastructure such as electricity, clean fuel, safe drinking water, latrine, banking services, and the asset status, including housing condition, access to tv, radio, telephone, two-wheeler, and four wheeler. Access to basic facilities, ownership of durable goods, a means of transport, quality of housing, etc., plays a significant role in contributing to the quality of life of a household (Deepti & Adhikari, 2015). The lack of access to basic facilities exacerbates the vulnerability to climate change (Yenneti et al., 2016).

3.5.4 Agricultural Vulnerability

The Agricultural Vulnerability Index looks into the lack of rights to land, its marginalisation, and disparities in the technological efficiency of land, enhancing their vulnerability to climate change. It also includes the technological efficiency of the sector, diversification practices in agriculture sector and the demographic dependence on the sector.

3.6 Tools used for the study

3.6.1 Vulnerability Indices

All the objectives of the thesis follow quantitative approach to assess vulnerability. Vulnerability indices are constructed by following conceptual frameworks prepared for each objective. The subindices constructed out of the selected indicators are aggregated to the composite indices using weightage. The following steps are used for constructing vulnerability indices:

1. Identification of a framework

For each objective of the study, conceptual frameworks are prepared based on the theoretical models used. The conceptual framework of each objective is shown in their respective chapters.

2. Identification of indicators

Indicator is defined as ‘‘an operational representation of a characteristic or a quality of a system able to provide information regarding the susceptibility, coping capacity and resilience of a system to an impact of a disaster’’ (Birkmann,2006). This study followed inductive approach and the proxy variables for each indicator are selected from secondary data sources.

3. Normalisation or standardisation of indicators

Each indicator is normalised or standardised to render it as a dimensionless measure or number for aggregation. In the first objective, the indicators are standardized to Z scores (zero mean and unit variance) . The other objectives included comparison of time periods or social groups or geographical areas and hence, normalisation is used. The equation used in Human Development Report for normalisation is followed in this thesis.

For the variables which have a positive relationship with vulnerability,

$$Normalized\ value = \frac{(\text{Value of indicator} - \text{Minimum value})}{(Maximum\ value - Minimum\ value)} \ldots\ldots\ldots (1)$$

The direction of variables which have negative relation with vulnerability is reversed using the formula,

$$Normalized\ value = \frac{(\text{Maximum value} - \text{Value of indicator})}{(Maximum\ value - Minimum\ value)} \ldots\ldots (2)$$

4. Principal Component Analysis

Principal Component Analysis (PCA) is a data reduction technique, which will identify the latent factors that can explain the high percentage of variation among the variables in the data (Borden et al, 2007). The latent factors or principal components produced are uncorrelated to each other, which indicates that the principal component analysis is measuring different "dimensions" of the data (Borden & Cutter,2008). The scores of these components are aggregated for creation of metric for assessing vulnerability of the units considered for study. Certain diagnostic tests are conducted before PCA to know the appropriateness of the tool. The determinant of correlation matrix of variables is used to know the presence of multicollinearity. Kaiser–Meyer–Olkin (KMO) value tests the adequacy of sampling and its value ranges from 0 to 1. The value greater than .70 is adequate, whereas the value below 0.5 is considered as unacceptable (Watkins,2018). Bartlett's test of Sphericity tests the hypothesis that correlation matrix is an identity matrix. Identity matrix indicates that variables are unrelated and not suitable for principal component analysis[6]. The communalities extracted from the selected variables indicate that each variable is explained proportionately. The variables with less than 0.5

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[6] *KMO and Bartlett's Test - IBM Documentation*

communality are dropped from the analysis, as the loss of information from the original indicators is high (Jha &Gundimeda,2019).

Eigen values produced in the analysis reflects the variance of principal components. As the standardized variables have variance equal to 1, components with eigen value greater than one represents factors with larger variances and explains more variability than original variables (Borden et al., 2007). The components produced through principal component analysis is difficult to interpret. Hence, a factor rotation is conducted to provide more meaningful interpretation from the analysis. The axes are rotated within factor space to bring them closer to the location of the variables. The factor axes are maintained at a 90-degree angle and is known as orthogonal rotation (Watkins, 2018). Varimax rotation is the most popular orthogonal rotation varimax rotation, as it minimizes the number of variables that load high on a single factor, increasing the percentage of variation between each factor (Borden &Cutter,2008).

5. Aggregation to indices

The rotated component scores are aggregated to indices with an unequal weighted approach to emphasize the dominant factors contributing to vulnerability (Siagian et al., 2014; Das et al., 2021). The weights assigned are the percentage of variance explained by each component, which is calculated by the variance of each principal component divided by the cumulative variance of extracted components (Das et al.,2021).

6. Classification of indices

The vulnerability indices are classified into five levels (Very High, High, Moderate, Low and Very Low), using their mean and standard deviation (S.D.). This classification is not an absolute measure, but a comparative measure of vulnerability of each study units. The spatial pattern of indices is plotted using QGIS software. This spatial mapping will emphasize the geographical units at higher and lower levels of vulnerability in relation to others, and will facilitate decision makers to focus their efforts towards most vulnerable (Guillard-Goncalves et al., 2015).

7. Validation of results

Validation of results is done by verifying the results from earlier studies in the study area.

3.6.2 ANOVA

ANOVA (Analysis of Variance) test is used to compare means of more than two groups. It tests the null hypothesis that there is no significant difference among groups. Post hoc tests are used to find which group differs from others. In the first objective, one way ANOVA test is used to test whether any differences exist between different zones of India. Whereas, in second and third objective, it tests the difference over time. Difference between rural and urban vulnerability is also tested in second objective. In fourth objective, differences among vulnerability of social groups are tested. Scheffe test is used as the post hoc test for finding out the group different from others.

3.6.3 Spatial Autocorrelation Techniques

The practice of spatial analysis mainly follows Tobler's first law of geography, which states that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). The spatial autocorrelation analysis is conducted to understand the spatial dependence and clustering (Vasishtha & Mohanty, 2021) of vulnerability among the study units. Univariate Local Moran's I and Univariate Local Indicators of Spatial Association (LISA) are used to examine the spatial autocorrelation and the spatial clustering patterns of vulnerability indices in this thesis. Univariate Local Moran's I statistic computes the overall spatial autocorrelation. Its value ranges from −1 to+1, indicating perfect dispersion and perfect clustering, respectively, while the zero value denotes no autocorrelation (Frigerio et al., 2018). The spatial analysis was conducted in GeoDa software with 999 randomizations and a 0.05 significance filter (Frigerio et al., 2018). A spatial weight matrix was constructed using the first-order queen contiguity method to quantify the spatial proximity of districts. In Queen's method, neighbours are defined as districts sharing a common edge or vertex of non–zero length (Khan et al., 2018). The scatter plot of Moran's I has four quadrants which show how the value at a specific location is associated with its spatial lag, i.e., the weighted average of its values in surrounding locations (Mohanty,2021). The upper right and lower left quadrants show that value at a given location is similar to its spatial lag. The quadrant in the upper right shows a high-high association, which means that units with a similar score surround a high score of a location. The lower left quadrant shows a low-low association, where a location with a low index score is surrounded by units with a similar score (Aksha et al., 2019). Whereas the quadrants in the upper left and lower right show a negative association with neighbours' values. (Mohanty,2021).

Univariate LISA cluster maps and significance maps are prepared to identify the locations of spatial clustering or outliers. The cluster maps show the spatial clustering in four types by colour coding: High-High (Red), Low-Low (Blue), Low–High (pale blue), and High-Low (pale red) (Barua et al., 2018). High- High and Low-Low are spatial clusters that contribute significantly to positive spatial autocorrelation, whereas Low–High and High-Low are spatial outliers that contribute significantly to negative autocorrelation (Anselin, 2003). Significance maps show the statistical significance level at which each district score contributes to the spatial autocorrelation outcome. The map has a colour coding from bright green to pale green and indicates significance levels at 1%, 5%, and 10% (Anselin, 2003).

Chapter 4

Social Vulnerability of Madhya Pradesh population in comparison to population of other Indian states

From the chapter 1, it is understood that losses due to climate change become severe when the variation in climatic parameters or the extreme events get compounded with the inherent vulnerability of the affected population. Literature on climate change vulnerability also points out the significant role of socioeconomic variables in deciding the vulnerability of a system to climate change (Gardner & Dikens,2007, Malik et al.,2012; Heltberg & Bonch-Osmolovskiy,2011). This objective aims to understand the existing factors contributing to the generalised social vulnerability of population, which leads to unequal impacts of climate change. The first section 4.1 states the need for conducting a social vulnerability assessment in Madhya Pradesh in comparison to population of other Indian states. Next section (4.2) deals with the data sources used and the scale of analysis. Section 4.3 explains the methodology used and 4.4 shows the results. While 4.5 discusses the results, 4.6 concludes the chapter.

4.1 Relevance of assessing social vulnerability of Madhya Pradesh population in comparison to population of other Indian states

In the social vulnerability approach to climate change, climatic hazards and changes in climatic parameters are considered as coexisting with socioeconomic changes, and the vulnerability to climate change can be reduced only by reducing the overall vulnerability of communities (Schelhas et al., 2012). The social vulnerability of a population is determined by its composition, marginalisation, dependence on natural resources, income level, access to resources and infrastructure, etc.

A country's regional and racial disparities can add to social vulnerability. In India, very high regional disparities exist in economic growth, socioeconomic development and access to basic amenities and resources owing to the higher development of some regions during the colonial rule, the abundance of natural resources in some regions, and social, political, and economic reasons. These disparities have not decreased over time but widened after the economic reforms in 1991 due to the reduction in public investment (Ohlan, 2013; Bhattacharya & Sakthivel,2004; Jahangir,2011). The backward states identified by the disparity studies are mainly the EAG states located in the Central and Eastern zones of India. These states lag behind others in economic growth and social sectors, which may have severe repercussions on their population. Madhya Pradesh is one among them and is located in central India.

Vulnerability assessments in India categorised the state of Madhya Pradesh as well as its districts as highly vulnerable to climate change, mainly due to the social vulnerability (Das,2013; Chakraborty & Joshi,2016; O'Brien et al.,2004b). The hotspots identified by these studies differ due to the differences in their methodologies, study contexts etc. Hence, this objective tries to assess social vulnerability of population of all states of India to identify how far Madhya Pradesh population is vulnerable compared to population of other states. As social vulnerability or contextual vulnerability is the internal property of a population irrespective of the stressor, this study tried to identify the drivers of social vulnerability of Indian population.

The study is conducted at district level using a Composite Social Vulnerability Index (CSVI) made out of Socioeconomic Vulnerability Index (SeVI) and Infrastructural Vulnerability Index (IVI). CSVI identifies whether the aggregation masks the actual vulnerability where adaptation interventions are needed. A separate discussion and mapping of each determinant of SeVI and IVI facilitates the identification of determinants of vulnerability in each district. It also contributes to the literature by state-level identification of districts and percentage of the population with different degrees of vulnerability in three indices (SeVI, IVI, and CSVI), which facilitates state-level policy interventions. By grouping the index scores into districts belonging to Bigger States, Smaller States, and Union Territories, the indices are further compared to identify whether the size of states (population and geographic size) has a role in social vulnerability. The spatial pattern of SeVI, IVI, and CSVI is also identified through ANOVA and spatial autocorrelation techniques to identify the existence of regional clusters.

4.2 Sources of data and scale of analysis

Studies on social vulnerability in India have used different data sources such as the Census of India, Household Survey Data of NSSO (National Sample Survey Organization) (Yenneti et al., 2016), Human Development Report, Economic Survey of India (Maiti et al., 2015), etc. The major limitation of using multiple data sources is that the variables may be from different years and thus cannot accurately represent the exact situation at a particular time. This study considered only one data source viz. Census of India, 2011, as this study is an adaptation of Cutter's model, which had most of the variables from US census data. Using a single data source may represent the social vulnerability at a particular time. An advantage is a possibility of assessing social vulnerability temporally by using time series data of several census decades (Letsie & Grab,2015).

As the study aims to assess the social vulnerability of whole Indian population, all the districts of India are considered for the study. In 2011, India had 640 districts belonging to 28 states and 7 union territories, as existing in 2011. GoI (2020) classifies Indian states into bigger and smaller states, depending on the population size and geographical size. Among the 640 districts, 533 (96% of the total population) belong to bigger states, 86 (2.7%) to smaller states, and 21 (1.7%) to Union Territories. The table 4.1 lists the number of bigger states, smaller states, and union territories included in the study with the number of districts, percentage of the population, percentage of geographical area, percentage of urbanization, and the zones to which they belong. As per the State Reorganization Act, 1956, the states and union territories of India belong to six zones: North, North East, Central, East, West, and South. Figure 4.1 shows the zone wise map of India with states and union territories.

Table 4.1 State wise Number of Districts[7]

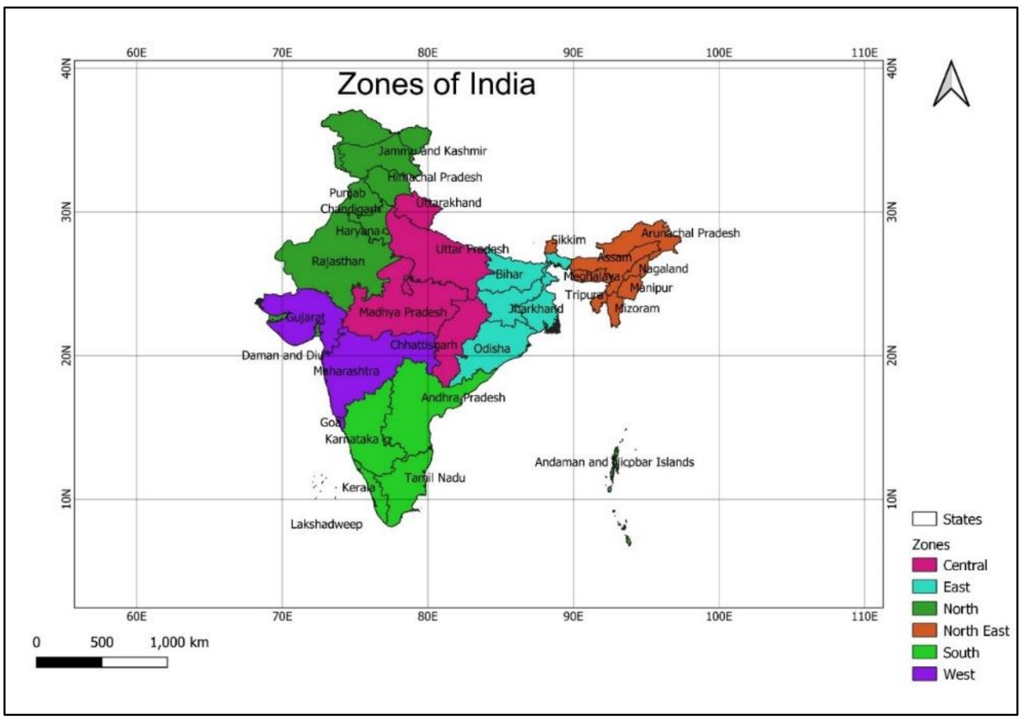
Sl. No.	State/ Union Territory	No. of Districts	Total population	% of population	Geographical area (sq.km.)	% of geographical area	% of urbanisation	Zone
Bigger States								
1	Andhra Pradesh	23	84580777	6.99	275045	8.37	33.4	South
2	Assam	27	31205576	2.58	78438	2.39	14.1	N. East
3	Bihar	38	104099452	8.6	94163	2.86	11.3	East
4	Chhattisgarh	18	25545198	2.11	135192	4.11	23.2	Central
5	Gujarat	26	60439692	4.99	196244	5.97	42.6	West
6	Haryana	21	25351462	2.09	44212	1.34	34.9	North
7	Jammu & Kashmir	22	12541302	1.04	222236	6.76	27.4	North
8	Jharkhand	24	32988134	2.72	79716	2.42	24.1	East
9	Karnataka	30	61095297	5.05	191791	5.83	38.7	South
10	Kerala	14	33406061	2.76	38852	1.18	47.7	South
11	Maharashtra	35	112374333	9.28	307713	9.36	45.2	West
12	Madhya Pradesh	50	72626809	6	308252	9.38	27.6	Central
14	Odisha	30	41974218	3.47	155707	4.74	16.7	East
15	Punjab	20	27743338	2.29	50362	1.53	37.5	North
16	Rajasthan	33	68548437	5.66	342239	10.4	24.9	North
17	Tamil Nadu	32	72147030	5.96	130060	3.96	48.4	South
18	Uttar Pradesh	71	199812341	16.5	240928	7.33	22.3	Central
19	West Bengal	19	91276115	7.54	88752	2.7	31.9	East
Total		**533**	**1157755572**	**95.6**	**2979902**	**90.6**		
Smaller States								
1	Arunachal Pradesh	16	1383727	0.11	83743	2.55	22.9	N. East
2	Goa	2	1458545	0.12	3702	0.11	62.2	West
3	Himachal Pradesh	12	6864602	0.57	55673	1.69	10	North
4	Manipur	9	2855794	0.24	22327	0.68	29.2	N. East
5	Meghalaya	7	2966889	0.25	22429	0.68	20.1	N. East
6	Mizoram	8	1097206	0.09	21081	0.64	52.1	N. East
7	Nagaland	11	1978502	0.16	16579	0.5	28.9	N. East

[7] The states, union territories and districts are presented as on 2011. Telangana was formed as a new state by separating from Andhra Pradesh on 2014 and Jammu and Kashmir state is bifurcated to two union territories: Jammu and Kashmir and Ladakh in 2019. The Union Territory Daman and Diu has been merged into Dadra and Nagar Haveli and is called as Dadra and Nagar Haveli and Daman and Diu since 26 January 2020. The total number of districts in India increased fom 640 in 2011 to 736 in 2020 by carving out new districts from existing districts.

8	Sikkim	4	610577	0.05	7096	0.22	25.2	N. East
9	Tripura	4	3673917	0.3	10486	0.32	26.2	N. East
10	Uttarakhand	13	10086292	0.83	53483	1.63	30.2	Central
Total		**86**	**32976051**	**2.7**	**296599**	**9.02**		
Union Territories								
1	Andaman & Nicobar Islands	3	380581	0.03	8249	0.25	37.7	South
2	Chandigarh	1	1055450	0.09	114	0	97.3	North
3	Dadra & Nagar Haveli	1	343709	0.03	491	0.01	46.7	West
4	Daman & Diu	2	243247	0.02	111	0	75.2	West
5	Lakshadweep	1	64473	0.01	30	0	78.1	South
6	NCT of Delhi	9	16787941	1.39	1483	0.05	97.5	North
7	Puducherry	4	1247953	0.1	490	0.01	68.3	South
Total		**21**	**20123354**	**1.7**	**10968**	**0.32**		
India		**640**	**1210854977**	**100**	**3287469**	**100**	**31.16**	

Source: GoI,2011

Note: N. East indicates North East Zone

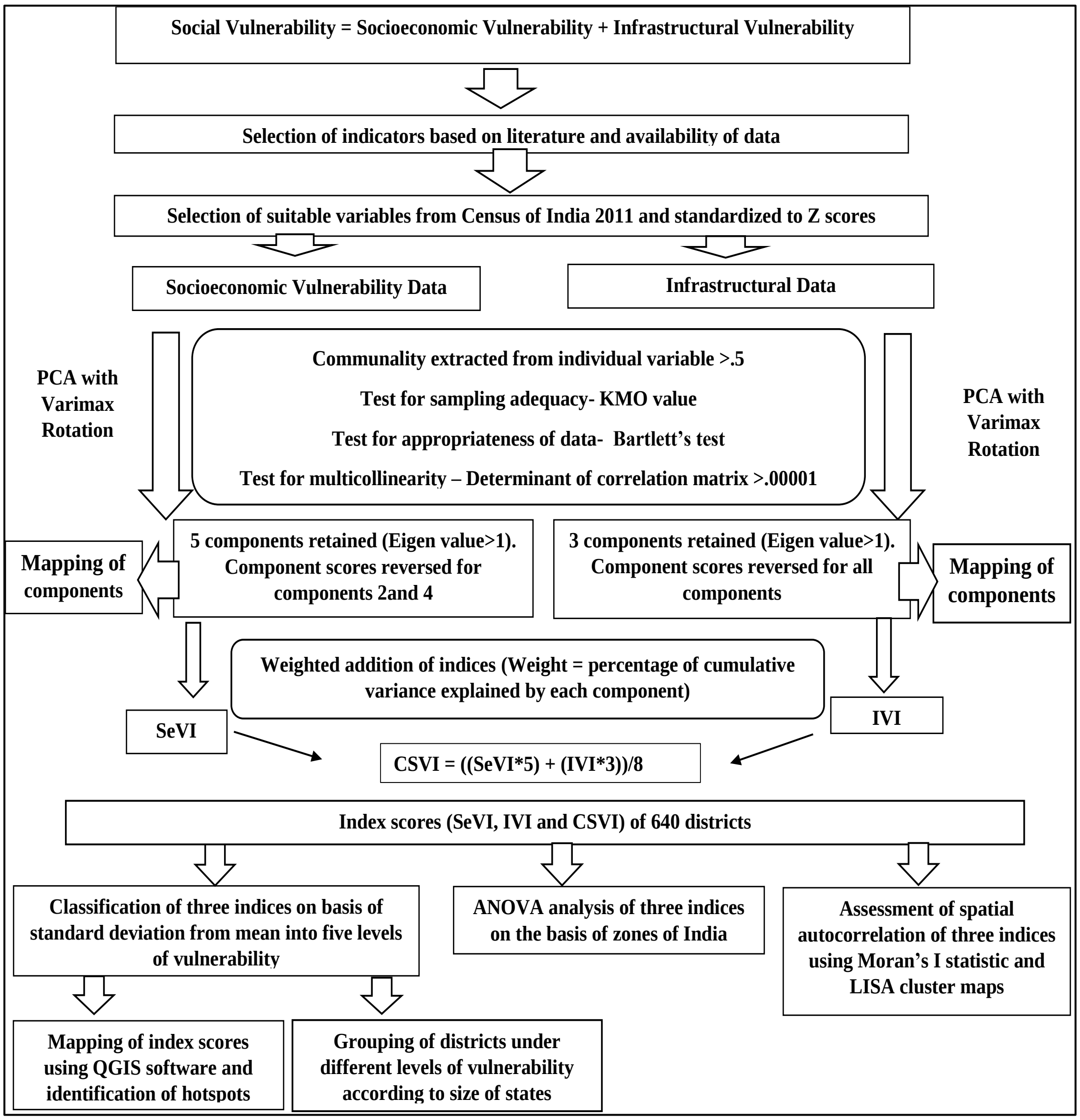


Source: Prepared using QGIS

Figure 4.1. States/ Union Territories of India with their respective zones

4.3 Method

The study used indicator approach to assess social vulnerability of all districts of India. Figure 4.2 outlines the steps involved in index creation using the inductive approach and the spatial analysis of indices.



Source: Author's preparation

Figure 4.2. Steps used for construction of SeVI and IVI

The proxy variables for each indicator are selected based on literature and data availability in the Indian context. The selected variables are categorized as Socioeconomic and Infrastructural variables. Socioeconomic variables represent population characteristics in a district (decadal change in population, density, dependent population, marginalised groups in a population, proportion of literate and employed population). Infrastructural variables include the access to assets and infrastructural facilities of households in a district, indicating their income level and ability to withstand adverse impacts. All these variables together indicate the income level of a household. All the variables are standardized to z scores with zero mean and unit variance and PCA is conducted. The variables *percentage of the population with disability* and *access to banking services* are removed due to communality extraction less than 0.5. Table 4.2 lists the variables selected, their relation to vulnerability, and the literature source of the variable.

Table 4.2 Variables used in SeVI and IVI

Concept	Description of Variable	Variable Name	Relation with vulnerability	Source of variable
		Socioeconomic Variables		
Decadal change in population	Population growth rate (2001-2011)	POPGR	Positive	Mazumdar & Paul (2016)
Population Density	Population Density	POPDEN	Positive	Letsie & Grab (2015)
Age	% of children (0-6) and elderly (60 or above) to total population	DEPPOP	Positive	de Sherbinin & Bardy (2015)
Gender	% of female to total population	FEMALE	Positive	Letsie & Grab (2015)
Family structure	% of female headed households to total households	FEMHH	Positive	de Sherbinin & Bardy (2015)
Race/Ethnicity/ Social Dependence	% of SC to total population % of ST to total population	SC ST	Positive Positive	de Sherbinin & Bardy (2015)
Houseless population	% of houseless population to total population	HLESSPOP	Positive	Mazumdar & Paul (2016)
Education	Literacy rate of male	LRM	Negative	Adapted from Maiti et al. (2015)
	Literacy Rate of female	LRF	Negative	Acosta-Michlik et al. (2005)
Employment	Male Work Participation Rate	WPRM	Negative	Morzaria – Luna, et al. (2014)

	Female Work Participation Rate	WPRF	Negative	Cutter et al. (2003)
Employment loss (single sector dependents have more probability for employment loss)	% of main workers depending on agricultural and allied sector	DEPMAIN	Positive	Mazumdar & Paul (2016)
	% of marginal workers depending on agricultural and allied sector	DEPMARG	Positive	Mazumdar & Paul (2016)
	Infrastructural Variables			
Infrastructure and lifelines	% of households having waste water outlet connected to closed drainage	DRAINAGE	Negative	Mazumdar & Paul (2016)
	% of households having access to electricity as source of light	LIGHT	Negative	Mazumdar & Paul (2016)
	% of households having access to drinking water within premises	DWPREM	Negative	Maiti et al. (2017)
	% of households having access to latrine within premises	LATRINE	Negative	Letsie & Grab (2015)
	% of households with dilapidated housing condition	DILAPID	Positive	Maiti et al. (2015)
Socioeconomic Status	% of households having access to radio	RADIO	Negative	Mazumdar & Paul (2016)
	% of households having access to television	TV	Negative	de Sherbinin & Bardy (2015)
	% of households having access to telephone	PHONE	Negative	Vincent (2004)
	% of households having access to two wheeler	TWOWL	Negative	Romero-Lankao et al. (2016)
	%of households having access to four wheeler	FOURWL	Negative	Romero-Lankao et al. (2016)

Source: Collected from various sources

Table 4.3 lists the descriptive statistics of each variable. It indicates no missing values for the 640 districts for all the 24 variables.

Table 4.3 Descriptive statistics of variables used

Variables	No. of cases	Min.	Max.	Range	Mean	S.D.
		Socioeconomic Vulnerability Index (SeVI)				
POPDEN	640	1	36155	36154	938.03	3054.31
POPGR	640	-58.5	206.1	264.6	18	13.5
FEMALE	640	34.8	54.2	19.4	48.5	1.6
DEPPOP	640	14	28.7	14.7	22.2	2.2
HLESSPOP	640	0	1.8	1.8	0.1	0.2
FEMHH	640	4.9	45	40.1	13.3	5.1
SC	640	0	50.2	50.2	14.9	9.1
ST	640	0	98.6	98.6	17.7	27
LRM	640	42	98.6	56.6	80.4	8.9
LRF	640	30.3	97.7	67.4	63.7	12.8
WPRM	640	39.3	75.8	36.5	53.2	5.1
WPRF	640	6.4	64	57.7	28.3	11.8
DEPMAIN	640	0.6	88.9	88.3	56	20.2
DEPMARG	640	2.3	96.3	94	67.6	19.5
		Infrastructural Vulnerability Index (IVI)				
DILAPID	640	0.2	17.7	17.5	5	3.1
LIGHT	640	1.9	99.7	97.8	65.9	28.3
LATRINE	640	5.6	98.9	93.2	46.4	26.3
DWPREM	640	2.4	93.9	91.4	42.3	22.9
RADIO	640	2.8	77.2	74.4	20.4	11.4
TV	640	5.8	95.4	89.6	43.6	24.1
PHONE	640	10	96.1	86.1	60.3	18.7
TWOWL	640	1	57.4	56.3	18.8	12.2
FOURWL	640	0.5	29	28.5	4.6	4.7
DRAINAGE	640	0.4	96.5	96.1	13.5	15.6

Min.- Minimum, Max.-Maximum, S.D.- Standard Deviation

Source: Author's calculation

Table 4.4 lists the results of statistical tests for developing SeVI and IVI. The Kaiser-Meyer-Olkin Measure (KMO) value of SeVI is 0.629, and IVI is 0.835, indicating that sampling is adequate. Bartlett's test of Sphericity is highly significant, with $p < 0.05$ for both, which implies the appropriateness of data (Mavhura et al., 2017). The determinant of correlation matrices has values greater than 0.00001, indicating no multicollinearity issue (Das et al., 2021). PCA with Varimax Rotation produced five factors for SeVI with 77.19 % of the variance and three factors for IVI with 78.14 % variance. The rotated component matrices for both indices are provided in tables 4.5 and 4.6.

Table 4.4 Results of Statistical tests used for PCA

Statistical tests		PCA with Socioeconomic variables	PCA with Infrastructural variables	Remarks
Correlation matrix	Determinant	0.000	0.001	>0.00001, No multicollinearity issue
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	KMO value	0.629	0.835	< 0.50 = unacceptable
Bartlett's Test of Sphericity	Approx. Chi-Square	5275.37	4690.65	Significant, not an identity matrix
	df	91	45	
	Sig.	0	0	
Communalities	Average	0.772	0.78	>0.7, Good
Total variance explained (Eigen values>1)	Component	5	3	>70%, Good
	% of variance	77.19	78.14	

Source: Author's findings

Table format adapted from: Das et al. (2021)

Table 4.5 Rotated Component Matrix of PCA for SeVI

Variable name	Component				
	1	2	3	4	5
DEPMAIN	.842				
LRF	-.831				
DEPMARG	.828				
LRM	-.744				
FEMALE		.845			
FEMHH		.784			
POPGR		-.541			
SC			-.878		
ST			.871		
WPRM				.888	
DEPPOP	.589			-.613	
WPRF	.509		.437	.526	
HLESSPOP					.798
POPDEN					.782

Extracted method: Principal Component Analysis. Rotation method: Varimax with Kaiser normalisation. Rotation converged in 8 iterations. Suppress small coefficients (absolute value below .40)

Table 4.6 Rotated Component Matrix of PCA for IVI

Variable name	Component		
	1	2	3
DWPREM	.876		
TWOWL	.795		
PHONE	.795		
TV	.771	.527	
FOURWL	.762		
DRAINAGE	.732		
LATRINE	.667		.423
DILAPID		-.906	
LIGHT	.542	.711	
RADIO			.947

Extracted method: Principal Component Analysis. Rotation method: varimax with Kaiser normalisation. Rotation converged in 6 iterations. Suppress small coefficients (absolute value below .40)

The principal components identified from PCA are labelled depending on the main variables loaded highly on it (greater than 0.5). The direction is determined depending on the factor loadings of the variables loaded in it and based on literature. A positive sign is assigned to components that increase vulnerability, whereas a negative sign is assigned to components that decrease vulnerability.

Principal component scores were added with an unequal weighted approach to emphasize the dominant determinants of socioeconomic and infrastructural vulnerability (Siagian et al.,2014; Das et al.,2021). The percentage of variance is calculated by the variance of each principal component divided by the cumulative variance of extracted components. The number of components in SeVI and IVI is used as weights for calculating the Composite Social Vulnerability Index (CSVI). The equation used is as follows:

$$CSVI = \frac{(\text{SeVI} * 5 + \text{IVI} * 3)}{8} \ldots\ldots\ldots\ldots (1)$$

Where 5 is the number of components in SeVI, 3 is the number of components in IVI, and 8 is the total number of components in both indices. The SeVI, IVI, and CSVI scores were classified into different categories depending on their standard deviation from the mean.

Following Frigerio et al. (2018), index scores of districts are classified into very low (< mean-1.5 S.D), low (mean-1.5 S.D. to mean-.5S.D.), Moderate (mean-.5 S.D to mean+.5 S.D.), high (mean + .5 to mean+1.5 S.D.), and very high (Mean >1.5 S.D.). Maps of SeVI, IVI, and CSVI and the determinants of SeVI and IVI are prepared using QGIS software.

The index scores of 640 districts are classified into three groups: Districts of bigger states, districts of smaller states, and districts of union territories to identify whether the size of the state has a role in social vulnerability. The index scores of districts are also grouped according to their respective states or union territories to understand the number of districts under different degrees of vulnerability and the percentage of state or UT population vulnerable in each group. This grouping of district scores by state groups wise (bigger, smaller, and UT) and individual state/UT wise will provide information suitable for policymaking at the national level, state level, and district level.

The following methods were used to identify the spatial clustering of social vulnerability: ANOVA analysis and Spatial autocorrelation techniques, viz. Univariate Local Moran's I and Univariate Local Indicators of Spatial Association (LISA). One-way ANOVA analysis is conducted to understand the zone wise concentration of three indices by grouping the 640 districts into six zones: North, North East, East, Central, West, and South. This technique tries to identify whether any significant differences exist in the mean indices of the six zones.

4.4 Results

4.4.1. Major factors contributing to socioeconomic and infrastructural vulnerability

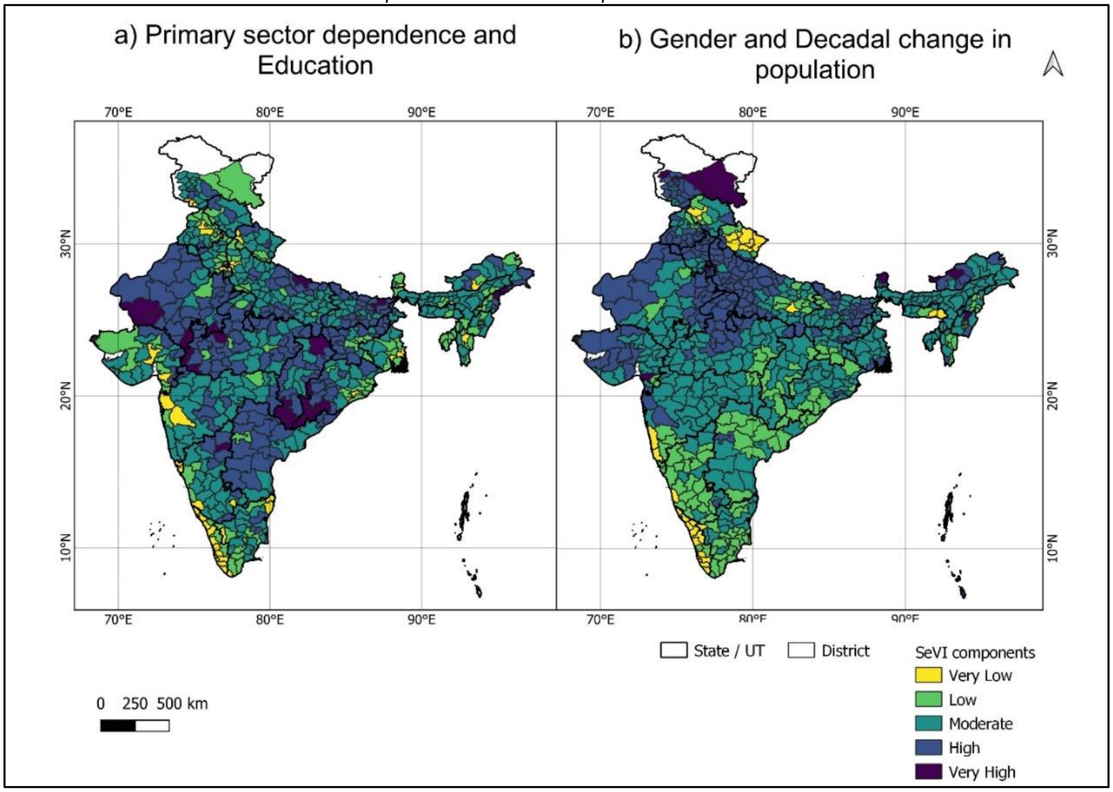
This section explains the determinants of socioeconomic vulnerability and infrastructural vulnerability identified in the study. The components are named, and direction is assigned based on the variables loading highly in the component. Table 4.7 lists the determinants (components derived by

PCA) of SeVI and IVI and figures 4.3 to 4.5 show the spatial distribution of each component of SeVI and IVI.

Table 4.7 Major components in SeVI and IVI

Component Number	Description	Variance explained (%)	Cumulative variance (%)	Direction
Socioeconomic Vulnerability				
1	Agricultural and allied sector dependence and education	25.3	25.3	Positive
2	Gender and decadal change in population	13.8	39.1	Negative
3	Marginalised population	13.4	52.5	Positive
4	Economic participation and dependence	13.2	65.6	Negative
5	Population density and houseless population	11.6	77.2	Positive
Infrastructural Vulnerability				
1	Access to basic infrastructure and assets	45	45	Negative
2	Housing condition and access to electricity	19.5	64.6	Negative
3	Access to radio	13.6	78.1	Negative

Source: Rotated component Matrix with Varimax Rotation and Kaiser Normalisation. Rotation converged in 8 iterations for SeVI and 7 iterations for IVI.



Source: Prepared using QGIS

Figure 4.3. Components of Socioeconomic Vulnerability (1 and 2)

4.4.1.1 Agriculture & allied sector dependence and education

This component explains 25% of the total variation in SeVI. The variables dependence of main[8] and marginal workers[9] on the agricultural and allied sector (positive) and the literacy rate of male and female (negative) loads highly in this component. Female work participation and percentage of the dependent population also loads positively in this component though it is not as high as the previous four variables. The agricultural and allied sector [10]constitutes about 57 % (274 million) of the total workforce in India. Small and marginal farmers who rely on rainfed monocropping, pastoralists, fisherfolks, and tribal populations who depend on forest-based products are the most likely to suffer from the localized impacts of climate change. Crop losses, increasing pest incidence, decreasing productivity of livestock, reduced water availability, loss of biodiversity and change in the vegetation type of forests can affect the livelihood of dependents of agricultural and allied sector, leading to indebtedness, food insecurity as well as migration (Botero & Salinas,2013; GoI,2012).

The lack of education limits the ability to understand climate related information or warnings on extreme events provided by the government and other agencies (Mazumdar & Paul,2016). It also limits their chances to diversify livelihood or implement proper adaptation measures. Educated people are likely to be employed in industry or service sectors and thus are not much affected by climate variability. Also, they have higher chances to recover from impacts of extreme events like floods or cyclones as their source of income does not depend on sectors sensitive to climatic variations. They are likely to be more aware of climate change impacts and more

---

[8] *Main workers- worked for more than six months in the year preceding the date of enumeration of cenus,2011*

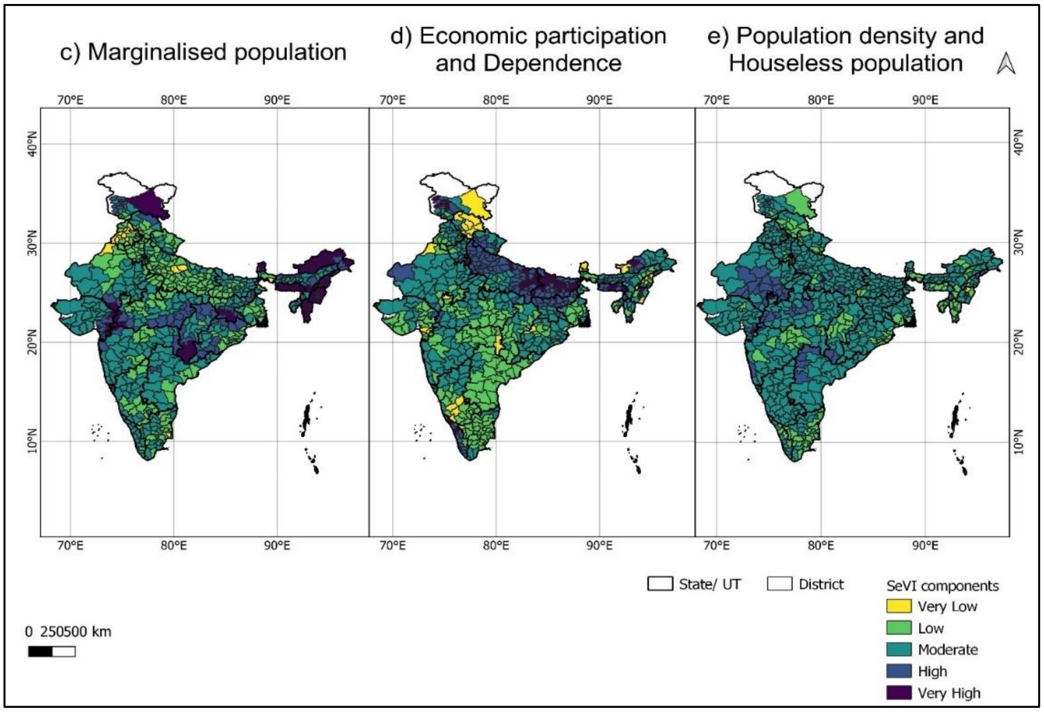
[9] *Marginal workers- worked for less than six months in the year preceding the date of enumeration of census,2011*

[10] *Agricultural and allied sector in India consists of cultivators and agricultural labourers, workers in plantation, livestock, forestry, fishing, hunting, and allied activities etc.*

adaptable. Though work participation is generally found to reduce social vulnerability, female work participation loads positively here as their employment is more in the primary sector (68% of women workers are in the primary sector) (GoI,2011). Moderate education of women and their labour force participation are negatively correlated due to preference towards men for the clerical and sales job and reluctance among women with high family status for menial jobs. (Chatterjee et.al.2018). This component is found concentrated in Rajasthan, Odisha, Madhya Pradesh, and Chhattisgarh due to the larger share of the rural population (Census,2011) (Figure 4.3a)

4.4.1.2 Gender and decadal change in population

This component explains 14 % of the variance in SeVI. Here, the percentage of female headed households has positive loading, whereas the decadal change in population loads with a negative value. Higher population growth will result in shortage of resources and affect public access to education and employment opportunities in an area (Mazumdar & Paul,2016). Social vulnerability assessments like Cutter et al. (2003) argue that areas with more female population are vulnerable. Indian states or union territories with high population growth rates have low sex ratios, as evidenced by the Census of India, 2011. In states having a better sex ratio, access of women to education and health facilities is more, and their mean age of marriage and first childbirth is high, leading to less population growth (IIPS & ICF,2017; GoI,2020). So, this study consider districts having more female and female households as less vulnerable and those with more population growth as more socioeconomically vulnerable. Thus, the direction of this component is reversed. The districts with a very high score are mostly in Jammu & Kashmir, Arunachal Pradesh, and Uttar Pradesh. A few districts from Manipur, Sikkim, Daman and Diu, Dadra and Nagar Haveli, Chandigarh, and NCT of Delhi also have very high scores. From the spatial distribution of this component (Figure 4.3b), it is evident that high and very high scores in this component are concentrated in North and West zones.



Source: Prepared using QGIS

Figure 4.4 Components of Socioeconomic Vulnerability (3,4 and 5)

4.4.1.3 Marginalised population

This component explains 13% of the variation in SeVI. Marginalised communities like SC and ST are recognized as highly deprived social groups by the constitution of India. They are primarily dependent on the welfare services of the government (Mazumdar& Paul,2016). Districts with more SC population loads negatively and with more ST population loads positively in this component. Dependence on forest resources for their survival, subsistence form of agriculture, high incidences of poverty, food insecurity and diseases, low education and poor information, lower access to resources, and isolated way of living make tribes more socioeconomically vulnerable than any other social groups in India (Chakravarty & Dand,2005). The gap in the selling prices for forest products and buying prices of food items is the primary reason for the higher incidence of poverty among these groups. These groups constitute the most significant proportion of migrants in India but are not recognized by official agencies due to the short-term and circulatory pattern of migration (Karat

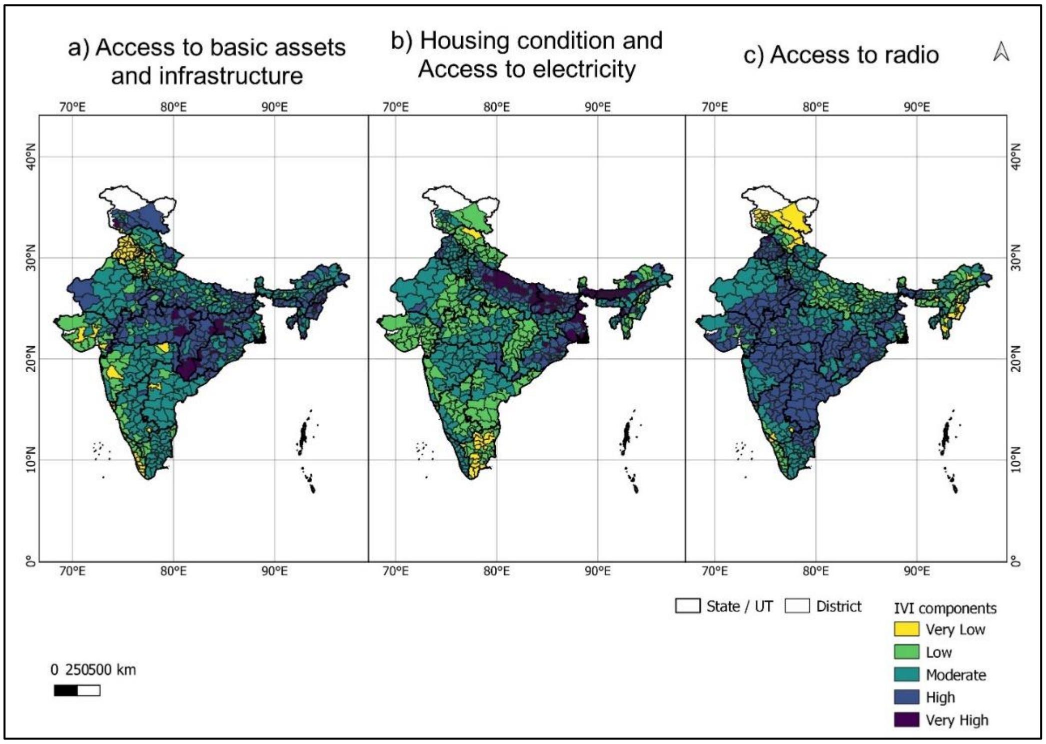
& Rawal,2014). Districts in the North East Region and tribal districts of Madhya Pradesh, Jharkhand, Chhattisgarh, Gujarat, Maharashtra, and Rajasthan possess very high scores in this component (Figure 4.4 c).

4.4.1.4 Economic participation and dependence

This component explains 13% of the variation in SeVI. It shows the ability of the general population to cope with impacts of climate change. Here, the work participation rate of male and female loads as positive and the percentage of dependent population loads negatively. The working population can recover quickly from the impacts of climate change. Whereas children and the elderly are economically dependent on others, increasing their vulnerability.Their proneness to diseases and lack of mobility during climatic extremes like floods and cyclones increases their vulnerability. Families with more dependents often have limited financial resources, reducing their coping capacity (Siagian et al., 2014). The districts with more work participation and a less dependent population tend to be less vulnerable. Hence, a negative sign is assigned to this component. Districts in Bihar, Uttar Pradesh, and Jammu and Kashmir score very high in this component (Figure 4.4 d).

4.4.1.5 Population density and houseless population

This component shows the vulnerability of the urban areas, in contrast to the vulnerability of rural areas emphasized by previous components. The variables, population density and houseless population load positively in this component and it explains 12% of the variation in SeVI. The highly populated cities are at high risk during climatic extremes like floods and cyclones. The absence of secure tenure, proper housing, and other basic amenities put the houseless population and slum dwellers more vulnerable to heat stress and other diseases associated with climate change. They are more vulnerable to poverty and food insecurity due to the higher food prices resulting from climate variability. Climate change induced migration also puts additional stress on urban areas. Districts in the NCT of Delhi and urban centres in other states possess very high scores in this component (Figure 4.4e).



Source: Authors' preparation using QGIS

Figure 4.5 Components of Infrastructural Vulnerability

4.4.1.6. Access to basic assets and infrastructure

About half (45%) of variation in IVI is explained by this component. Access to basic facilities (drinking water, latrine, closed drainage, and electricity), communication devices (television and telephone), and transport (two wheelers and four wheelers) loads positively in this component. Low access to drinking water and sanitation can lead to diarrhoea during extreme precipitation and flood events (GoI,2012). Access to communication facilities like television and telephone helps in warning during climatic extremes. Access to transport facilitates easy evacuation during floods and cyclones. The asset status of people is an indicator of their quality of life, and those with improved quality of life are generally found to be less socially vulnerable. A negative sign is assigned to this component to reverse the direction. This component possesses a high score in tribal districts of Jharkhand, Madhya Pradesh, Chhattisgarh, and Odisha (Figure 4.5a).

4.4.1.7. Housing condition, electricity and television access

This component explains 20% of the variation in IVI and includes access to electricity and television (positive loading) and the percentage of households with dilapidated housing conditions (negative loading). Dilapidated houses are found to be highly vulnerable to damages during floods and cyclones. Access to electricity improves productivity, education, entertainment, and thus the quality of life. Access to television provides information as well as entertainment. Here also, a negative sign is assigned to reverse its direction. This component possesses a very high score, mainly in the districts of Uttar Pradesh, Assam, Bihar, and West Bengal (Figure 4.5b)

4.4.1.8. Access to Radio

This component explains 14% of IVI variance and contains only one variable, viz., radio access. Radio serves as an effective means of communication in rural areas by disseminating weather forecasts and early warning messages. It also serves as an effective instrument for extension services by government departments to the primary sector. The sign of this component is reversed while calculating the index. Only the Gurdaspur district in Punjab is identified as having a very high vulnerability in this component (Figure 4.5c).

4.4.2. Identification of the most vulnerable districts

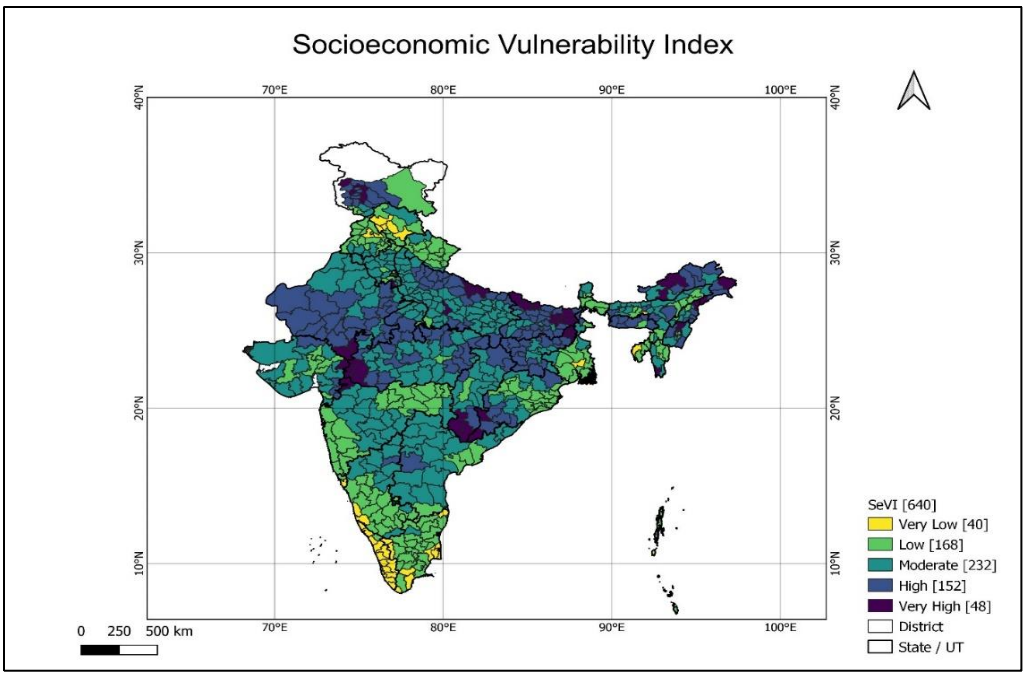
SeVI value ranges from -1.11 to 1.57, while IVI is from -1.92 to 1.13, and CSVI is from -1.29 to 1.32. The most vulnerable districts, are obtained by classifying SeVI, IVI, and CSVI, as explained in Section 4.3. Indian districts possess higher socioeconomic vulnerability than infrastructural vulnerability (Table 4.8). When 48 districts (6% of the Indian population possess very high SeVI, only 13 districts (0.8% of the population) possess a very high IVI. Very high CSVI is found in 35 districts (3.9 % population)

Table 4.8 Number of districts and percentage of Indian population under each level of vulnerability

Level of vulnerability	Number of districts			Percentage of population		
	SeVI	IVI	CSVI	SeVI	IVI	CSVI
Very Low	40	58	57	5.9	12.6	9.7
Low	168	118	146	27.5	16.7	24.0
Moderate	232	221	221	40.9	36.4	38.6
High	152	230	181	19.8	33.5	23.7
Very High	48	13	35	5.9	0.8	3.9

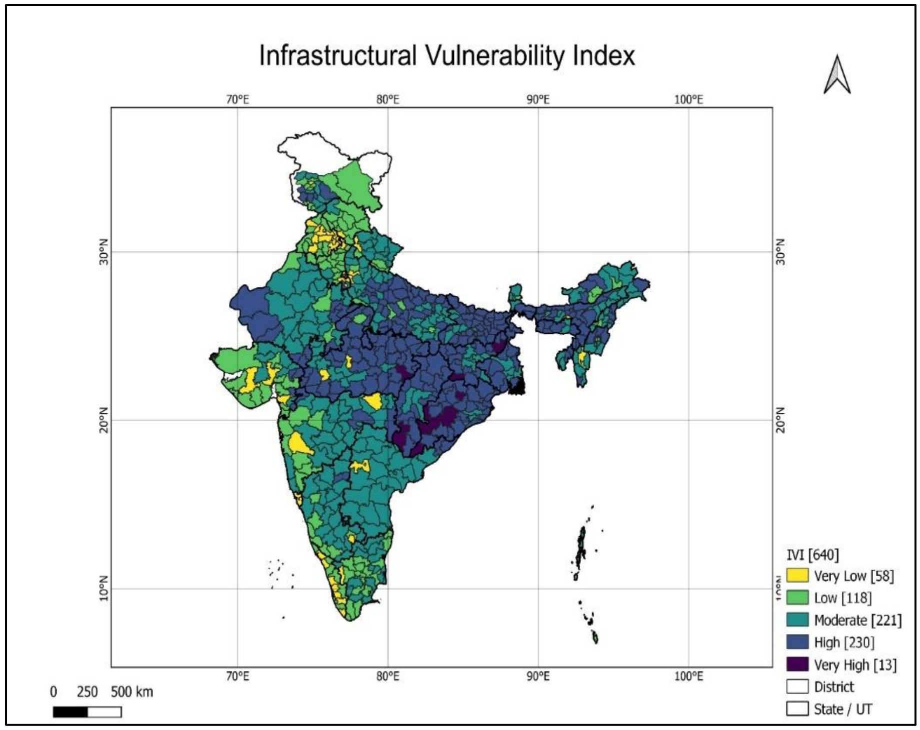
Source: Author's findings

Figures 4.6,4.7 and 4.8 displays the districts under different levels of vulnerability in three indices. Table 4.9 lists the most vulnerable districts under each index.



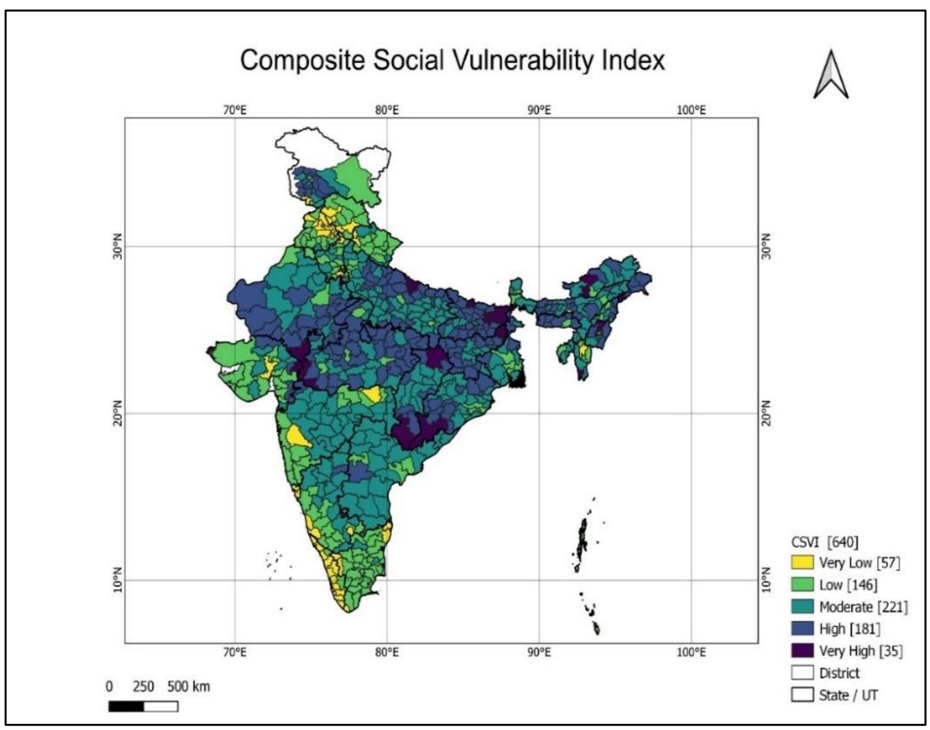
Source: Prepared using QGIS

Figure 4.6 Socioeconomic Vulnerability Index



Source: Prepared using QGIS

Figure 4.7 Infrastructural Vulnerability Index



Source: Prepared using QGIS

Figure 4.8 Composite Social Vulnerability Index

Table 4.9 Very high vulnerable districts under each index

SeVI		IVI		CSVI	
District	**State**	**District**	**State**	**District**	**State**
Alirajpur	Madhya Pradesh	Bijapur	Chattisgarh	Alirajpur	Madhya Pradesh
Jhabua	Madhya Pradesh	Pakur	Jharkhand	Kurung Kumey	Arunachal Pradesh
Kurung Kumey	Arunachal Pradesh	Malkangiri	Odisha	Jhabua	Madhya Pradesh
Barwani	Madhya Pradesh	Debagarh	Odisha	Bijapur	Chattisgarh
Bijapur	Chattisgarh	Kalahandi	Odisha	Pakur	Jharkhand
Senapati	Manipur	Kandhamal	Odisha	Barwani	Madhya Pradesh
Tirap	Arunachal Pradesh	Nabarangapur	Odisha	Banswara	Rajasthan
Kolkata	West Bengal	Baudh	Odisha	Narayanpur	Chattisgarh
Mewat	Haryana	Dindori	Madhya Pradesh	Nabarangapur	Odisha
Central	New Delhi	Simdega	Jharkhand	Dakshin Bastar Dantewada	Chattisgarh
Shrawasti	Uttar Pradesh	Narayanpur	Chattisgarh	Malkangiri	Odisha
Banswara	Rajasthan	Nuapada	Odisha	Sahibganj	Jharkhand
Badgam	Jammu & Kashmir	Dumka	Jharkhand	Shrawasti	Uttar Pradesh
Ganderbal	Jammu & Kashmir			Purnia	Bihar
Dohad	Gujarat			Godda	Jharkhand
Pakur	Jharkhand			Dohad	Gujarat
Dakshin Bastar Dantewada	Chattisgarh			Dungarpur	Rajasthan
Purnia	Bihar			Senapati	Manipur
East Kameng	Arunachal Pradesh			Madhepura	Bihar
Pratapgarh	Rajasthan			Katihar	Bihar

Narayanpur	Chattisgarh			Saharsa	Bihar
Dungarpur	Rajasthan			Sitamarhi	Bihar
Bahraich	Uttar Pradesh			East Kameng	Arunachal Pradesh
Madhepura	Bihar			Mewat	Haryana
Sitamarhi	Bihar			Pratapgarh	Rajasthan
Balrampur	Uttar Pradesh			Araria	Bihar
Katihar	Bihar			Bahraich	Uttar Pradesh
Sheohar	Bihar			Tirap	Arunachal Pradesh
Lawngtlai	Mizoram			Khagaria	Jammu & Kashmir
Nabarangapur	Odisha			Sheohar	Bihar
Sahibganj	Jharkhand			Koraput	Odisha
Dhar	Madhya Pradesh			Kishanganj	Bihar
Ramban	Jammu & Kashmir			Rayagada	Odisha
Saharsa	Bihar			Lawngtlai	Mizoram
Araria	Bihar			Surguja	Chattisgarh
Kanpur Nagar	Uttar Pradesh				
Mon	Nagaland				
Purba Champaran	Bihar				
Upper Subansiri	Arunachal Pradesh				
Nandurbar	Maharashtra				
North East	New Delhi				
Anjaw	Arunachal Pradesh				
Pashchim Champaran	Bihar				

Godda	Jharkhand				
Khagaria	Bihar				
Malkangiri	Odisha				
Anantnag	Jammu & Kashmir				
Kupwara	Jammu & Kashmir				

Source: Author's findings

Table 4.10 Number of districts in each state under different levels of vulnerability

State	No. of districts	SeVI					IVI					CSVI				
		VL	L	M	H	VH	VL	L	M	H	VH	VL	L	M	H	VH
Bigger States																
Andhra Pradesh	23	0	4	17	2	0	2	0	19	2	0	0	4	18	1	0
Assam	27	1	8	15	3	0	1	0	8	18	0	1	1	15	10	0
Bihar	38	0	0	6	22	10	0	0	5	33	0	0	0	4	25	9
Chhattisgarh	18	0	1	10	4	3	0	0	2	14	2	0	0	8	6	4
Gujarat	26	0	7	14	4	1	3	13	6	4	0	1	13	6	5	1
Haryana	21	0	6	14	0	1	4	13	3	1	0	3	10	7	0	1
Jammu & Kashmir	22	0	3	2	12	5	1	9	7	5	0	1	3	6	12	0
Jharkhand	24	0	0	6	15	3	0	0	6	15	3	0	0	6	15	3
Karnataka	30	2	17	10	1	0	1	7	21	1	0	3	11	15	1	0
Kerala	14	13	1	0	0	0	7	7	0	0	0	12	2	0	0	0
Madhya Pradesh	50	0	1	24	21	4	2	1	9	37	1	0	4	12	31	3
Maharashtra	35	0	18	15	1	1	4	7	21	3	0	2	12	20	1	0

Odisha	30	0	15	7	6	2	0	0	2	21	7	0	3	14	9	4
Punjab	20	2	14	4	0	0	11	9	0	0	0	9	10	1	0	0
Rajasthan	33	0	0	11	19	3	0	3	19	11	0	0	2	11	17	3
Tamil Nadu	32	9	21	2	0	0	2	15	15	0	0	5	25	2	0	0
Uttar Pradesh	71	0	1	46	20	4	2	5	31	33	0	0	5	39	25	2
West Bengal	19	1	13	3	1	1	1	0	5	13	0	0	5	10	4	0
Total	**533**	**28**	**130**	**206**	**131**	**38**	**41**	**89**	**179**	**211**	**13**	**37**	**110**	**194**	**162**	**30**
Smaller States																
Arunachal Pradesh	16	0	0	3	8	5	0	3	9	4	0	0	1	6	6	3
Goa	2	1	1	0	0	0	2	0	0	0	0	2	0	0	0	0
Himachal Pradesh	12	5	6	1	0	0	1	10	1	0	0	5	7	0	0	0
Manipur	9	0	2	4	2	1	0	2	4	3	0	0	2	3	3	1
Meghalaya	7	0	1	0	6	0	0	0	2	5	0	0	1	0	6	0
Mizoram	8	0	4	3	0	1	1	1	5	1	0	1	3	3	0	1
Nagaland	11	0	2	5	3	1	0	2	5	4	0	0	3	4	4	0
Sikkim	4	0	2	2	0	0	0	1	3	0	0	0	2	2	0	0
Tripura	4	1	3	0	0	0	0	0	2	2	0	0	1	3	0	0
Uttarakhand	13	0	10	3	0	0	1	3	9	0	0	1	9	3	0	0
Total	**86**	**7**	**31**	**21**	**19**	**8**	**5**	**22**	**40**	**19**	**0**	**9**	**29**	**24**	**19**	**5**
Union Territories																
Andaman & Nicobar Islands	3	1	2	0	0	0	0	2	1	0	0	1	2	0	0	0
Chandigarh	1	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0
Dadra & Nagar Haveli	1	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0

Daman & Diu	2	1	1	0	0	0	0	2	0	0	0	1	1	0	0	0
Lakshadweep	1	1	0	0	0	0	0	1	0	0	0	1	0	0	0	0
NCT of Delhi	9	0	2	4	1	2	9	0	0	0	0	4	3	2	0	0
Puducherry	4	2	2	0	0	0	2	1	1	0	0	3	1	0	0	0
Total	**21**	**5**	**7**	**5**	**2**	**2**	**12**	**7**	**2**	**0**	**0**	**11**	**7**	**3**	**0**	**0**
Grand Total	**640**	**40**	**168**	**232**	**152**	**48**	**58**	**118**	**221**	**230**	**13**	**57**	**146**	**221**	**181**	**35**

VL= Very Low, L=Low, M= Medium, H= High, V= Very High

Source: Author's' findings

Table 4.10 is prepared to understand the number of districts of each state or union territory under each level of vulnerability. Here, the districts are grouped under Bigger, Smaller States, and Union Territories to facilitate more comparison. The table show that socioeconomic and infrastructural vulnerability are concentrated in bigger states. 38 out of 48 very high socioeconomically vulnerable districts and 13 infrastructural vulnerable districts belong to bigger states. CSVI also follows a similar pattern with the 30 most vulnerable districts located in bigger states. Districts with very high SeVI are found in bigger states of East, Central, and North Zones. Among the ten states having very high SeVI, seven belong to Empowered Action Group States. Bihar, Jammu and Kashmir, Madhya Pradesh, and Uttar Pradesh have more socioeconomically vulnerable districts. The other three are North East states viz. Arunachal Pradesh with five districts and one each from Manipur, Mizoram, and Nagaland.

Among the 50 districts of Madhya Pradesh, 4 possess very high socioeconomic vulnerability. Alirajpur has the highest socioeconomic vulnerability among all the Indian districts. Jhabua and Barwani are the second and fourth highest socioeconomic vulnerable districts. Dhar is also included in the very high socioeconomically vulnerable category. 21 districts possess high socioeconomic vulnerability, 24 possess moderate and only one district viz. Jabalpur possess low socioeconomic vulnerability. No districts in Madhya Pradesh possess very low socioeconomic vulnerability.

IVI follows a higher concentration than SeVI as its most vulnerable 13 districts are located in 4 bigger states only, viz. Odisha, Jharkhand, Chhattisgarh, and Madhya Pradesh which belong to the East and Central zones. Dindori of Madhya Pradesh is one among the very high infrastructurally vulnerable districts. 37 districts possess high infrastructural vulnerability, 9 possess moderate, 1 low and only 2 viz. Indore and Bhopal are found to be very low vulnerable among the whole Indian districts.

Most vulnerable CSVI hotspots are concentrated in Bihar, Jharkhand, Odisha, Chhattisgarh, Madhya Pradesh, Uttar Pradesh, and Rajasthan, belonging to the East, Central, and North zones. Three districts from Arunachal Pradesh and one each from Manipur and Mizoram are also very high socially vulnerable. Alirajpur of Madhya Pradesh is identified as the most socially vulnerable district among the Indian districts. Jhabua and Barwani are also included in the very high social vulnerability category. 31 districts of Madhya Pradesh are identified as high socially vulnerable, 12 as moderate and 4 districts viz. Indore, Bhopal, Gwalior and Jabalpur as low vulnerable. No districts are found to possess very low social vulnerability.

Table 4.11 lists the proportion of each state’s population under different levels of vulnerability (SeVI, IVI, and CSVI).

Table 4.11 Percentage of state population in each level of vulnerability

State	SeVI					IVI					Composite SVI				
	VL	**L**	**M**	**H**	**VH**	**VL**	**L**	**M**	**H**	**VH**	**VL**	**L**	**M**	**H**	**VH**
Bigger States															
Andhra Pradesh	0.0	21.0	69.5	9.5	0.0	10.9	0.0	83.1	6.0	0.0	0.0	20.9	74.3	4.8	0.0
Assam	4.0	31.7	52.0	12.3	0.0	4.0	0.0	28.8	67.2	0.0	4.0	3.5	59.2	33.3	0.0
Bihar	0.0	0.0	17.2	56.0	26.7	0.0	0.0	16.7	83.3	0.0	0.0	0.0	14.3	66.0	19.7
Chhattisgarh	0.0	13.1	62.0	21.3	3.6	0.0	0.0	29.0	69.5	1.5	0.0	0.0	65.5	21.6	12.9
Gujarat	0.0	33.4	55.3	7.9	3.5	28.3	43.4	19.5	8.8	0.0	11.9	54.5	18.3	11.8	3.5
Haryana	0.0	25.2	70.5	0.0	4.3	19.8	61.7	14.2	4.3	0.0	12.6	50.9	32.2	0.0	4.3
Jammu & Kashmir	0.0	15.8	9.3	48.7	26.2	9.9	39.9	34.7	15.5	0.0	12.2	13.5	25.1	49.2	0.0
Jharkhand	0.0	0.0	38.3	51.5	10.2	0.0	0.0	38.3	53.1	8.6	0.0	0.0	38.3	51.5	10.2
Karnataka	5.3	58.1	34.6	1.9	0.0	15.7	18.7	63.6	1.9	0.0	21.1	29.1	47.9	1.9	0.0
Kerala	97.6	2.4	0.0	0.0	0.0	55.3	44.7	0.0	0.0	0.0	94.2	5.8	0.0	0.0	0.0
Madhya Pradesh	0.0	3.4	55.0	34.3	7.3	7.8	2.8	17.6	70.9	1.0	0.0	14.0	25.7	56.0	4.3
Maharashtra	0.0	50.9	44.9	2.7	1.5	23.6	29.5	42.0	4.9	0.0	12.5	37.8	48.3	1.5	0.0
Odisha	0.0	52.3	25.2	18.2	4.4	0.0	0.0	11.6	75.3	13.1	0.0	14.3	51.4	24.4	10.0
Punjab	10.1	72.9	17.0	0.0	0.0	58.3	41.7	0.0	0.0	0.0	48.6	48.6	2.8	0.0	0.0
Rajasthan	0.0	0.0	40.7	53.4	5.9	0.0	15.4	61.0	23.6	0.0	0.0	12.5	40.1	41.5	5.9
Tamil Nadu	26.0	65.5	8.5	0.0	0.0	11.2	52.0	36.7	0.0	0.0	19.1	77.8	3.1	0.0	0.0
Uttar Pradesh	0.0	1.0	65.8	27.5	5.7	3.2	10.4	45.6	40.8	0.0	0.0	9.0	55.8	32.8	2.3
West Bengal	6.0	70.4	15.4	3.3	4.9	4.9	0.0	32.8	62.3	0.0	0.0	32.8	48.5	18.7	0.0
Percentage to total population of bigger states	**5.5**	**26.9**	**41.5**	**20.3**	**5.8**	**11.2**	**16.3**	**37.1**	**34.6**	**0.8**	**8.5**	**23.4**	**39.6**	**24.5**	**4.0**
Percentage to total Indian population	**5.3**	**25.7**	**39.7**	**19.4**	**5.6**	**10.7**	**15.6**	**35.5**	**33.1**	**0.8**	**8.2**	**22.4**	**37.8**	**23.4**	**3.8**

Smaller States															
Arunachal Pradesh	0.0	0.0	22.7	49.3	28.0	0.0	25.9	54.2	19.9	0.0	0.0	12.8	31.8	35.0	20.4
Goa	43.9	56.1	0.0	0.0	0.0	100.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0	0.0
Himachal Pradesh	62.6	36.9	0.5	0.0	0.0	8.5	84.0	7.6	0.0	0.0	56.5	43.5	0.0	0.0	0.0
Manipur	0.0	34.1	39.1	10.0	16.8	0.0	34.1	37.7	28.1	0.0	0.0	34.1	32.7	16.4	16.8
Meghalaya	0.0	27.8	0.0	72.2	0.0	0.0	0.0	36.6	63.4	0.0	0.0	27.8	0.0	72.2	0.0
Mizoram	0.0	61.5	27.7	0.0	10.7	36.5	5.9	46.9	10.7	0.0	36.5	25.0	27.7	0.0	10.7
Nagaland	0.0	29.0	36.4	21.9	12.6	0.0	32.7	38.4	28.9	0.0	0.0	42.5	28.6	28.9	0.0
Sikkim	0.0	70.5	29.5	0.0	0.0	0.0	46.4	53.6	0.0	0.0	0.0	70.5	29.5	0.0	0.0
Tripura	47.0	53.0	0.0	0.0	0.0	0.0	0.0	70.8	29.2	0.0	0.0	47.0	53.0	0.0	0.0
Uttarakhand	0.0	61.6	38.4	0.0	0.0	16.8	44.6	38.6	0.0	0.0	16.8	61.0	22.2	0.0	0.0
Percentage to total population of smaller states	**20.2**	**45.5**	**19.8**	**10.7**	**3.7**	**12.5**	**38.2**	**35.0**	**14.3**	**0.0**	**22.5**	**43.6**	**20.0**	**11.1**	**2.7**
Percentage to total Indian population	**0.6**	**1.2**	**0.5**	**0.3**	**0.1**	**0.3**	**1.0**	**1.0**	**0.4**	**0.0**	**0.6**	**1.2**	**0.5**	**0.3**	**0.1**
Union Territories															
Andaman & Nicobar Islands	62.6	37.4	0.0	0.0	0.0	0	72.3	27.7	0.0	0.0	62.6	37.4	0.0	0.0	0.0
Chandigarh	0.0	0.0	100.0	0.0	0.0	100	0	0	0	0	100.0	0.0	0.0	0.0	0.0
Dadra & Nagar Haveli	0.0	0.0	0.0	100.0	0.0	0	100	0	0	0	0.0	0.0	100.0	0.0	0.0
Daman & Diu	21.4	78.6	0.0	0.0	0.0	0	100	0	0	0	21.4	78.6	0.0	0.0	0.0
Lakshadweep	100.0	0.0	0.0	0.0	0.0	0	100	0	0	0	100.0	0.0	0.0	0.0	0.0
NCT of Delhi	0.0	35.4	42.5	5.3	16.8	100	0	0	0	0	52.6	30.6	16.8	0.0	0.0
Puducherry	19.4	80.6	0.0	0.0	0.0	79.5	16.0	4.5	0	0	95.5	4.5	0.0	0.0	0.0
Percentage to total population of UT	**3.0**	**36.2**	**40.7**	**6.1**	**14.0**	**93.6**	**5.6**	**0.8**	**0.0**	**0.0**	**56.8**	**27.5**	**15.7**	**0.0**	**0.0**
Percentage to total Indian population	**0.0**	**0.6**	**0.7**	**0.1**	**0.2**	**1.6**	**0.1**	**0.0**	**0.0**	**0.0**	**0.9**	**0.5**	**0.3**	**0.0**	**0.0**

VL= Very Low, L=Low, M= Medium, H= High, V= Very High

Source: Author's findings

Around 6% of population of bigger states and 4% of population of smaller states possess socioeconomic vulnerability. About 14% of population of union territories possess very high socioeconomic vulnerability but this population constitute only 0.2% of the total Indian population. Arunachal Pradesh of North East Zone has the highest proportion of state population under very high socioeconomic vulnerability, followed by Bihar (East Zone) and Jammu and Kashmir (North Zone). 7.3% of Madhya Pradesh population is found to be very high socioeconomically vulnerable, 34.3% has high vulnerability, 55% has moderate vulnerability. Only 3.4% possess low socioeconomic vulnerability.

0.8% of population of bigger states are found to be very high infrastructurally vulnerable. This very highly vulnerable population is located in only four states: Odisha, Jharkhand, Chhattisgarh and Madhya Pradesh. Odisha (13.1%) and Jharkhand (8.6%) of the East Zone have the highest proportion of the population under every high infrastructural vulnerability. 1.5% of Chhattisgarh population and 1% of Madhya Pradesh population also possess very high infrastructural vulnerability. Around 71% of Madhya Pradesh population possess high infrastructural vulnerability. It is more than twice the share of its population under high socioeconomic vulnerability. Around 18% of its population possess moderate vulnerability and 3% possess low vulnerability. As 4 cities are found very low infrastructurally vulnerable, they constitute around 8% of the state population.

4% of population of bigger states possess very high social vulnerability. Though 2.7% of population of smaller states possess very high social vulnerability, they constitute only 1% of total Indian population. Arunachal Pradesh, Bihar, Manipur, Chhattisgarh, Mizoram , Jharkhand, and Odisha of the North East, East, and Central zones have the highest proportion of state population under very high CSVI. Madhya Pradesh stands ninth in the share of population under very high social vulnerability (4.3%). About 56%

of its population is under high social vulnerability, 26% under moderate and 14% under low vulnerability.

4.4.3 Regional disparities in social vulnerability

The zone wise one-way ANOVA test was conducted for CSVI and its subindices, to test whether social vulnerability and its subindices differ across the zones of India.

Table 4.12 Results of zone wise ANOVA of SeVI

Row mean-column mean	North	Northeast	East	Central	West
Northeast	0.05 (0.983)				
East	0.130 (0.352)	0.081 (0.875)			
Central	0.123 (0.331)	0.073 (0.889)	-0.007 (1.000)		
West	-0.171 (0.214)	-0.221 (0.065)	-0.302* (0.001)	-0.295* (0.000)	
South	-0.482* (0.000)	-0.532* (0.000)	-0.612* (0.000)	-0.605* (0.000)	-0.310* (0.000)
Equal mean test across regions	34.51* (0.000)				
Equal variance test across regions	21.80* (0.001)				

Note: Significant at 0.05 level

Source: Authors' preparation

The ANOVA results signify that Socioeconomic Vulnerability is found highest in East Zone, followed by the Central, Northeast, and North Zones (Table 4.12). The South Zone, possessing very low socioeconomic vulnerability, is significantly different from all other zones. The West Zone, the second least vulnerable, is significantly different from the East and Central zones. In comparison, Infrastructural vulnerability is concentrated in East, Central, and North-East zones, and they differ significantly from the South, West, and North Zones (Table 4.13). East, the most infrastructural vulnerable, significantly differs from all other zones.

Table 4.13 Results of zone wise ANOVA of IVI

Row mean-column mean	North	Northeast	East	Central	West
Northeast	0.661* (0.000)				
East	1.093* (0.000)	0.431* (0.000)			
Central	0.787* (0.000)	0.125 (0.666)	-0.307* (0.000)		
West	0.21 (0.219)	-0.45* (0.000)	-0.882* (0.000)	-0.576* (0.000)	
South	0.142 (0.511)	-0.519* (0.000)	-0.951* (0.000)	-0.644* (0.000)	-0.068 (0.982)
Equal mean test across regions	76.79* (0.00)				
Equal variance test across regions	54.42* (0.00)				

Note: Significant at 0.05 level., Source: Author's preparation

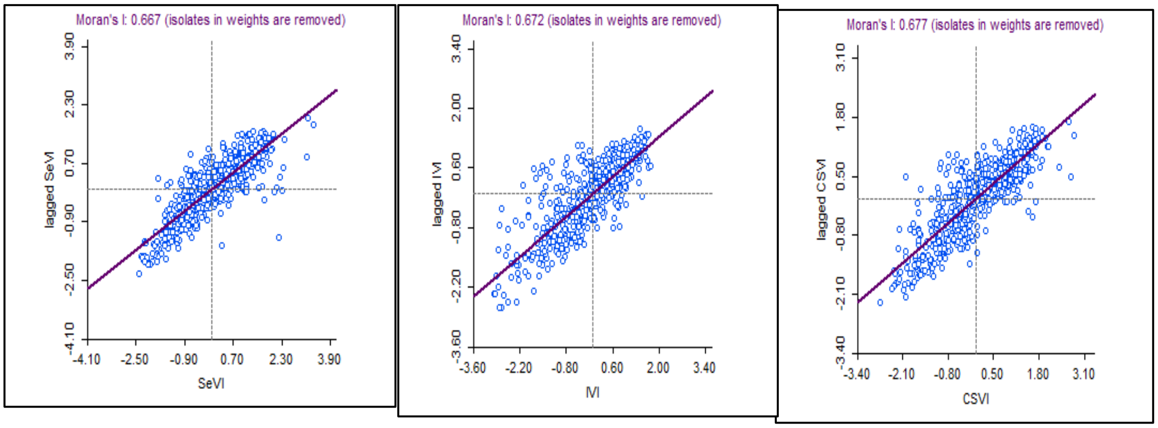
Table 4.14 Results of zone wise ANOVA of CSVI

Row mean-column mean	North	Northeast	East	Central	West
Northeast	0.279* (0.000)				
East	0.491* (0.000)	0.212* (0.017)			
Central	0.372* (0.000)	0.928 (0.696)	-0.120 (0.321)		
West	-0.028 (0.219)	-0.307* (0.000)	-0.520* (0.000)	-0.400* (0.000)	
South	-0.248* (0.001)	-0.527* (0.000)	-0.739* (0.000)	-0.620* (0.000)	-0.219* (0.029)
Equal mean test across regions	55.48* (0.00)				
Equal variance test across regions	23.28* (0.00)				

Note: Significant at 0.05 level. , Source: Author's preparation

The ANOVA results shows that the Central Zone, where Madhya Pradesh is located, is the second highest socially vulnerable zone in India. It possesses second highest socioeconomic vulnerability as well as infrastructural vulnerability

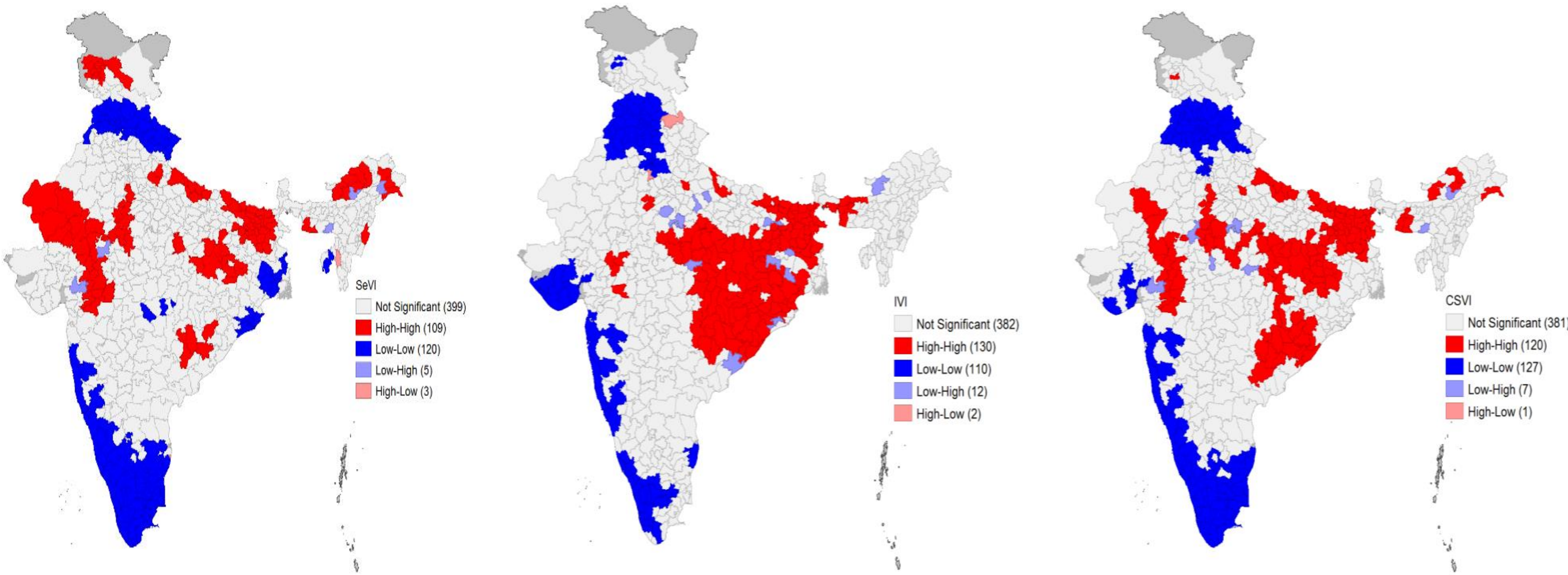
.4.4.4 Spatial clustering of social vulnerability



Source: Prepared using GeoDA

Figure 4.9 Univariate Moran's I plot of a) SeVI, b) IVI and c) CSVI

Univariate Moran's I calculated for the three indices found values as 0.667, 0.672 and 0.677 for SeVI, IVI and CSVI respectively with p value less than 0.05 and 999 permutations. It signifies a moderate but significant positive spatial association of these indices. Out of the 640 districts, 109 were identified as High – High for SeVI, 130 for IVI and 120 for CSVI. LISA cluster maps prepared for three indices validates the ANOVA findings of zonal concentration of vulnerability. Clustering of SeVI hotspots was mainly found in Bihar, Rajasthan, Jammu Kashmir, Jharkhand, Uttar Pradesh, Madhya Pradesh, Chhattisgarh, belonging to East, Central, North zones and in Arunachal Pradesh from North East zone. IVI clusters are mainly located in Bihar, Odisha, Jharkhand, Madhya Pradesh, Chhattisgarh, West Bengal, Uttar Pradesh from East, Central zones and Assam from North East zone. CSVI clusters are concentrated in Bihar, Jharkhand, Madhya Pradesh, Odisha, Uttar Pradesh, Rajasthan, Arunachal Pradesh and Assam from East, Central, North and North East zones. Thus, social vulnerability and its subindices are clustered in Madhya Pradesh also, along with other states.



Source: Prepared using GeoDa

Figure 4.10. LISA cluster maps of SeVI, IVI and CSVI

4.5 Discussion of the results

The objective of this study was to identify the social vulnerability of the Madhya Pradesh population in comparison to population of other states and union territories of India. To achieve this objective, a national level social vulnerability assessment is conducted, by considering the district as the unit of study. Though local specific studies are available on social vulnerability in India, analysis of social vulnerability covering all the districts of India is limited, as per the author's knowledge. Though studies like Vittal et al. (2020) and Yenneti et al. (2016) are available on a national scale, they have limitations on coverage of variables and data sources. Mazumdar & Paul (2016) proved that a bifurcated social vulnerability index is more prevalent in the Indian context as it can identify the dimension where policy attention is required. Following this study, available data on demographic and socioeconomic variables are bifurcated to socioeconomic vulnerability data and infrastructural data. The composite social vulnerability index, the weighted average of the socioeconomic vulnerability index and infrastructural vulnerability index, is also calculated to compare with other social vulnerability studies. The study is further advanced by spatial analysis of three indices to identify the clusters of social vulnerability. The study found that agriculture and allied sector dependence, low education and employment levels, high population growth, and a larger share of socially and economically dependent populations contribute to very high socioeconomic vulnerability. At the same time, lower access to basic assets and infrastructure contributed to very high infrastructural vulnerability. Mapping each component of SeVI and IVI will help identify the dominant determinant of vulnerability in each particular district, enabling the effective implementation of adaptation measures. The study found that more districts in India possess socioeconomic vulnerability than infrastructural vulnerability. But Madhya Pradesh is found to possess more infrastructural vulnerability, as evident from the number of districts and population share under very high vulnerability category for both indices. Alirajpur district of Madhya Pradesh possess the highest socioeconomic vulnerability and the highest social vulnerability among all the Indian districts. Jhabua, Barwani and Dhar are also included among the 48 very high socioeconomically vulnerable districts. Dindori is identified as one among the 13 very high infrastructurally vulnerable districts in India. Jhabua and Barwani are also identified among the 35 socially vulnerable districts.

Moran's I value indicates a significant spatial association of SeVI, IVI and CSVI. The ANOVA results and LISA cluster maps point out significant clustering of vulnerability in particular zones. East Zone remains the highest vulnerable, socioeconomically and infrastructural. Central Zone, where Madhya Pradesh is located, possess the second highest socioeconomic and infrastructural vulnerability and hence the overall social vulnerability is also second highest here.

The study found concentration of both socioeconomic and infrastructural vulnerability in bigger states especially the Empowered Action Group (EAG) states including Madhya Pradesh. The other EAG states such as Bihar, Jharkhand, Chhattisgarh, Uttar Pradesh, Odisha, and Rajasthan are located in the East, Central, and North zones of India and most of them are the bordering states of Madhya Pradesh. North-East states show a very high proportion of state populations under both socioeconomic and infrastructural vulnerabilities. The North East Zone possess significantly high infrastructural vulnerability than North, South, and West Zones. But the population categorised as very highly vulnerable in North-East states is meagre compared to bigger states under very high vulnerability. A larger share of the population in EAG states, combined with their relative socioeconomic backwardness, contributes to the very high vulnerability of these states.

This study points out the need for interventions in socioeconomically backward districts of EAG states and North-East states to enable them to better adapt to the impacts of climate change. As agricultural and allied sector dependence is the main determinant of socioeconomic vulnerability in India, proper adaptation measures in the agricultural sector, livelihood diversification, and skill development could reduce the excessive dependence. Improving literacy, especially for women, would help diversify livelihood and increase awareness of disasters.

Strengthening employment assurance and food security programs can help vulnerable sections. Increasing the infrastructural quality like housing, access to drinking water, sanitation, and electricity could improve the population's living standard, and increasing the asset status would make them resilient towards climate related impacts. Effective implementation and proper monitoring of these policy measures are required to ensure they reach the targeted population quickly.

The results of this study match with the social vulnerability hotspots identified by Yenneti et al. (2016), Azhar et al. (2017), Das (2013), Sendhil et al. (2018), etc., which were conducted in different contexts using different datasets and methodologies. The hotspots mainly belong to Central, eastern and northern states, especially the districts in EAG states. The findings of this study match with findings from previous studies and hence, valid. The usage of a bifurcated vulnerability index and identification of the spatial distribution of each component makes this study more advanced than previous ones. Also, identifying vulnerability at each state or union territory level and comparing districts based on the size of states (geographical size and population) and zone wise facilitates local level policymaking.

One feature of this study is that the indices can be updated as new data becomes available, which will allow time series analysis of the social vulnerability. The indicator approach gives an aggregated picture, i.e., the vulnerability at the macro level, which may not accurately represent the ground level reality at the community level or household level. Antwi-Agyei et al. (2013) opined that national level assessments could mask local level variability, i.e., regions that seem less vulnerable may not be so. It necessitates ground-level studies in hotspots to assess social vulnerability to climate variability and extremes, which can be done later.

4.6 Conclusion

This study found that socioeconomic and infrastructural vulnerability of India is concentrated more in bigger states, especially the EAG States, to which Madhya Pradesh belongs. The zonewise ANOVA analysis as well as the spatial analysis points out the highest concentration of the socioeconomic and infrastructural vulnerability in East zone. Central zone, where Madhya Pradesh is located, possess second highest socioeconomic and infrastructural vulnerability. In India, more districts are found to possess very high relative socioeconomic vulnerability than infrastructural vulnerability. Whereas, in Madhya Pradesh, more districts possess infrastructural vulnerability than socioeconomic vulnerability. Half of the districts of Madhya Pradesh and 42 % of its population possess high or very high socioeconomic vulnerability. Whereas, 38 districts and 72% of its population possess high or very high infrastructural vulnerability. 34 districts and around 60% of its population possess high or very high social vulnerability. The study identifies higher dependence on the agricultural and allied sectors and illiteracy as the dominant determinants of socioeconomic vulnerability. Limited access to infrastructure and assets is identified as the major determinant of infrastructural vulnerability. The study results are found valid as it matches with results of previous studies. It is clear from the policy perspective that the focus of adaptation efforts should be on livelihood diversification, asset creation, and increased access to basic infrastructure. Particular targeting is needed on EAG states including Madhya Pradesh, especially on the tribal population of these states, in the context of increasing climate variability and extremes.

As the state is found to be highly exposed to climate change in introduction chapter and more than half of the population in the state of Madhya Pradesh is identified as socially vulnerable in objective 1, a study on vulnerability to climate change is essential in the state. As vulnerability has a dynamic nature, a spatiotemporal assessment of vulnerability is more helpful than only spatial assessment. Next chapter discusses about the second objective i.e. spatiotemporal assessment of vulnerability to climate change in Madhya Pradesh.

Chapter 5

Spatiotemporal pattern of Vulnerability to Climate Change in Madhya Pradesh

The higher exposure to climate change in Madhya Pradesh (as discussed in chapter 1) and the higher social vulnerability of its population (as found in previous chapter) can produce adverse impacts. The vulnerability to climate change is assessed using a Climate Vulnerability Index (CVI), which is a weighted average of Climate index (CI) and a Composite Social Vulnerability Index (CSVI). The composite social vulnerability is further segregated into Socioeconomic and Infrastructural vulnerability to identify the most vulnerable dimension of social vulnerability. The trends of vulnerability to climate change and its sub dimensions are assessed over three decades: 1991, 2001, and 2011 to capture the dynamic nature of vulnerability. As the state possess higher disparities among rural and urban areas, the rural urban disparity in vulnerability is also assessed. The chapter contains two parts. The first part explains the spatiotemporal assessment of vulnerability to climate change at district level. The second part conducts the same exercise for rural and urban areas of districts.

5a. Spatiotemporal Vulnerability to climate change at district level

5a.1 Relevance of climate change vulnerability assessment in Madhya Pradesh

The state of Madhya Pradesh has higher exposure to changes in climatic variables as discussed in section 1.3. Earlier studies on climate change vulnerability identified Madhya Pradesh as well as its districts as highly vulnerable due to high population growth rate, a higher share of marginalised communities and marginal workers, high dependence on agriculture, high unemployment rate, high poverty, lack of education and low access to basic civic amenities (O' Brien et al., 2004b; Sharma et al., 2015a; Chakraborty & Joshi, 2016; Sendhil et al., 2018). Studies like Das (2013), Yenneti et al (2016) and our first objective have identified higher social vulnerability in Madhya Pradesh. The projected changes in climatic conditions in the next couple of decades (MPSKMCCC,2018) and the higher vulnerability condition identified in Madhya Pradesh in the literature make a detailed study of vulnerability to climate change a necessity in this state.

As climate change is an external stressor and social vulnerability is an internal property, a separate assessment of changes in climatic parameters and social vulnerability will enable the identification of the most vulnerable dimension and, thus, targeted policymaking. The segregated social vulnerability index used in the first objective is combined with climate index to form climate vulnerability index i.e., Climate Vulnerability Index (CVI) is the weighted average of the Climate Index and Composite Social Vulnerability Index (CSVI). Composite Social Vulnerability Index (CSVI), in turn, is a weighted average of its sub-indices: Socioeconomic Vulnerability Index (SeVI) and Infrastructural Vulnerability Index (IVI). The construction of the Climate Vulnerability Index in this way will help understand whether the study units are vulnerable due to higher variations in climate or due to social vulnerability. It also explains which dimension of social vulnerability needs more focus in each district: socioeconomic or infrastructural.

The concept of vulnerability is dynamic and context-specific, i.e., the condition of vulnerability can vary from time to time and from place to place. However, the studies on integrated vulnerability to climate change generally consider vulnerability at a particular point in time only (Maiti et al., 2015; Jeganathan et al.,2021; Menezes et al.,2018). The studies which assess the social vulnerability dimension of vulnerability to different hazards (Cutter & Finch ,2008; Frigerio et al.,2018; Santos et al.,2022) have attempted spatiotemporal assessments in different countries. Yenneti et al. (2016) and Das et al. (2021) also attempted this assessment in India. However, these studies used indicators related to social vulnerability only and tried to identify how the social vulnerability of a population changes over time. Our study modifies this approach by attempting a spatiotemporal assessment with an integrated climate vulnerability index. Along with social vulnerability indices, the Climate Index is also constructed for three decades, and the temporal pattern of CI, CSVI and its sub-indices are assessed. In this way, this study tries to answer how the vulnerability to climate changes across places and across time in both dimensions.

Thus, this study advances from the earlier approaches to assess climate change vulnerability in the following ways: First, it tries to assess integrated vulnerability to climate change by using a Climate index (CI) and a Composite Social Vulnerability Index (CSVI). The composite social vulnerability is further segregated into Socioeconomic and Infrastructural vulnerability to identify the most vulnerable dimension of social vulnerability. Second, this study assesses the trends of vulnerability to climate change and its sub dimensions over three decades: 1991, 2001, and 2011.

Section 5a.2 provides details of the data sources used and section 5a.3 explains the methods used for the study. Section 5a.4 shows the results of the study, while 5a.5 discusses the results and 5a.7 concludes the study

5a.2 Sources of data and scale of analysis

The variables used in SeVI and IVI for district level are collected from three rounds of the population census of Madhya Pradesh, viz. 1991, 2001, and 2011. Only a single data source, Census of India[11], is used for these two indices to maintain data consistency over three decades and due to the data availability constraints for new districts formed between 1991 and 2011.The number of districts is considered as exiting on 2011[12] and so the data of new districts formed between 1991 and 2011 is calculated by appropriate methodology[13]. Studies on vulnerability to

11 Data for SeVI and IVI are collected from Primary Census Abstract and Tables on Household Amenities, published by the Office of Registrar General and Census Commissioner of India.

12 As on 2022, Madhya Pradesh has 52 districts. The new districts Agar Malwa (formed in 2013) and Niwari (formed in 2018) is part of Shajapur and Tikamgarh respectively in this data.

13 Madhya Pradesh had 45 districts in 1991. Later, seven got separated during the formation of Chhattisgarh state. From 1991 to 2011, twelve new districts were formed from the existing districts. So, the data of 26 districts are calculated by combining data at appropriate lower administrative scales (Tehsil/ Community Development Block/Village /Town level data).

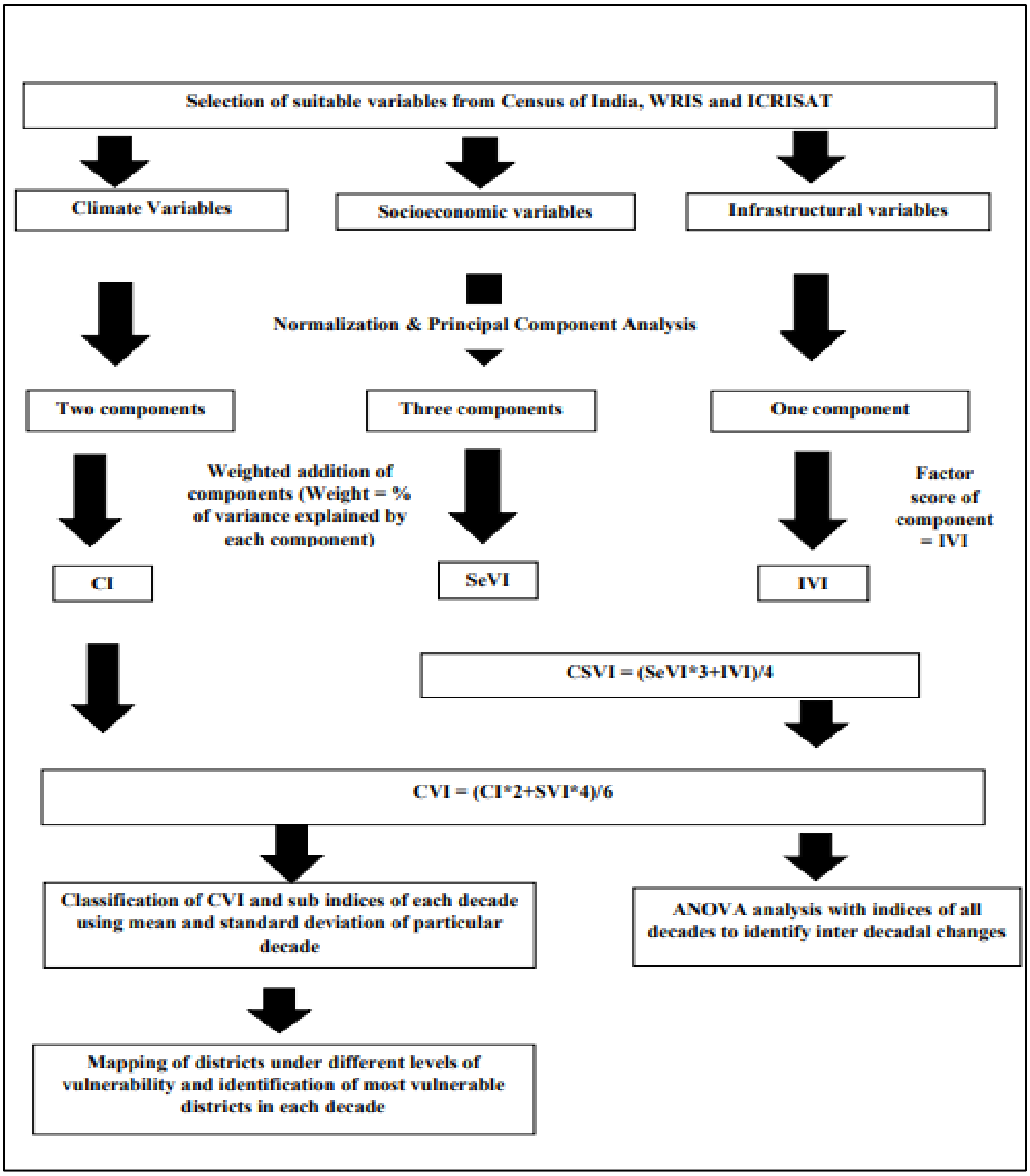
climate change in India have followed different periods for calculating climate exposure: 40 years (Tripathi,2014), 30 years (Maiti et.al., 2015) 25 years (Maiti et al., 2017). As there is no consensus on the time period, this study considered 30 years based on the definition of the World Metrological Organization. Moreover, Satapathy et al (2014) also recommends calculating climate exposure using data of 30 years. Thus, the variables for Climate Index are calculated for interval of 30-year periods: 1962-1991, 1972-2001, and 1982-2011 for representing the exposure to climate change in 1991, 2001, and 2011 respectively. The annual data of rainfall at the district level of Madhya Pradesh is collected from the website of the Indian Water Resources Information System (IWRIS). IWRIS has prepared the district-level rainfall by averaging 0.25*0.25 gridded rainfall data of Indian Meteorological Department (IMD). The annual mean maximum and annual mean minimum temperature are computed using the monthly maximum and minimum temperature data at the district level collected from the district-level database of International Crops Research Institute for the Semi-Arid Tropics (ICRISAT). ICRISAT has collected the spatial data of maximum and minimum temperature from http://www.climatologylab.org/terraclimate.html and aggregated the pixel data to the district level using ArcGIS[14].

5a.3. Methodology

Climate Vulnerability Index (CVI) is constructed as an aggregate of the Climate Index (CI) and Composite Social Vulnerability Index (CSVI). CSVI is an aggregate of two sub-indices: Socioeconomic Vulnerability Index (SeVI) and the Infrastructural Vulnerability Index (IVI). CI, SeVI and IVI are constructed using the indicator approach and CSVI and CVI are constructed by aggregating the subindices with weightage. Figure 5a.1 shows the steps used for creating the index. The proxy

[14] *Methodology for calculating maximum and minimum temperature is available at* *http://data.icrisat.org/dld/src/crops.html*

variable selection for each indicator is based on the literature on climate change vulnerability and social vulnerability, and data availability for three decades.



Source: Prepared by authors

Figure 5a.1 Steps used for construction of CVI

Table 5a.1. Variables used in SeVI, IVI and CI

Concept	Description of Variable	Variable name	Relation with vulnerability	Source of variable
		Socioeconomic Variables		
Decadal change in population	Population growth rate	POPGR	Positive	Mazumdar & Paul (2016)
Population density	Population Density	POPDEN	Positive	Patnaik & Narayanan (2009)
Dependent population	% of children (0-6) to total population	CHILD	Positive	de Sherbinin & Bardy (2015)
Female population	% of female to total population	FEMALE	Positive	Letsie & Grab (2015)
Marginalised sections	% of marginalised population (SC and ST) to total population	MARGPOP	Positive	de Sherbinin & Bardy (2015)
Education	Literacy rate	LR	Negative	Yenneti et.al. (2016)
	Gender gap in literacy rate	LRGAP	Positive	MPSKMCCC (2018)
Employment	% of main workers depending on agricultural sector	MAINAG	Positive	Mazumdar & Paul (2016)
	% of marginal workers (work for less than 6 months) to total population	MARGW	Positive	Chakraborty & Joshi (2016)
	Gender gap in work participation rate	WPRGAP	Positive	MPSKMCCC (2018)
		Infrastructural Variables		
Infrastructure	% of households having access to electricity as source of light	LIGHT	Negative	Mazumdar & Paul (2016)
	% of households having access to latrine within premises	LATRINE	Negative	Letsie & Grab (2015)
	% of households having access to drinking water within premises	DWPREM	Negative	Maiti et. al. (2017)
	% of households having access to clean fuel	FUEL	Negative	Romero-Lankao et.al. (2016)
		Climatic variables		
Change in temperature	Rate of change in annual mean maximum temperature	TMAX	Positive	Choudhary & Sirohi (2022)
	Rate of change in annual mean minimum temperature	TMIN	Positive	Choudhary & Sirohi (2022)
Variation in rainfall	Coefficient of variation in annual rainfall	RAINCV	Positive	Maiti et. al. (2015)

Source: Collected from various sources

Table 5a.1 lists the variables used in the study and table 5a.2 shows the descriptive statistics of these variables. Socioeconomic variables denote demographic characteristics such as decadal change in population, population density, percentage of female population and socially and economically dependent population and their education and employment. Infrastructure variables denote access to basic necessities such as drinking water, electricity, sanitation, and clean fuel. Variables for climate change include changes in annual mean maximum and minimum temperature and variation in rainfall.

Table 5a.2. Descriptive statistics of variables used

Variables	No. of cases	Min.	Max.	Range	Mean	S.D.
			Socioeconomic Vulnerability Index (SeVI)			
POPDEN	150	65.3	854.3	789.0	211.9	120.8
POPGR	150	9.7	51.0	41.3	24.1	6.3
FEMALE	150	44.7	50.5	5.9	48.0	1.2
CHILD	150	12.0	23.9	11.8	17.8	2.7
MARGPOP	150	16.9	93.0	76.2	38.3	16.8
LR	150	15.9	81.1	65.2	57.2	14.4
LRGAP	150	10.6	39.7	29.2	25.1	6.1
MAINAG	150	16.2	91.8	75.6	70.9	14.7
MARGW	150	1.0	23.7	22.7	10.0	4.9
WPRGAP	150	3.5	54.9	51.4	26.7	12.7
			Infrastructural Vulnerability Index (IVI)			
LIGHT	150	20.83	96.46	75.63	59.72	19.21
LATRINE	150	3.08	78.11	75.03	20.99	13.93
DWPREM	150	4.31	50.35	46.04	22.55	10.34
FUEL	150	0.41	68.05	67.64	11.62	11.10
			Climate Index (CI)			
TMAX	150	-0.01	0.04	0.05	0.01	0.01
TMIN	150	0.01	0.05	0.04	0.02	0.01
RAINCV	150	16.64	39.83	23.19	23.54	3.88

Min.- Minimum, Max.-Maximum, S.D.- Standard Deviation

Source: Author's calculation

To facilitate spatiotemporal comparison, values of each variable are normalised using maximum and minimum values of each calculated from 150 observations (50 districts*3 decades). For the variables which have a positive relationship with vulnerability, the formula used for normalisation is as follows:

$$Normalised\ value = \frac{(\text{Value of indicator – Minimum value})}{(Maximum\ value - Minimum\ value)} \ldots\ldots\ldots (1)$$

The direction of variables which have negative relation with vulnerability is reversed using the formula,

$$Normalised\ value = \frac{(\text{Maximum value} - \text{Value of indicator})}{(Maximum\ value - Minimum\ value)} \ldots\ldots (2)$$

The PCA with varimax rotation is conducted separately for each category of variables after normalisation. Table 5a.3 shows the results of PCA for each category of variables.

Table 5a.3.Results of statistical tests used for PCA

Statistical Tests		CI	SeVI	IVI	Criteria
Correlation Matrix	**Determinants**	0.934	0	0.022	>.00001, No multicollinearity issue
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	**KMO value**	0.5	0.70	0.76	< 0.50 = unacceptable
Bartlett's Test of Sphericity	$\chi^2_{(DF)}$	$10.11^{***}_{(3)}$	$1119.10^{***}_{(45)}$	$560.81^{***}_{(6)}$	Significant, not an identity matrix
Communalities	**Average**	0.75	0.8	0.8	>.7, Good
Components retained	**Component**	2	3	1	Eigen value>1
Variance Explained	**% of variance**	75	79	78	>60%, Acceptable

Source: Author's findings; Note: Table format adapted from: Das et al. (2021)

The values of the determinants of correlation matrices are greater than 0.00001 in all cases, indicating the absence of multicollinearity (Das et al., 2021). The Kaiser-Meyer-Olkin Measure (KMO) value was detected as 0.5 or more in all cases, indicating sampling adequacy. Bartlett's Sphericity test was highly significant, with p <0.05 for all cases. The communalities extracted for each variable were greater than 0.5 (Siagian et al., 2014), and the average communality of variables in each case was greater than 0.7 (Das et al.,2021). It indicates that the principal components best explain the variance of each variable. PCA with varimax rotation produced two principal components for CI and two principal components for SeVI. The rotated component matrices for both indices are provided in tables 5a.4 and 5a.6. Varimax rotation was impossible for infrastructural variables, as PCA produced only one component out of four variables. The component matrix for IVI is provided in table 5a.5.

Table 5a.4 Rotated Component Matrix of PCA for SeVI

Variable Name	Component		
	1	2	3
POPDEN	-0.901		
MAINAG	0.850		
LRGAP	0.631		-0.589
POPGR		0.871	
CHILD	0.461	0.843	
LR	0.497	0.786	
WPRGAP	-0.514	-0.543	
FEMALE			0.843
MARGPOP			0.839
MARGW		-0.438	0.677

Extracted method: Principal Component Analysis. Rotation method: Varimax with Kaiser normalisation. Rotation converged in 6 iterations. Suppress small coefficients (absolute value below .40)

Table 5a.5 Component Matrix of PCA for IVI

Variable name	Component 1
LATRINE	0.969
FUEL	0.949
LIGHT	0.804
DWPREM	0.800

Extraction method: Principal Component Analysis

Table 5a.6 Rotated Component Matrix of PCA for CI

Variable Name	Component	
	1	2
TMAX	0.795	
TMIN	0.788	0.107
RAINCV		0.993

Extracted method: Principal Component Analysis. Rotation method: Varimax with Kaiser normalisation. Rotation converged in 3 iterations. Suppress small coefficients (absolute value below .40)

The components are labelled based on strongly loaded variables (correlation greater than 0.5). While the unrotated component score is considered the value of IVI, the weighted addition of the rotated component score of socioeconomic variables and climatic variables resulted in SeVI and CI. The weightage is provided to give more importance to the dominant determinant of socioeconomic vulnerability. The weight assigned is the percentage of cumulative variance explained by each component extracted. The SeVI and IVI are aggregated with weightage to construct Composite Social Vulnerability Index to represent the social vulnerability of the districts. Following Hahn et al. (2009), the number of components extracted from PCA for each subindex is used as the weight for the sub-indices.

CSVI= (SeVI*3+IVI*1)/4……. (3)

Where, 3 and 1 are the number of components extracted from PCA of socioeconomic and infrastructural variables, respectively. 4 represents the total number of components. The CSVI is aggregated with CI to construct the Climate Vulnerability Index (CVI).

CVI= (CI*2+CSVI*4)/6…. (4)

Where 2 is the number of components extracted from PCA for climatic variables, 4 is the total number of components extracted out of PCA for socioeconomic and infrastructural variables, and 6 represents the total number of components.

Following Frigerio et al. (2018), the scores of CVI and their sub-indices for each decade are classified using the mean and standard deviation of index scores in the particular decade. The classification is as follows: Very Low (<Mean-1.5 S.D.), Low (Mean -1.5 S.D. and Mean-0.5 S.D.), Moderate (Mean -0.5 S.D. and Mean+0.5 S.D.), High (Mean +0.5 S.D. and Mean+1.5 S.D.) and Very High (>Mean+1.5 Standard Deviation). The spatial maps of the districts at different vulnerability levels in each decade are plotted using QGIS software. To identify the inter-decadal changes in CVI and its subindices, the index scores of 150 observations (50 districts*3) are considered together, and ANOVA is conducted.

5a.4 Results

5a.4.1 Components of Principal Component Analysis

This section explains the major components of vulnerability derived from PCA of socioeconomic, infrastructural, and climatic variables (Table 5a.7). 79% of the variance in the socioeconomic vulnerability index is explained by three components derived from ten socioeconomic variables. A single component explains 78% of the variance in the infrastructural vulnerability index, viz., access to infrastructure. 75% of the variance in the climate index is explained by two components derived from three climatic variables.

Table 5a.7. Major determinants of vulnerability to climate change

Component number	Description	Variance explained (%)	Cumulative Variance (%)
Socioeconomic Vulnerability Index			
1	Population density, agriculture dependence and gender disparity	27.7	27.7
2	Decadal change, dependence and access to education and employment	27.6	55.4
3	Marginalised sections of population and gender gap in education	23.9	79.2
Infrastructural Vulnerability Index			
1	Access to infrastructure	78.1	78.1
Climate Index			
1	Change in temperature	41.8	41.8
2	Variation in rainfall	33.5	75.3

Source: Rotated component Matrix with Varimax Rotation and Kaiser Normalization for SeVI and CI and unrotated component matrix and Kaiser Normalization for IVI.

5a.4.1.1 Population density, agriculture dependence, and gender disparity

This component explains the 28% variance in socioeconomic vulnerability. Agriculture dependence and the gender gap in literacy load highly in this component. The percentage of child population and literacy rate also loads positively in this component with low correlation. The dependence on the agriculture sector is more among the less educated population, due to lack of oppurtunities in other sectors (Sharma, 2016). In districts with low education among women, their work participation in agriculture will be high, and hence gender gap in employment will be less. This might be the possible reason for the negative loading of the gender gap in employment in this component. Chatterjee et al. (2018)’s finding of negative correlation between education and labour force participation supports this result. Population density got negative loading in this component, which is contradicting the findings of Patri et al. (2022) that it is positively related to vulnerability, The districts which possess high population density in Madhya Pradesh are mainly cities like Indore, Bhopal, Jabalpur and Gwalior. They possess relatively better access to education, employment diversification, and infrastructure and hence are less vulnerable than districts with low population density. This component is higher in 1991 and 2001 compared to 2011 in most districts due to decrease in agriculture dependence and gender gap in literacy, and the increase in population density and work participation over time.

5a.4.1.2 Decadal change, dependence and access to education and employment

This component explains 28% of the variance in SeVI. Decadal changes in population, the share of dependent populations, and lack of access to education load positively, and the gap in employment loads negatively in this component. Districts with high population growth rates have a higher share of the child population and higher agricultural dependence, leading to fewer gender gaps in employment. Lack of literacy also leads to high childbirth and higher population growth rates over a decade. This component score was also found to decrease in 2011 compared to 1991 and 2001 due to the decline in population growth rate and increase in literacy rate in most of the districts. The higher growth rate in population limits access to resources, making the population vulnerable to the impacts of climate change, like food insecurity and diseases. Access to education leads to more employment diversification and knowledge enhancement, thereby enhancing adaptation to climate change.

5a.4.1.3 Marginalised sections of population and gender gap in education

This component explains 24% variance in SeVI. The percentage of marginalised sections of the population (SC & ST), female population, and marginal workers load highly in this component. Marginalised groups possess a higher share of the female population than forward castes in the population. The share of marginalised communities and the female population among marginal workers increases over time due to losses in the agriculture sector and short-term migration to urban areas due to climate change (Subrahmanian,2015). Unlike first and second component scores, this component score was not found to decrease due to the almost similar share of female and marginalised sections in the population and the increased share of marginal workers during the study period. Though there has been a reduction in the gap in literacy over the decades, less loading of this variable compared to other variables has led to a higher component score in 2011 than in other decades. It is also found that Alirajpur and Jhabua districts possess the highest component scores in all decades due to the high share of marginalised communities in the population of those districts.

5a.4.1.4 Access to Infrastructure

Infrastructural facilities remain essential for reducing the vulnerability of the population to climate change. Access to electricity, drinking water, clean fuel, and toilets improves living conditions for the population. Access to drinking water and toilet facilities reduces the chances of diseases like diarrhoea (Kumar & Das,2014), reduces death and productivity loss and saves time and expenses for health maintenance (Ghosh & Cairncross, 2014). Access to electricity as a source of light improves productivity and saves time for education and employment, especially among women (IEA et al., 2022). The use of inefficient fuel is one of the leading causes of indoor air pollution, risking health and leading to premature deaths among women and children. It is also one of the sources of greenhouse gases like carbon dioxide (IEA et al.,2022). Thus, increasing access to clean fuel is beneficial for adaptation and mitigation efforts to climate change.

5a.4.1.5 Change in temperature per year

The first component explains 42% of the variation in the climate index. The rate of change in annual mean maximum and minimum temperature is loaded positively in this component. The rate of change in maximum and minimum temperature is found to be highest in the recent 30-year period compared to previous 30-year periods of study. The rate of change of annual mean maximum temperature of around 30 districts in 1972-1991 and around 24 districts in 1982-2001 was negative, which indicates a decreasing tendency in annual maximum temperature in those periods. At the same time, all 50 districts had a positive rate of change in maximum temperature in the last period, and this was the highest rate of change among the three periods. This indicates the high warming trend in Madhya Pradesh in recent periods. The rate of change in minimum temperature is found to be positive in all periods of study for all districts and high in the 1982-2011 and 1962-1991 periods. The increase in temperature can directly impact the population of Madhya Pradesh through its effects on health, productivity, livelihood, income, etc. Increased temperature can lead to increased transmission of vector-borne diseases and loss of productivity due to heat stress, heat waves, etc. The impact of high temperature on yield and increased occurrence of pests and diseases in the agriculture & allied sector can affect the livelihood and income of a major share of the population in the state. An increase in temperature can seriously impact the livelihood, income, and health of the population in Madhya Pradesh. This component is highest in districts in northern and northeastern parts of the state, like Bhind, Morena, Rewa, Singrauli, etc., in the 1982-2011 period.

5a.4.1.6 Variation in annual rainfall

This component explains 33% of the variation in the Climate Index. The increase in short-term high rain events and the decrease in long-term moderate rain events can affect agriculture and allied sectors, where most of the population depends on livelihood. The extreme events associated with rainfall, like drought, flood, etc., can lead to higher economic losses, morbidities, mortalities, livelihood loss, forced migration, etc. (Pradhan & Narayanan, 2020; Pradhan & Narayanan, 2022). Districts like Alirajpur and Jhabua possess the highest coefficient of variation in rainfall in all the study periods and thus have the highest score in this component.

5a.4.2 Identification of most vulnerable districts

The CVI and its sub-indices of each decade are classified into five levels of vulnerability using the mean and standard deviation of the particular decade, as mentioned in section 5a.3. Table 5a.8 lists the number of districts and the percentage of the state population under each vulnerability level and table 5a.9 lists the most vulnerable districts under each index. Figures 5a.2 to 5a.4 plot the districts under different levels of vulnerability in each decade.

Table 5a.8 Number of districts under each level of vulnerability

Level of Vulnerability	SeVI			IVI			CSVI			CI			CVI		
	1991	2001	2011	1991	2001	2011	1991	2001	2011	1991	2001	2011	1991	2001	2011
Very Low	4(13)	4(13)	4(14)	3(9)	3(10)	4(14)	4(13)	4(13)	4(14)	4(7)	3(4)	0(0)	4(13)	4(13)	4(14)
Low	8(18)	7(17)	9(19)	5(11)	8(15)	5(8)	7(16)	7(13)	6(13)	8(15)	10(20)	18(32)	9(22)	5(9)	11(22)
Moderate	25(49)	27(51)	26(50)	27(53)	22(46)	24(49)	26(51)	26(54)	28(56)	22(48)	27(54)	19(44)	26(47)	30(61)	23(46)
High	10(16)	9(15)	7(13)	15(26)	16(28)	17(28)	10(17)	9(15)	9(14)	14(27)	7(17)	8(15)	8(14)	9(14)	10(16)
Very High	3(4)	3(4)	4(5)	0(0)	1(1)	0(0)	3(3)	4(5)	3(3)	2(2)	3(4)	5(9)	3(4)	2(2)	2(2)
Total	50(100)	50(100)	50(100)	50(100)	50(100)	50(100)	50(100)	50(100)	50(100)	50(100)	50(100)	50(100)	50(100)	50(100)	50(100)

Source: Computed by authors. Note : Figures in parenthesis indicates the percentage of Madhya Pradesh population under each level

Table 5a.9 Most vulnerable districts in each index

SeVI			IVI			CSVI			CI			CVI		
1991	**2001**	**2011**	**1991**	**2001**	**2011**	**1991**	**2001**	**2011**	**1991**	**2001**	**2011**	**1991**	**2001**	**2011**
Alirajpur	Alirajpur	Alirajpur	Nil	Dindori	Nil	Alirajpur	Alirajpur	Alirajpur	Alirajpur	Alirajpur	Bhind	Alirajpur	Alirajpur	Alirajpur
Jhabua	Jhabua	Jhabua				Jhabua	Jhabua	Jhabua	Ashoknagar	Jhabua	Alirajpur	Jhabua	Jhabua	Jhabua
Barwani	Barwani	Barwani				Dindori	Dindori	Dindori		Ratlam	Morena	Barwani		
		Dindori					Barwani				Jhabua			
											Ratlam			

Source: Computed by authors

Table 5a.10. Results of decade wise ANOVA of CVI and sub-indices

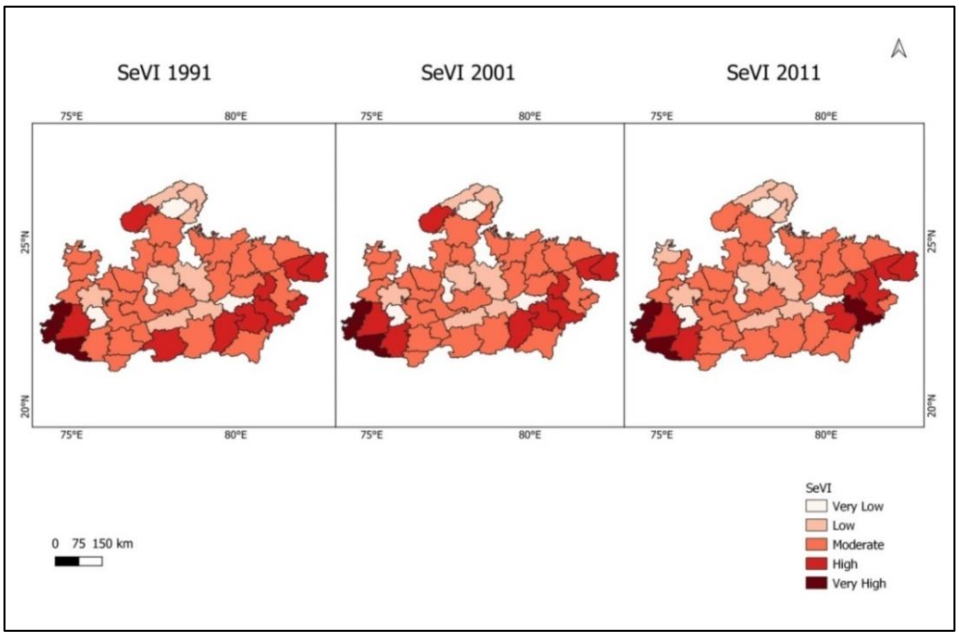
Row mean-column mean	SeVI		IVI		CSVI		CI		CVI	
	1991	**2001**	**1991**	**2001**	**1991**	**2001**	**1991**	**2001**	**1991**	**2001**
2001	-0.236$^{\#}$		-0.645*		-0.338*		-0.361*		-0.346*	
	(0.07)		(0.004)		(0.01)		(0.01)		(0.000)	
2011	-0.635*	-0.399*	-0.786*	-0.14	-0.673*	-0.334*	0.623*	0.984*	-0.241*	0.105
	(0.000)	(0.001)	(0.000)	(0.759)	(0.000)	(0.01)	(0.000)	(0.000)	(0.022)	(0.475)
Equal mean test across regions	19.13*		9.82*		17.45*		35.98*		8.53*	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Equal variance test across regions	0.141		5.825$^{\#}$		0.48		2.15		1.103	
	(0.932)		(0.054)		(0.78)		(0.341)		(0.576)	

**Significant at 0.05 level # Significant at 0.01 level. Source: Prepared by authors*

5a.4.2.1 Socioeconomic Vulnerability Index

SeVI of all decades shows an almost similar spatial pattern. Districts in the southwest of the state, like Alirajpur, Jhabua, and Barwani, have had very high SeVI levels in all decades. In the eastern side of the state, Mandla, Umaria, Sidhi, and Singrauli remain high socioeconomically vulnerable throughout the study period (Figure 5a.2).

It was also found that four districts of the state have more than 50% urban population (Table 5a.8) viz. Indore, Bhopal, Gwalior, and Jabalpur have exhibited low vulnerability over the decades. In 2011, the number of districts under very high SeVI increased from 3 to 4 as Dindori also became relatively very high vulnerable in this decade. Therefore, the percentage of the population socioeconomically vulnerable also increased from 4% to 5% in this decade (Table 5a.9). However, the value of SeVI of Dindori in 2011 is less than that of former decades, in line with the decreasing tendency of vulnerability in all districts. ANOVA of SeVI for three decades shows that overall socioeconomic vulnerability has significantly decreased (Table 5a.10).



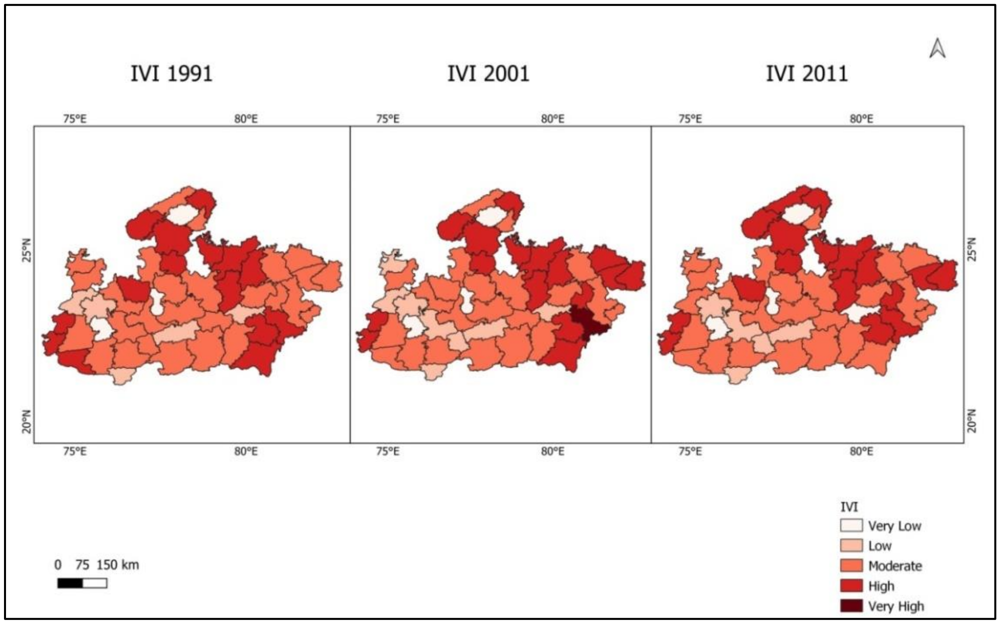
Source: Prepared with QGIS software

Figure 5a.2. Socioeconomic Vulnerability Index

IVI of all decades also follows an almost similar spatial pattern throughout the decades. In 1991 and 2011, no districts were categorized as very high vulnerable. In 2001, only one district Dindori was found to be very high vulnerable (Table 5a.8). The districts in eastern and northern parts of Madhya Pradesh like Panna, Tikamgarh, Mandla, Chhatarpur, Damoh, Sheopur, Bhind, Ashoknagar, Shivpuri, and districts in Western Madhya

Pradesh like Alirajpur and Jhabua remain high infrastructurally vulnerable throughout the study period (Figure 5a.3).

5a.4.2.2 Infrastructural Vulnerability Index

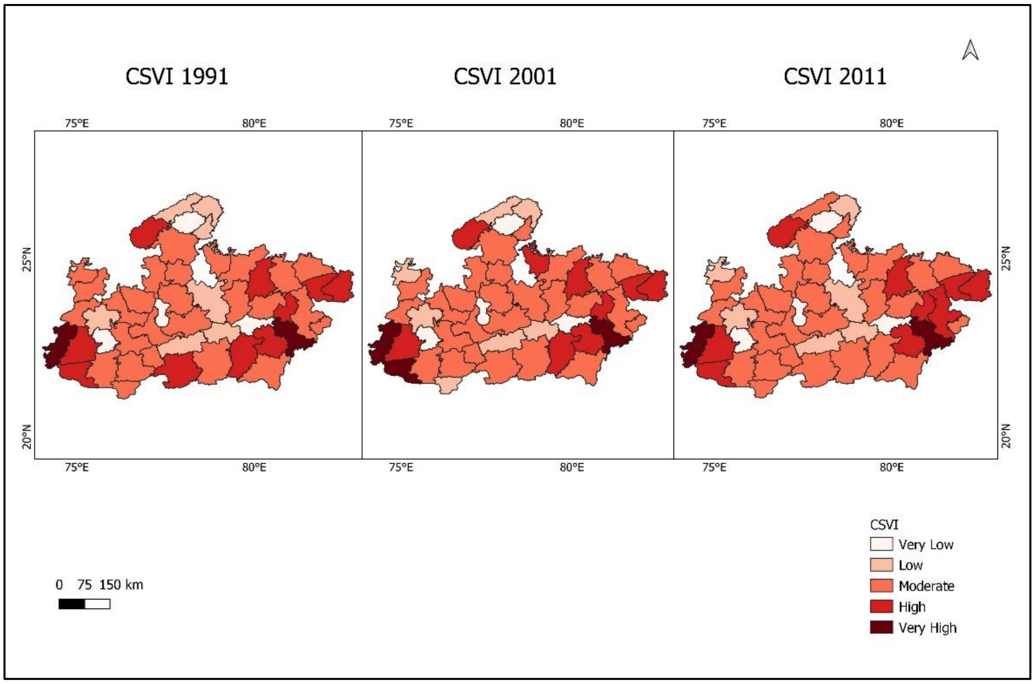


Source: Prepared with QGIS software

Figure 5a.3.Infrastructural Vulnerability Index

ANOVA results show that though infrastructural vulnerability in 2001 and 2011 has a significant decrease from 1991, the decrease in 2011 from 2001 is not significant (Table 5a.10). The population with high vulnerability also remains constant in 2001 and 2011 (Table 5a.9). It is also found that the percentage of the population with high infrastructural vulnerability in 2011 is twice the population with socioeconomic vulnerability in that decade (Table 5a.9). This is mainly because of growing disparities among different regions of the state in access to infrastructure as evident from studies like Majumder (2003). While eastern and northern Madhya Pradesh districts possess almost similar IVI scores in all decades, urban centres like Indore, Bhopal, and Gwalior also possess similar IVI scores throughout the study period.

5a.4.2.3 Composite Social Vulnerability Index

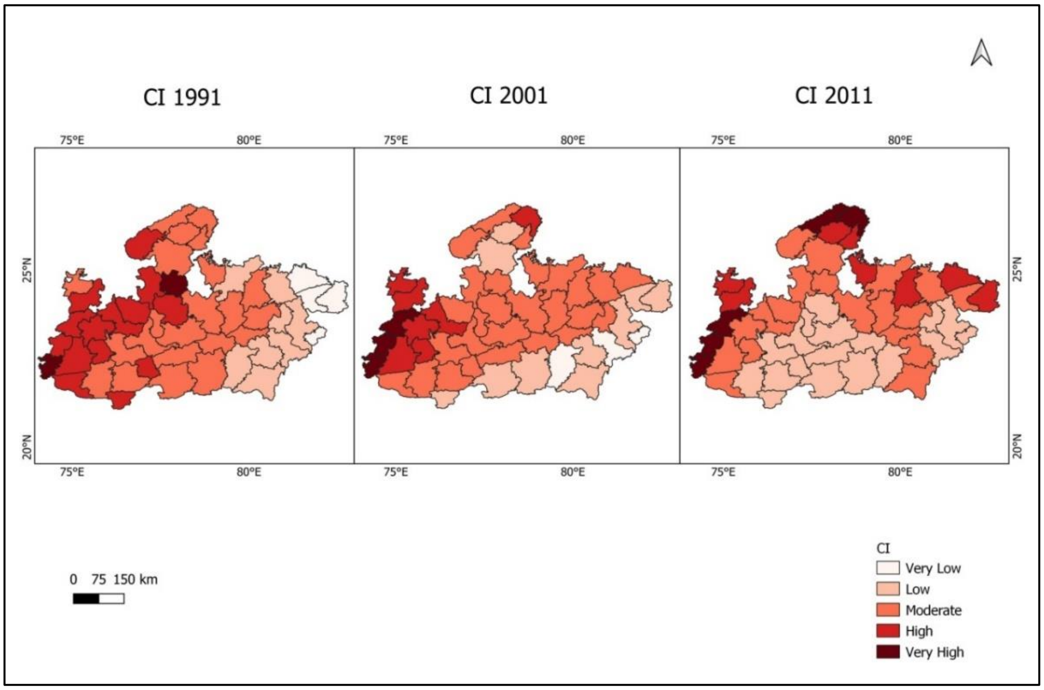


Source: Prepared with QGIS software

Figure 5a.4. Composite Social Vulnerability Index

CSVI, the aggregate of SeVI and IVI, shows a similar spatial pattern throughout the decades of study. Jhabua, Alirajpur, and Dindori remain the most socially vulnerable, as Jhabua and Alirajpur possess very high socioeconomic vulnerability, and Dindori have had very high infrastructural vulnerability in all decades. (Figure 5a.4 and Table 5a.8). It is also found that the four districts of the state have more than 50% urban population (Table 5a.9) viz. Indore, Bhopal, Gwalior, and Jabalpur have exhibited low vulnerability over the decades. In 2001, the number of districts under very high CSVI increased from 3 to 4, and the share of the most vulnerable population increased from 3% to 5%. The number of districts was reduced to 3 in 2011, and the share of the relatively very high socially vulnerable population was 3%. ANOVA of CSVI with pooled CSVI scores of decades shows that the mean CSVI of 2011 is significantly less than the mean CSVI of 2001 and 1991, indicating a significant decrease in social vulnerability (Table 5a.10).

5a.4.2.4. Climate Index

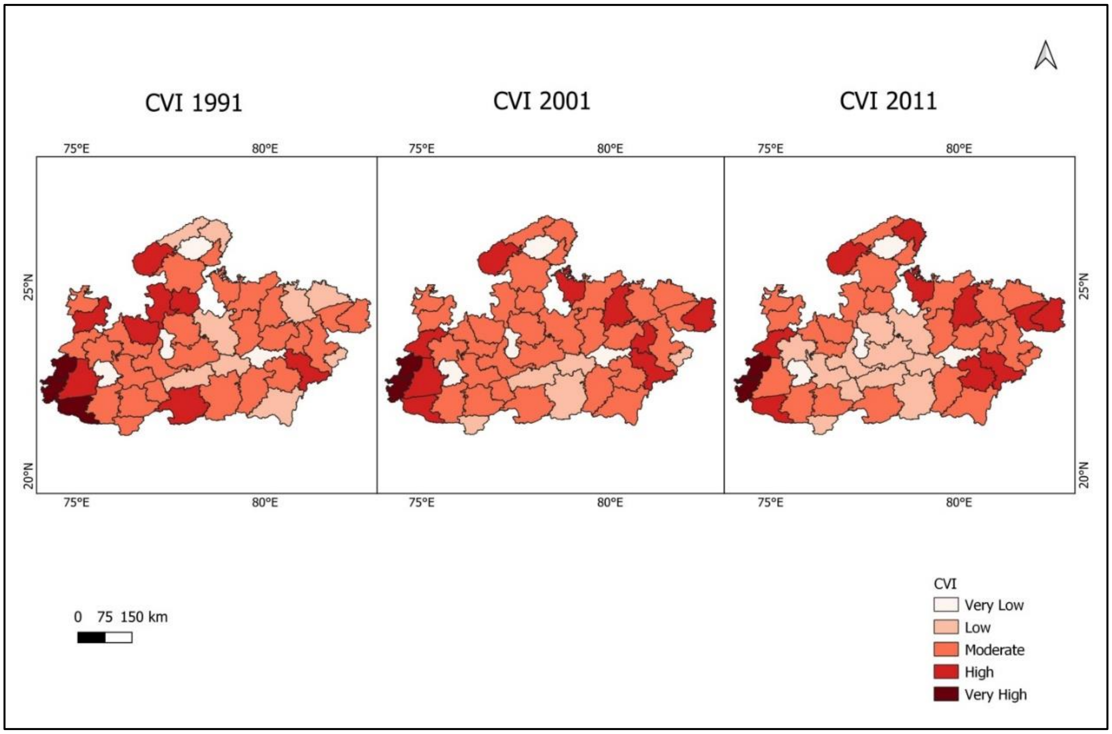


Source: Prepared with QGIS software

Figure 5a.5. Climate Index

Districts with very high CI scores are found more in 1982-2011 due to the more intense changes in climatic parameters in this period (Table 5a.8). Also, the pattern of climate index is shifting in Madhya Pradesh as evident from the figure 5a.5. The districts like Singrauli and Rewa which possessed very low relative CI in 1991 possess high CI in 2011 as the rate of change in maximum temperature was very high in these districts. Alirajpur district possesses very high CI throughout the study period due to the higher variation in rainfall in these districts. As the number of districts with very high CI increased in 2011, the share of the population exposed to climate change increased over two decades from 2% to 9% (Table 5a.9). ANOVA of CI for three decades shows that the mean CI of 2001 has a significant increase from 1991 and that of 2011 has a significant increase from former decades (Table 5a.10).

5a.4.2.5 Climate Vulnerability Index



Source: Prepared with QGIS software

Figure 5a.6 Climate Vulnerability Index

It is found from Table 5a.8 that the number of districts with very high climate vulnerability has decreased from 3 to 2 during 1991-2011. However, the number of districts in the high category has increased from 8 to 10. Also, the percentage of the population with high and very high climate vulnerability in 1991 decreased from 18% to 16% in 2001; it again increased to 18% in 2011. At the same time, the districts with very low climate vulnerability (Bhopal, Indore, Gwalior, and Jabalpur) remained the same throughout the study period (Figure 5a.6), and the number of districts with low vulnerability increased in 2011. However, the population with very low vulnerability remains the same in 1991 and 2011. ANOVA results found that overall climate vulnerability significantly decreased in 2001 and 2011 compared to 1991. However, climate vulnerability increased in 2011 from 2001, though not significant (Table 5a.10). The significant increase in CI from 2001 to 2011 may have contributed to this nonsignificant increase in climate vulnerability. However, the other subindices showed a decrease in the same period.

5a.5 Discussion of results

Identifying the pattern of vulnerability to climate change in Madhya Pradesh is necessary in the context of the increasing impacts of climate change and the prevailing socioeconomic backwardness in the state. By applying the place-based vulnerability approach developed by Borden et al. (2007) in the context of climate change, this objective assessed vulnerability to climate change in Madhya Pradesh. By following Mazumdar & Paul (2016) and Torok et al. (2021), an integrated climate vulnerability index is prepared using a Climate Index and a Composite Social Vulnerability Index, which is further bifurcated into Socioeconomic Vulnerability Index and Infrastructural Vulnerability Index. This study also brings a dynamic nature to the climate vulnerability index through a temporal analysis of the vulnerability, practised mainly by social vulnerability studies (Yenneti et al., 2016; Das et al.,2021). This index construction method facilitated the vulnerability assessment temporally and spatially for three decades. The study found that social vulnerability has decreased over the decades due to decreased socioeconomic and infrastructural vulnerability. However, overall climate vulnerability has increased, though not significantly, in the most recent decade due to a significant change in climate in the recent 30-year period. It was also found that infrastructural vulnerability is more prominent than socioeconomic vulnerability in Madhya Pradesh, as the number of districts and the percentage of the population under high and very high IVI is more than twice that of SeVI in 2011. The spatial pattern of CVI and its sub-indices in 2011 shows an apparent clustering of low vulnerability in central Madhya Pradesh and high vulnerability in the peripheral districts. Districts like Alirajpur and Jhabua remain highly vulnerable to climate change throughout the study period due to the very high socioeconomic vulnerability and infrastructural vulnerability coupled with higher exposure to climate change. A prominent feature of these districts is that they are primarily tribal-dominated districts. The higher share of a marginalised population, low access to education, high agriculture sector dependence, the high growth rate in population, a large share of dependent population, limited access to infrastructure, etc., make them very highly vulnerable to climate change. It was also found that districts like Indore, Bhopal, Gwalior, and Jabalpur, which possessed high or moderate exposure to climate change during the study period, possess very low overall vulnerability to climate change. The high urbanisation in these districts leads to higher access to education and, thus, less dependence on the agriculture sector. The low disparity in education leads to a lower birth rate and, thus, a lower share of children in the population. Also, these districts are found to have a lower share of marginalised communities, which are the most deprived population in Madhya Pradesh. Higher access to basic infrastructure also played a big role in reducing the vulnerability of these districts. Thus, it is evident from this study that the relatively high social vulnerability due to socioeconomic backwardness and limited infrastructure access is leading to high vulnerability to climate change. The findings by Patri et al. (2022) and Ge et al. (2021) that urbanisation can significantly reduce vulnerability and losses from disaster and the findings by Azhar et al. (2017) that tribal districts possess high vulnerability validate the results of this study.

In the context of increasing exposure to climate change, the overall vulnerability can be reduced only by reducing the existing socioeconomic and infrastructural vulnerability. Marginalised workers and marginalised populations primarily constitute high levels of socioeconomic vulnerability. The proportion of marginalised workers increases due to climate change-induced migration and losses in agriculture (Subramanian,2015; Motkuri &Naik,2016; Bhagat,2017; Pradhan & Narayanan,2020; Pradhan & Narayanan, 2022). Also, the loss of income from forest products leads marginalised communities to turn to marginal workers. They are primarily unskilled or lack education, so they cannot find a better position in the job market. Livelihood diversification policies and increased educational facilities and skills training can somewhat solve this issue. Strengthening programs like MGNREGA (Mahatma Gandhi National Rural Employment Guarantee Program), TPDS (Targeted Public Distribution System), skill development programs of state government like Mukhya Mantri Kaushalya Yojana, Mukhya Mantri Kaushal Samvardhan Yojana and ensuring its reach to the most vulnerable is a necessity. The share of women employed as marginal workers is higher in Madhya Pradesh as there exists a higher gender disparity in education and land ownership. Therefore, educational and skill development policies should target women. Ensuring access to basic facilities like drinking water, sanitation, electricity, and clean fuel through proper intervention schemes can enhance the overall human development in the state. It can reduce their vulnerability to climate change. Most districts possessing high and very high socioeconomic and infrastructural vulnerability are tribal dominated. Therefore, targeted policy interventions are essential for improving access to infrastructure, livelihood diversification, and access to education in tribal areas.

The vulnerable districts in Madhya Pradesh identified by different studies on vulnerability to climate change or related disasters in India (Chakraborthy & Joshi, 2016; Azhar et al., 2017; MPSKMCCC, 2018) matches with our findings and thus validate our study. MPSKMCC's (2018) findings of an increase in climate change vulnerability towards mid-century (2050) match our finding of an increase in overall climate vulnerability in 2011 from 2001, though not significant. The vulnerable districts under the current climate scenario identified by this study also match our findings and thus validate our study.

This study advances from the earlier studies on social vulnerability to climate change in India by applying a bifurcated social vulnerability index with a climate index and an analysis of three decades. The segregation of the climate vulnerability index into different sub-indices helps to identify the dominant vulnerability dimension in each district and facilitates targeted policy intervention (Mazumdar & Paul, 2016). The lack of data for specific indicators generally used in climate change vulnerability in the 1991 census limited the number of indicators used in the study, especially in infrastructural vulnerability. The lack of availability of demographic data like the population in different age groups, disabled population, houseless population, etc., of the 1991 census at the tehsil/block /village level constrained the calculation of the share of the elderly population, disabled and houseless at the district level in 1991. Hence, these variables are omitted from the analysis, though considered essential variables in vulnerability literature. Though this study is conducted at the district level, it also suffers from aggregation issues in the indicator approach. During aggregation, the vulnerabilities of communities or specific groups get masked, necessitating ground-level study. Though the study uses data from three decades, the latest is from 2011 only. The decadal census of India was delayed due to COVID-19, which constrained the availability of the latest demographic data. However, the population census is the most comprehensive data source for obtaining data regarding socioeconomic and infrastructural variables. It is the only data source suitable for the temporal analysis of these variables in India. The advantage of this source is that the study can be updated further once the latest data becomes available.

5a.6 Conclusion

This part of the chapter assesses the pattern of social vulnerability to climate change over three decades in Madhya Pradesh. Based on the results of the study, socioeconomic and infrastructural vulnerability has been reduced over the decades. However, the overall climate vulnerability showed an increase in 2011, though not significant. From the policy perspective, livelihood diversification, providing education, and increasing access to basic infrastructure could reduce the vulnerability to climate change.

Strengthening the employment assurance programs like MGNREGA and skill development programs like Mukhya Mantri Kaushalya Yojana and Mukhya Mantri Kaushal Samvardhan Yojana could increase employment opportunities in Madhya Pradesh. Food security must be ensured by strengthening the Targeted Public Distribution System (TPDS).

Most importantly, vulnerable women need more education and employment. The tribal population needs special policy attention as their livelihood depends mainly on natural resources and has the least coping capacity compared to other population groups to the impacts of climate change. These policy measures should focus on relatively less developed regions to ensure a balanced development of Madhya Pradesh and, thus, more effective coping strategies for the impacts of climate change.

5b. Spatiotemporal Vulnerability to climate change at rural and urban areas of districts

5b.1 Relevance of assessing differences in rural and urban vulnerability

As per the Census of India (2011), the ratio of rural to urban population in Madhya Pradesh is 72:28. There exist considerable disparities between these rural and urban areas, as discussed in section 3.1. Studies on vulnerability to climate change in India are assessed mainly at the state, district, or household level (Bahinipati, 2011; Mohanty & Wadhawan, 2021; Tripathi,2014; Maiti et al., 2017; Maiti et al., 2015; Sahana et al.,2021; Vittal et al.,2020; Singh,2020). Though most of the states in India face high rural-urban disparity, an assessment for identifying the disparities between the vulnerability of rural and urban areas has not been attempted in India. A few studies have attempted climate change vulnerability assessments separately for rural (Rao et al.,2016) or urban areas (Yenneti et al.,2016). However, there is a gap in the literature on climate change vulnerability comparing rural and urban areas at each spatial unit of analysis. Though scholars in Australia and China (Ge et al.,2017; Ge et al.,2021; Wang et al.,2022) made attempts to assess the rural-urban disparity of vulnerability to climate change or natural hazards, they focused on social vulnerability only and the biophysical dimension is not considered for assessment. This objective tries to assess the climate change vulnerability of rural and urban areas of Madhya Pradesh using a Climate Vulnerability Index constructed using an indicator approach. The Climate Vulnerability Index is constructed out of the Climate Index (CI), representing biophysical vulnerability or exposure and the Composite Social Vulnerability Index (CSVI), representing the social vulnerability of the population. Like part 5a, spatiotemporal assessment of climate change vulnerability is conducted in rural and urban areas by preparing CVI and its sub-indices for three decades: 1991,2001, and 2011.

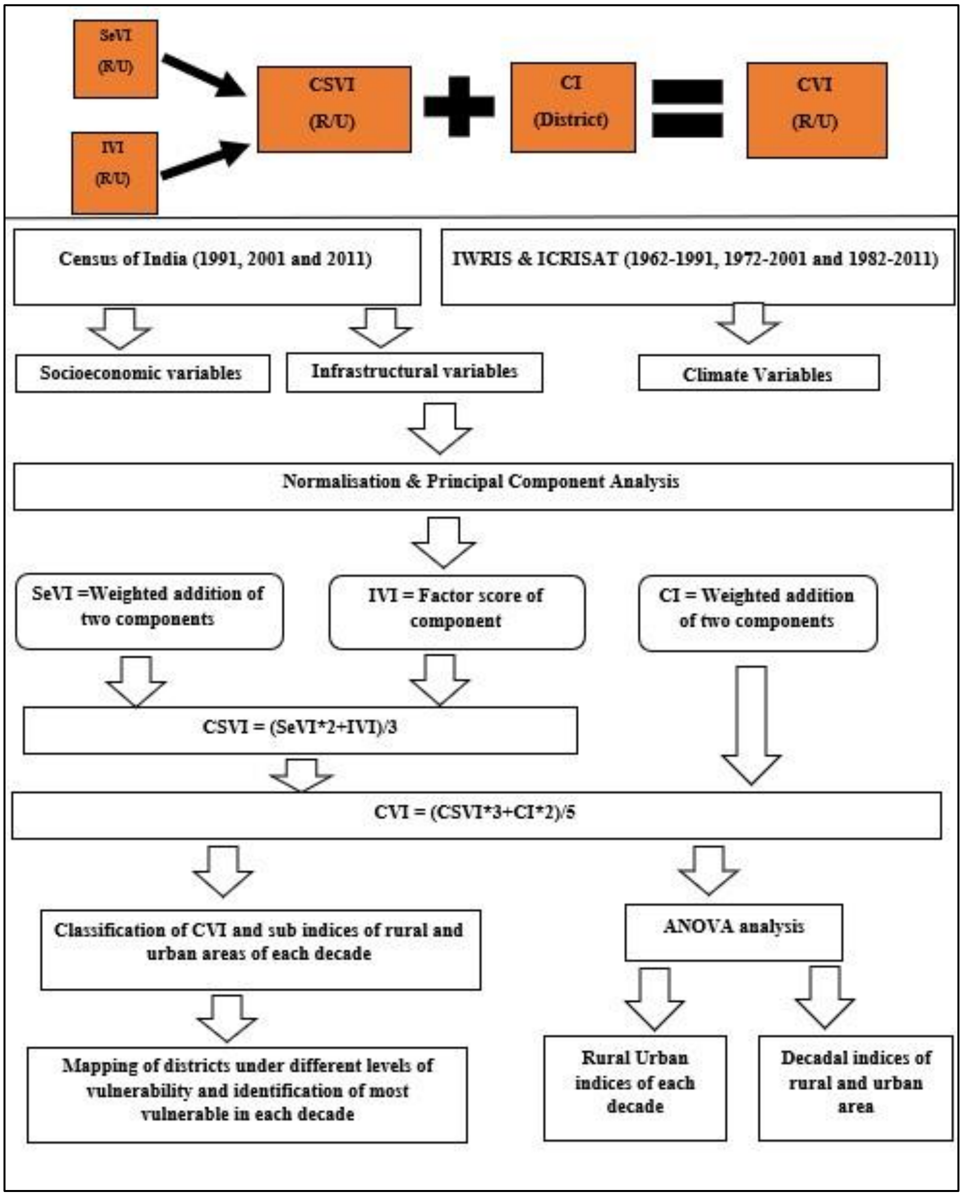
Thus, the study addresses the existing gaps in the literature on vulnerability to climate change in the following ways: First, it assesses vulnerability to climate change at two spatial levels, rural and urban areas of each district of Madhya Pradesh. Second, the index for vulnerability to climate change consists of subindices whose identification facilitates the identification of the most vulnerable dimension in each study area. Third, the assessment was conducted over three decades, 1991, 2001, and 2011, to understand the pattern of vulnerability to climate change. The next Section, 5b.2, explains the sources of data. 5b.3 explains the methodology, 5b.4 shows the results, 5b.5 discusses the results and 5b.6 concludes the study.

5b.2 Sources of data and scale of analysis

Similar to part 5a, the data for constructing SeVI and IVI are collected from the Census of India. It is the only source available for rural-urban data at the district level. Like 5a, the study is conducted for three decades: 1991,2001 and 2011. The number of districts in the state was considered to be exiting in 2011. In 1991, the state had only 45 districts, from which seven were separated into Chhattisgarh state, and 12 new districts were formed from existing districts from 1991 to 2011. Hence, only 24 districts out of 50 possess the same geographical area throughout the time period. For the rest of the districts, rural and urban areas of 1991 and 2001 are computed by aggregating data at the town level/village level. As the secondary data for climatic variables are available at the station or grid levels, it cannot be calculated for each district's rural and urban areas. Hence, the climate index prepared in part 5a is used here. The data sources used for the climate index are explained in part 5a.

5b.3 Methodology

SeVI and IVI are prepared for rural and urban areas of each district using an inductive approach and averaged with weightage to form CSVI. This CSVI of rural as well as urban areas is combined with the district-level climate index to assess how the vulnerability to climate change differs in both areas.



Source: Prepared by authors

Figure 5b.1 Steps used for construction of CVI (Rural & Urban)

Figure 5b.1 shows the steps involved in creating a climate vulnerability index of rural and urban areas of each district. Indicators are selected based on the literature on vulnerability to climate change and natural hazards. The limited availability of rural-urban specific data at the district level and in the 1991 decade has constrained the number of proxy variables selected for the study. The selected variables are categorized into Socioeconomic, Infrastructural, and Climatic Variables. The variables used in the analysis are listed in Table 5b.1. Table 5b.2 shows the descriptive statistics of the variables used.

Table 5b.1 Variables used in SeVI, IVI and CI

Concept	Variable Description	Variable Name	Relation with vulnerability	Source of variable
	Socioeconomic Variables (Rural & Urban)			
Dependent population	% of children (0-6) to total population	CHILD	Positive	de Sherbinin & Bardy (2015)
Female population	% of female to total population	FEMALE	Positive	Letsie & Grab (2015)
Marginalised sections	% of Marginalised population (SC and ST) to total population	MARGPOP	Positive	de Sherbinin & Bardy (2015)
Education	Literacy rate	LR	Negative	Yenneti et al. (2016)
	Gender gap in literacy rate	LRGAP	Positive	MPSKMCCC (2018)
Employment	% of main workers depending on agricultural sector	MAINAG	Positive	Mazumdar & Paul (2016)
	% of marginal workers to total population	MARGW	Positive	Chakraborty & Joshi (2016)
	Gender gap in work participation rate	WPRGAP	Positive	MPSKMCCC (2018)
	Infrastructural Variables (Rural & Urban)			
Access to infrastructure	% of households having access to electricity as source of light	LIGHT	Negative	Mazumdar & Paul (2016)
	% of households having access to latrine within premises	LATRINE	Negative	Letsie & Grab (2015)
	% of households having access to drinking water within premises	DWPREM	Negative	Maiti et al. (2017)
	% of households having access to clean fuel (Electricity, LPG and natural gas)	FUEL	Negative	Romero-Lankao et al. (2016)

Climatic Variables (District)				
Change in temperature	Rate of change in annual mean maximum temperature	TMAX	Positive	Choudhary & Sirohi (2022)
	Rate of change in annual mean minimum temperature	TMIN	Positive	Choudhary & Sirohi (2022)
Variation in rainfall	Coefficient of variation in annual rainfall		RAINCV	Maiti et al. (2015)

Source: Collected from various sources

Table 5b.2. Descriptive statistics of variables used

Variables	No. of cases	Min.	Max.	Range	Mean	S.D.
			Socioeconomic Vulnerability Index (SeVI)			
FEMALE	300	43.3	50.7	7.5	47.8	1.2
CHILD	300	10.7	24.5	13.9	17.0	3.1
MARGPOP	300	8.6	97.3	88.7	31.8	17.2
LR	300	11.1	88.9	77.8	63.8	17.1
LRGAP	300	8.3	43.1	34.8	23.1	7.5
MAINAG	300	1.5	95.7	94.2	50.7	35.4
MARGW	300	0.3	28.1	27.9	7.6	5.9
WPRGAP	300	0.7	56.8	56.2	31.3	13.6
			Infrastructural Vulnerability Index (IVI)			
LIGHT	300	15.6	98.5	82.9	68.7	22.2
LATRINE	300	1.1	90.3	89.2	34.5	27.6
DWPREM	300	3.2	74.4	71.2	32.4	20.7
FUEL	300	0.0	82.7	82.7	20.6	21.8
			Climate Index (CI)			
TMAX	150	-0.01	0.04	0.05	0.01	0.01
TMIN	150	0.01	0.05	0.04	0.02	0.01
RAINCV	150	16.64	39.83	23.19	23.54	3.88

Source: Author's preparation

To facilitate spatiotemporal comparison of rural and urban areas of all decades, values of each variable are normalised using maximum and minimum values of each calculated from 300 observations (50 districts*3 decades* 2 areas of residence). The variables which have a positive relationship with vulnerability are normalised using the formula:

$$Normalized\ value = \frac{(\text{Value of indicator} - \text{Minimum value})}{(Maximum\ value - Minimum\ value)} \ldots\ldots\ldots (1)$$

Whereas, the variables which has a negative relation with vulnerability is reversed using the formula,

$$Normalized\ value = \frac{(\text{Maximum value} - \text{Value of indicator})}{(Maximum\ value - Minimum\ value)} \ldots\ldots (2)$$

After the normalisation of each variable, Principal Component Analysis (PCA) is conducted for socioeconomic and infrastructural variables with 300 observations and climatic variables with 150 observations.

Table 5b.3.Results of statistical tests used for PCA

Statistical Tests		CI	SeVI	IVI	Remarks
Correlation Matrix	**Determinants**	0.93	0.001	0.006	>.00001, No multicollinearity issue
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	**KMO value**	0.5	0.7	0.8	< 0.5 = unacceptable
Bartlett's Test of Sphericity	$X^2_{(DF)}$	10.11^{***} (3)	2225.11^{***} (28)	1503.08^{***} (6)	Significant, not an identity matrix
Communalities	**Average**	0.8	0.77	0.87	>.7, Good
Components retained	**Component**	2	2	1	Eigen value>1
Variance Explained	**% of variance**	80	78.6	87.4	>60%, Acceptable

Source: Author's preparation

Table 5b.3 shows the results of PCA for each category of variables. The determinant values of correlation matrices for the three indices are greater than 0.00001, indicating no multicollinearity in the variables used. Sampling was found adequate as all cases reported the Kaiser-Meyer-Olkin Measure (KMO) value as greater than 0.5. The data was found adequate as Bartlett's test of Sphericity was highly significant, with p <0.05 for three indices. PCA with varimax rotation resulted in two components each for SeVI and CI. The rotated component matrices for both indices are provided in tables 5b.4 and 5b.6. For IVI, only one component was extracted, so no rotation was possible. The component matrix of IVI is provided in table 5b.5.

Table 5b.4. Rotated Component Matrix of PCA for SeVI

Variable Name	Components	
	1	**2**
CHILD	.935	
LR	.890	
LRGAP	.879	
WPRGAP	-.743	
MAINAG	.718	.557
FEMALE		.850
MARGPOP		.806
MARGW		.803

Extraction method: Principal Component Analysis. Rotation method: Varimax with Kaiser normalisation. Rotation converged in 3 iterations. Suppress small coefficients (absolute value below .40)

Table 5b.5. Component Matrix of PCA for IVI

Variable Name	Component 1
LATRINE	.982
FUEL	.951
DWPREM	.930
LIGHT	.872

Extraction method: Principal Component Analysis

Table 5b.6 Rotated Component Matrix of PCA for CI

Variable Name	Component	
	1	**2**
TMAX	0.795	
TMIN	0.788	0.107
RAINCV		0.993

Extracted method: Principal Component Analysis. Rotation method: Varimax with Kaiser normalisation. Rotation converged in 3 iterations. Suppress small coefficients (absolute value below .40)

The components are labelled based on the variable that is loaded strongly to them. While the scores of rotated components are added with weightage to form SeVI and CI, the unrotated component score is considered IVI. The weight assigned while constructing SeVI and CI is the percentage of cumulative variance explained by each component. It is assigned to give more importance to the dominant component. SeVI and IVI of rural and urban are combined with weightage to construct CSVI of rural and urban areas. Here, the weightage used is the number of components as used by Hahn et al. (2009).

$$CSVI= (SeVI*2+IVI*1)/3 \ldots\ldots (3)$$

Where, 2 represents the number of components extracted from socioeconomic variables, and 1 represents the number of components extracted from infrastructural variables.3 represents the total number of components. The resultant CSVI is aggregated with CI to form CVI.

$$CVI=(CI*2+CSVI*3)/5 \ldots (4)$$

Where, 2 represents the number of components extracted from climatic variables and, 4 represents the total number of components extracted from socioeconomic and infrastructural variables. 6 represents the total number of components.

The CVI and subindices for rural and urban of each decade are classified using mean and standard deviation in each case, as used by Frigerio et al. (2018). The classification is as follows: Very Low (<mean-1.5 S.D.), Low (mean-1.5 S.D. to mean-.5 S.D.), Moderate (mean-.5 S.D. to mean +.5 S.D.), High (mean +.5 S.D. to mean +1.5 S.D.) and Very High (>mean+1.5 S.D.). Spatial maps with varying levels of vulnerability are produced with QGIS software. To identify the disparities between rural and urban vulnerability to climate change, one-way ANOVA is conducted with rural and urban CVI, CSVI, SeVI, and IVI of all decades together (300 observations). Also, the interdecadal changes of rural and urban CVI and subindices are assessed using one-way ANOVA with 150 observations for each rural and urban area.

5b.4. Results

5b.4.1 Components of Principal Component Analysis

Table 5b.7 shows the major components extracted from the PCA conducted for socioeconomic and infrastructural variables in rural and urban areas and climatic variables at the district level.

Table 5b.7. Major components in SeVI, IVI and CI

Component number	Description	Variance explained (%)	Cumulative Variance (%)
Socioeconomic Vulnerability Index			
1	Dependent population, education and employment	46.5	46.5
2	Marginalised sections of population and agricultural dependence	32.2	78.6
Infrastructural Vulnerability Index			
1	Access to infrastructure	87.4	87.4
Climate Index			
1	Change in temperature	41.8	41.8
2	Variation in rainfall	33.5	75.3

Source: *Rotated component Matrix with Varimax Rotation and Kaiser Normalization for SeVI.*

5b.4.1.1 Dependent population, Education and Employment

This component explains 47% of the variation in SeVI. The percentage of dependent population (children), literacy rate, gender gap in literacy, and dependence of main workers on the agriculture sector load positively on this component. Childbirth is found more in areas where access to education is low, especially where a high gender disparity in literacy exists (Saurabh et al.,2013). In these areas, agricultural dependence will be higher as the nonliterate population has less chance of getting employed in other economic sectors. Though the gender gap in work participation is expected to increase vulnerability, this variable is found to be negatively correlated with this component. In Madhya Pradesh, more women are employed in agriculture, generally as labourers. The higher poverty rate and limited opportunities in other sectors due to lack of education increase their participation in the agricultural sector as marginal workers. As the share of children increases, the dependent population increases in the economy.

As the agriculture sector is very prone to climatic variations, the higher dependence on this sector makes the population highly vulnerable to climate change. Educated people can be better informed about the impacts of climate change, thus reducing their vulnerability. Also, their existent vulnerability will be less as they are more prone to be employed in sectors other than agriculture. This component score was very high in rural areas in

1991 and very low in urban areas in 2011. The decrease in the share of children among the population due to the spread of family planning measures, improvement in overall literacy rate, and reduction in the gender gap in literacy resulted in lowering dependence on the agriculture sector over the decades. The lower dependence on the agriculture sector, higher literacy rate, lower gender gap in literacy, and low share of children in urban areas compared to their rural counterparts lead to low scores in this component for the former. The work participation gap was lowest in tribal districts like Alirajpur, Jhabua, Dindori and Mandla in 1991 and 2001 due to the higher female participation in agricultural activities. This gap was found to be highest in 2011 among urban areas of most of the districts and rural areas of some districts like Bhind, Morena, etc. This component score is found highest in rural areas of northern districts like Morena, Shivpuri, Gwalior and Datia and lowest in urban areas of Seoni, Balaghat, Betul and Jabalpur in south-eastern districts of Madhya Pradesh.

5b.4.1.2 Marginalised sections of population and agricultural dependence

The percentage of marginalised communities (SC and ST), female population, marginal workers, and dependence on agriculture constituted this component and explained 32% of the variation in SeVI. The female population is correlated with marginalised groups as these groups, especially tribals, have the highest share of females than other social groups. Agriculture sector dependence is higher among marginalised communities than other groups due to their isolated forms of living and limited access to education. Additionally, short-term labour migration has been witnessed among marginalised communities resulting from loss of output in the agriculture sector due to climate change (Keshri & Bhagat,2013; Pradhan & Narayanan,2020). The women left behind after the migration of males have to face the burden of household management (Laczko & Aghazarm, 2009; Goodrich et al.,2017). These females will likely become marginal agricultural workers as they are less educated. The score of this component has slightly increased over the decades, and not much difference is found between rural and urban areas. This is mainly due to the almost constant share of the tribal population in rural areas and a slight increase in urban population in some districts due to increased migration over the decades. It is also due to the increasing share of the female population in all areas due to government interventions to improve the sex ratio in Madhya Pradesh. The increasing share of marginal workers due to losses in the agriculture sector and resultant migration also contributed to a slight increase over the decades. This component score was the highest in rural areas of Alirajpur, Shahdol, Mandla, Dindori, etc., in 2011 and lowest in rural and urban areas of Singrauli, Morena, Bhind, etc., in 1991.

5b.4.1.3 Access to infrastructure

This component explains 87% of the variation in IVI and includes access to necessities like electricity, toilet, drinking water, and clean fuel. Access to electricity can enhance productivity and save time, especially among women, and thus may reduce the gender disparities in education and employment (IEA et al.,2022). Access to drinking water and toilet facilities also aids in maintaining proper health, improves productivity, and reduces healthcare costs (Ghosh & Cairncross, 2014). Using clean fuel can reduce premature deaths due to indoor pollution to an extent (IEA et al.,2022). Reducing the emission of carbon dioxide can add to the efforts to mitigate climate change. This component is high among the rural areas in all decades and is found lowest in urban areas, especially in the four cities Indore, Bhopal, Gwalior, and Jabalpur.

5b.4.1.4 Change in temperature

This component explains 42% of the variation in the Climate Index. The rate of change in annual mean maximum temperature and annual mean minimum temperature loads positively in this component. Contrary to the earlier component scores, this component has a higher score in the recent decade, 2011, due to the higher rate of increase in maximum temperature in the recent 30-year period. Though some districts had a decreasing rate of change in maximum temperature in earlier 30-year periods reflecting the exposure in 1991 and 2001, the rate of change was positive and highest for all the districts in the recent period. The minimum temperature is also found to be positive in all study periods. The increase in maximum and minimum temperature can impact the agriculture sector, health, productivity, income, etc., of the population. The districts like Bhind, Morena, Rewa, and Singrauli had the highest score in this component in 2011.

5b.4.1.5 Variation in annual rainfall

This component explains 33% of the variation in the Climate Index. The variation in rainfall has increased in the last 30 years, reflecting higher exposure in the recent decade. The increase in extreme rainfall days and reduction in moderate rainfall affects agriculture, water resources, etc., and can lead to extreme events like drought and flood. This can affect a major population share through high morbidity, mortality, livelihood loss, income loss, etc. Alirajpur and Jhabua districts have higher variations in rainfall for all three decades (1991, 2001 and 2011) and therefore remain very high throughout the period.

5b.4.2 Identification of the most vulnerable to climate change

5b.4.2.1 Changes in pattern of Socioeconomic Vulnerability

Table 5b.8. Number of districts under different levels of SeVI

SeVI	Rural			Urban		
	1991	2001	2011	1991	2001	2011
Very Low	3(7)	3(6)	1(2)	4(28)	3(21)	3(26)
Low	11(21)	11(23)	15(30)	12(24)	12(30)	12(28)
Moderate	25(53)	26(54)	23(49)	17(25)	20(30)	20(32)
High	8(14)	7(12)	8(14)	13(18)	12(16)	12(12)
Very High	3(5)	3(5)	3(5)	4(3)	3(2)	3(2)
Total	50(100)	50(100)	50(100)	50(100)	50(100)	50(100)

Source: Author's calculation

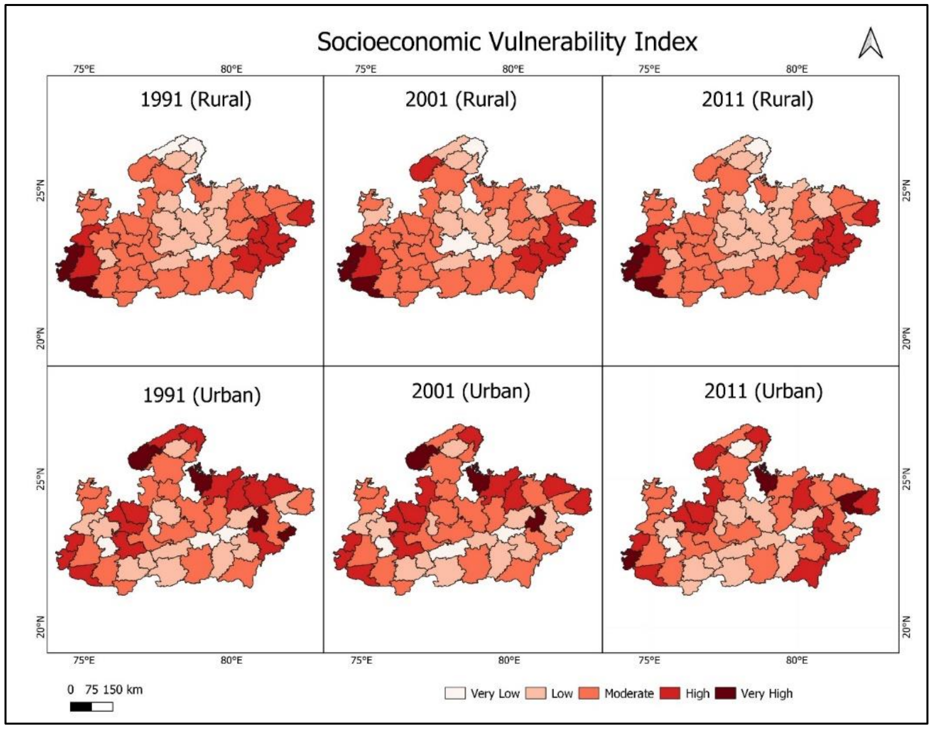
Figures in parenthesis indicate the percentage of rural/urban population of Madhya Pradesh under each level

Table 5b.9.Districts under very high category of SeVI

Rural			Urban		
1991	**2001**	**2011**	**1991**	**2001**	**2011**
Alirajpur	Alirajpur	Jhabua	Tikamgarh	Tikamgarh	Alirajpur
Jhabua	Jhabua	Alirajpur	Umaria	Umaria	Tikamgarh
Barwani	Barwani	Barwani	Anuppur	Sheopur	Sidhi
			Sheopur		

Source: Author's calculation

This section explores how the spatiotemporal pattern of climate change vulnerability and its sub-dimensions differs in rural and urban areas. Table 5b.8 shows the classification of SeVI scores into different levels based on the mean and standard deviation of each area of residence (rural and urban) in each decade. The rural areas of Jhabua, Alirajpur, and Barwani remained very high socioeconomically vulnerable in all the decades (Figure 5b.2 & Table 5b.9). Hence, the number of rural areas of districts and the percentage of rural population under very high socioeconomic vulnerability remain constant in all the decades (Table 5b.8). Rural areas of 8 districts viz. Dindori, Mandla, Singrauli, Dhar, Umaria, Ratlam, Anuppur and Shahdol were identified as highly vulnerable in 1991 (Figure 5b.2). In 2001, rural areas of Umaria and Ratlam became moderately vulnerable and rural Sheopur became highly vulnerable, making the number of high districts to 7. However, in 2011, rural Umaria and Ratlam again changed to high vulnerability, while rural Sheopur became moderately vulnerable. Hence, the number of rural areas with high socioeconomic vulnerability remained the same in 1991 and 2011 (Table 5b.8). Table 5b.18 shows the results of the ANOVA analysis conducted with rural areas of all decades (50 rural areas*3 decades =150 observations). The F value is significant, which implies that significant differences exist between decadal means of SeVI. The Scheffe test (posthoc test) results show that the mean SeVI of 2011 is significantly less than between 1991 and 2001. The mean SeVI of 2001 is also less than in 1991, though not significant (Table 5b.19). These results imply that socioeconomic vulnerability is decreasing in rural areas of Madhya Pradesh over the study period.



Source: Prepared by authors using QGIS

Figure 5b.2. Socioeconomic Vulnerability Index (Rural & Urban)

The spatial pattern of socioeconomic vulnerability is changing in urban areas in each decade, unlike in rural areas. Urban Tikamgarh remains very high socioeconomically vulnerable in all the decades (Figure 5b.2). In 1991, urban areas of Umaria, Anuppur and Sheopur were identified as very high socioeconomically vulnerable, but in 2001, urban Anuppur became moderately vulnerable. Hence, the number of urban areas under very high socioeconomic vulnerability reduced from 4 to 3 in 2001, and the percentage of urban population under the very high vulnerable category was reduced from 3% to 2% (Table 5b.8). The very high vulnerability position of urban Umaria and Sheopur in 2001 changed to high vulnerability in 2011 as they possessed low SeVI score than urban Sidhi and Alirajpur (Table 5b.9). Urban Alirajpur shifted from a high SeVI in 1991 and 2001 to a very high position in 2011. In contrast, urban Sidhi, which possessed a low SeVI in 1991, shifted to a very high SeVI in 2011. Though the SeVI of urban Sidhi in 2011 is less than in 1991, their vulnerability has worsened. The reason is the faster reduction of SeVI in urban parts of other districts than in Sidhi. As two new urban areas became more vulnerable and two older urban areas changed to low vulnerability positions, the number of very high districts in 2011 remained the same, and the population percentage remained almost the same (Table 5b.8). Urban areas of Rajgarh Jhabua, Shajapur, Barwani, Panna and Bhind remain very high socioeconomically vulnerable in all decades. While urban areas of Satna and Singrauli moved from high to moderate, those in Sheopur and Umaria moved from very high to high vulnerability positions. At the same time, the vulnerability position of urban areas of Singrauli, Guna and Balaghat changed to high. Due to the changes in the vulnerability position of these urban areas, the number of urban areas in the high vulnerability category changed from 13 to 12, and the percentage of highly vulnerable urban population reduced from 18% to 12% (Table 5b.8).

The results of ANOVA analysis show a significant decrease in the socioeconomic vulnerability of urban areas over the decades, as the mean SeVI in 2001 is significantly different than in 1991, and that of 2011 is significantly different from the former two decades (Table 5b.19). The ANOVA analysis with all 300 observations (rural & urban together) of SeVI signifies that rural areas possess significantly high socioeconomic vulnerability than urban areas (Table 5b.18).

5b.4.2.2 Changes in pattern of Infrastructural Vulnerability

Table 5b.10 Number of districts under each level of IVI

IVI	Rural			Urban		
	1991	**2001**	**2011**	**1991**	**2001**	**2011**
Very Low	3(3)	2(2)	3(4)	5(33)	4(23)	3(22)
Low	14(30)	15(31)	14(28)	6(15)	10(27)	11(29)
Moderate	17(37)	15(34)	15(35)	23(30)	21(29)	22(31)
High	12(22)	14(27)	15(26)	12(19)	12(18)	10(14)
Very High	4(8)	4(6)	3(7)	4(3)	3(2)	4(4)
Total	50(100)	50(100)	50(100)	50(100)	50(100)	50(100)

Source: Author's calculation

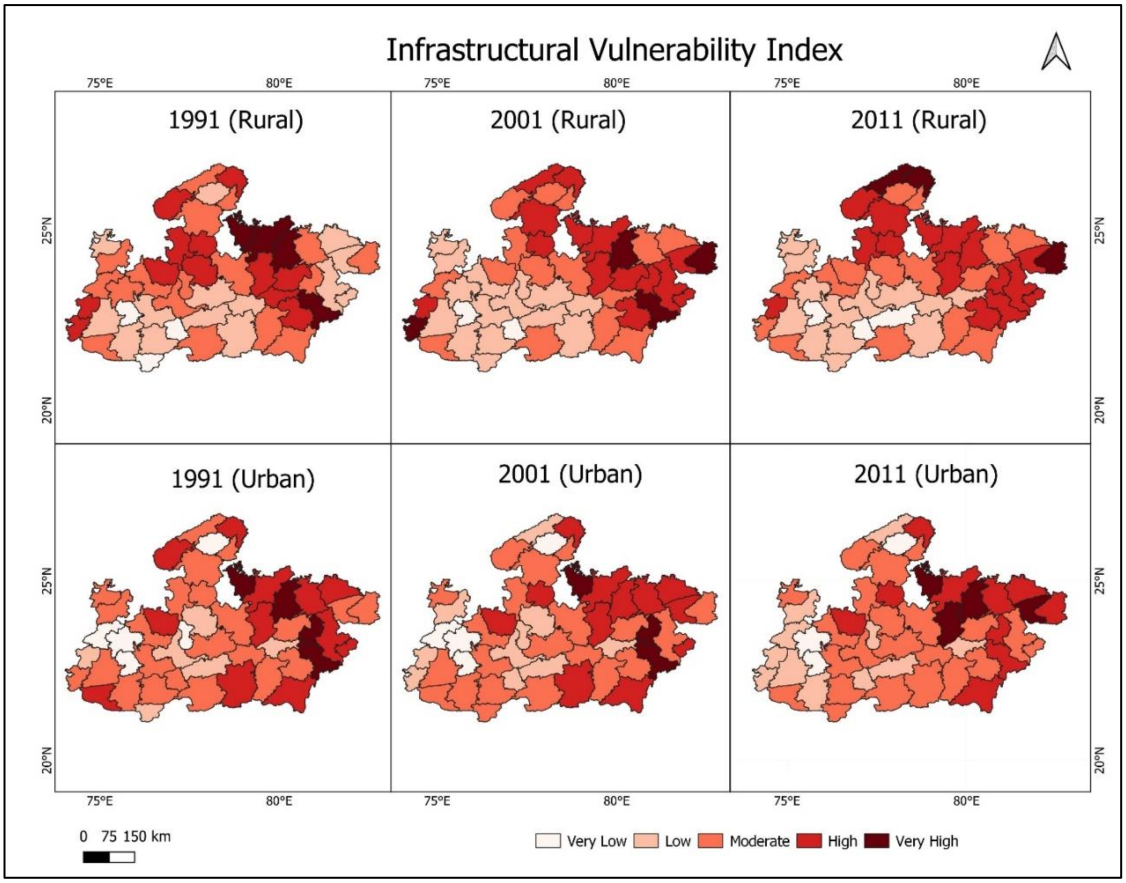
Note: Figures in parenthesis indicate the percentage of rural/urban population of Madhya Pradesh under each level

Table 5b.11 Districts under very high category of IVI

Rural			Urban		
1991	**2001**	**2011**	**1991**	**2001**	**2011**
Panna	Panna	Singrauli	Dindori	Dindori	Tikamgarh
Chhatarpur	Dindori	Morena	Tikamgarh	Tikamgarh	Sidhi
Tikamgarh	Singrauli	Bhind	Panna	Umaria	Panna
Dindori	Alirajpur		Umaria		Damoh

Source: Author's calculation

Table 5b.10 shows the classification of IVI scores into different levels based on the mean and standard deviation of each area of residence (rural & urban) in each decade. Figure 5b.3 shows its spatial pattern.



Source: Prepared by authors using QGIS

Figure 5b.3. Infrastructural Vulnerability Index (Rural & Urban)

The number of rural areas and the percentage of rural population with very high infrastructural vulnerability is higher than those under socioeconomic vulnerability (Tables 5b.8 & 5b.10). Though the number of rural areas that were very high infrastructurally vulnerable remained the same in 1991 and 2001, the districts in this category were not the same in two decades (Table 5b.8 & 5b.10). Rural areas of Panna and Dindori remain in the very high category in both decades. However, rural Chhatarpur and Tikamgarh moved to the high vulnerability category (Figure 5b.3). In contrast, the vulnerability position of rural Singrauli and Alirajpur has worsened from high to very high, making the number of most vulnerable to 4. In 2011, the vulnerability of rural Alirajpur reduced from very high to high. However, rural Morena and Bhind became very high (Figure 5b.3 & Table 5b.10). As Bhind, Morena and Singrauli possess more rural population (Table 3.4) the percentage of rural population in the very high vulnerability category is higher than in 2001. However, the number of districts decreased from 4 to 3 (Table 5b.10). The number of rural areas in the high vulnerability category has increased from 12 to 15. The percentage of rural population infrastructurally vulnerable also increased from 22% to 26% from 1991 to 2011 (Table 5b.10). The rural areas of Mandla, Damoh, Jhabua and Ashoknagar remain highly vulnerable in all decades (Figure 5b.3 & Table 5b.10). ANOVA results show that the mean IVI of 2001 and 2011 in rural areas is significantly less than in 1991. Though the mean IVI of 2011 is less than 2001, the difference is not significant (Table 5b.19).

Though the number of very high urban areas reduced from 4 to 3 in 2001, it again increased to 4 in 2011. Also, the percentage of the urban population in this category was highest in 2011 (Table 5b.10). Only urban Tikamgarh remains in the very high infrastructural vulnerability category in all the decades (Table 5b.11). Urban Dindori and Umaria remained very high infrastructurally vulnerable in 1991 and 2001. Still, their position changed to high vulnerability in 2011 (Figure 5b.3). However, Urban Panna shifted from very high to high in 2001. In 2011, it shifted to very high. Urban Sidhi, which was moderately vulnerable, shifted to high in 2001 and very high in 2011. In contrast, urban Damoh shifted from high to very high over the decades (Figure 5b.3). Urban Sidhi had a lower IVI score in 2011 than in

1991. However, its vulnerability position has worsened over the years as the reduction in this area is slower compared to infrastructural vulnerability reduction in urban areas of other districts. The urban areas with high infrastructural vulnerability have reduced from 12 to 10. The percentage of urban population highly infrastructural vulnerable has reduced from 19% to 14% from 1991 to 2011 (Table 5b.10). ANOVA results show that infrastructural vulnerability has significantly reduced in urban areas over decades, as the mean IVI of 2001 in urban areas is significantly less than in 1991, and that of 2011 is significantly less than the former two decades (Table 5b.19). The ANOVA analysis with all 300 observations (rural & urban together) of IVI shows that rural areas possess significantly high infrastructural vulnerability than urban areas (Table 5b.18).

5b.4.2.3Changes in pattern of social vulnerability

Table 5b.12 Number of districts under each level of CSVI

CSVI	Rural			Urban		
	1991	2001	2011	1991	2001	2011
Very Low	2(5)	3(6)	2(3)	4(30)	6(40)	5(37)
Low	10(19)	13(26)	14(26)	8(18)	10(13)	12(18)
Moderate	28(58)	23(51)	21(49)	23(34)	19(31)	16(26)
High	6(12)	6(10)	10(18)	12(16)	13(15)	15(16)
Very High	4(6)	5(8)	3(4)	3(2)	2(2)	2(2)
Total	50(100)	50(100)	50(100)	50(100)	50(100)	50(100)

Source: Author's calculation

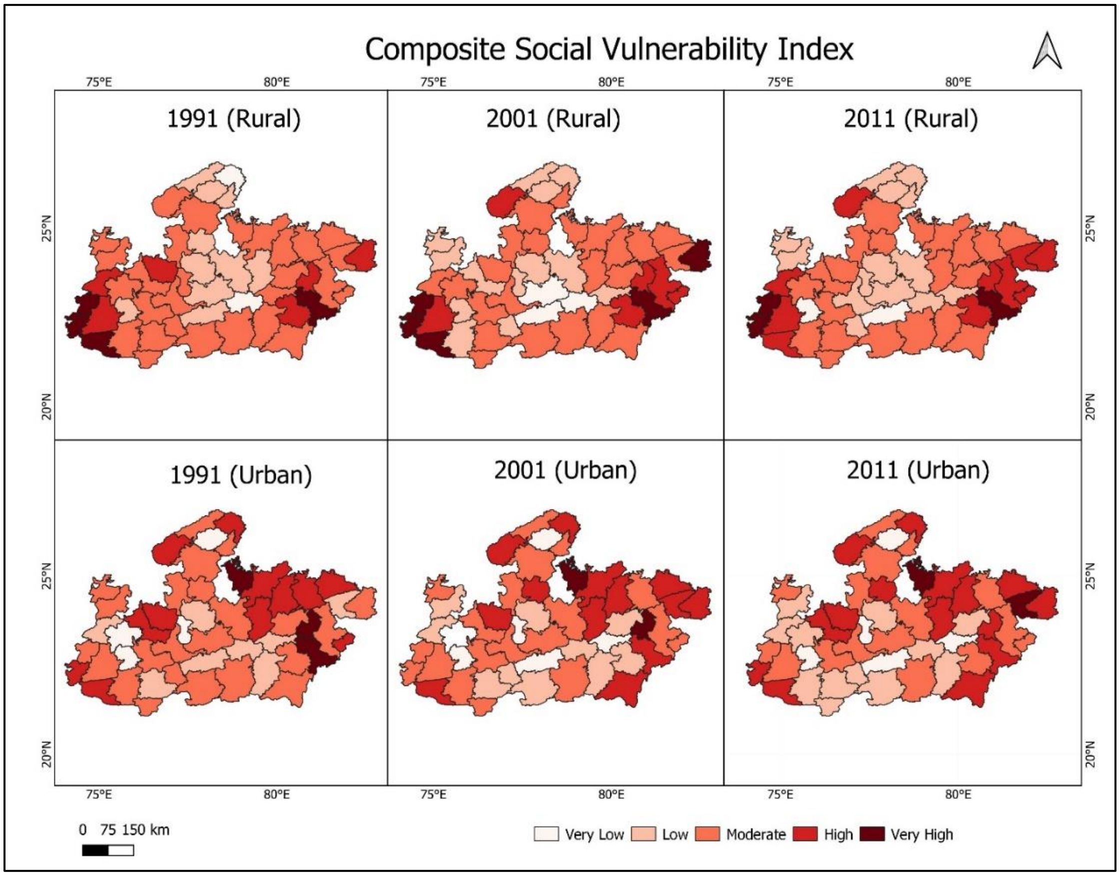
Note: Figures in parenthesis indicate the percentage of rural/urban population of Madhya Pradesh under each level

Table 5b.13. Districts under very high category of CSVI

Rural			Urban		
1991	**2001**	**2011**	**1991**	**2001**	**2011**
Alirajpur	Alirajpur	Jhabua	Tikamgarh	Tikamgarh	Tikamgarh
Jhabua	Jhabua	Alirajpur	Umaria	Umaria	Sidhi
Barwani	Singrauli	Dindori	Dindori		
Dindori	Barwani				
	Dindori				

Source: Author's calculation

Table 5b.12 shows the classification of CSVI scores into different levels based on the mean and standard deviation of each area of residence (rural and urban) in each decade. Figure 5b.4 shows its spatial pattern.



Source: Prepared by authors using QGIS

Figure 5b.4. Composite Social Vulnerability Index (Rural & Urban)

Rural areas of Alirajpur, Jhabua, Barwani and Dindori were identified as very high socially vulnerable in 1991. The very high socioeconomic vulnerability and high infrastructural vulnerability of rural Alirajpur and Jhabua contribute to their very high social vulnerability. At the same time, the very high infrastructural vulnerability and high socioeconomic vulnerability of Dindori lead to its very high social vulnerability (Figures 5b.2,5b.3 and 5b.4). Though rural Barwani possesses moderate infrastructural vulnerability, the very high socioeconomic vulnerability leads to its very high social vulnerability. In 2001, rural Singrauli also became very high socially vulnerable due to the very high infrastructural vulnerability and high socioeconomic vulnerability.Therefore, the number of rural areas with very high vulnerability increased from 4 to 5 in 2001, and the percentage of the population socially vulnerable increased from 6% to 8%. However, in 2011, the percentage of the rural population socially vulnerable reduced to half (4%), as vulnerable rural areas have reduced to three, viz. Jhabua, Alirajpur and Dindori (Tables 5b.12&5b.13). The number of highly vulnerable rural areas increased from 6 to 10 in 2011, and the percentage of rural population highly vulnerable also increased from 12% to 18% (Table 5b.12). ANOVA results show that the mean CSVI of 2001 is significantly less than in 1991, and that of 2011 is significantly less than in former decades (Table 5b.19).

The number of urban areas with very high social vulnerability has halved from 3 to 2 as urban areas of Umaria and Dindori reduced vulnerability, and the vulnerability of urban Sidhi has worsened to very high (Figure 5b.4 & Table 5b.12). The share of the urban population socially vulnerable remains at 2% in all decades. Urban Tikamgarh remained very high socially vulnerable as it has a very high socioeconomic and infrastructural vulnerability in all decades. The number of high socially vulnerable urban areas has increased from 12 in 1991 to 15 in 2011 (Table 5b.12). The ANOVA results show that social vulnerability has significantly decreased in urban areas over the decades (Table 5b.19). The ANOVA analysis with all 300 observations (rural & urban together) of SeVI shows that rural areas possess significantly high social vulnerability than urban areas (Table 5b.18).

5b.4.2.4. Changes in pattern of Climate

The number of districts with very high CI is found to be more in 2011 due to the high rate of change in temperature and higher rainfall variation in the 30 years associated with 2011 (Tables 5b.14 and 5b.15). The population share in the very high CI category also increased from 2% to 9% from 1991 to 2011.

Table 5b.14 Number of districts under each level of CI

CI	1991	2001	2011
Very Low	4(7)	3(4)	0(0)
Low	8(15)	10(20)	18(32)
Moderate	22(48)	27(54)	19(44)
High	14(27)	7(17)	8(15)
Very High	2(2)	3(4)	5(9)
Total	50(100)	50(100)	50(100)

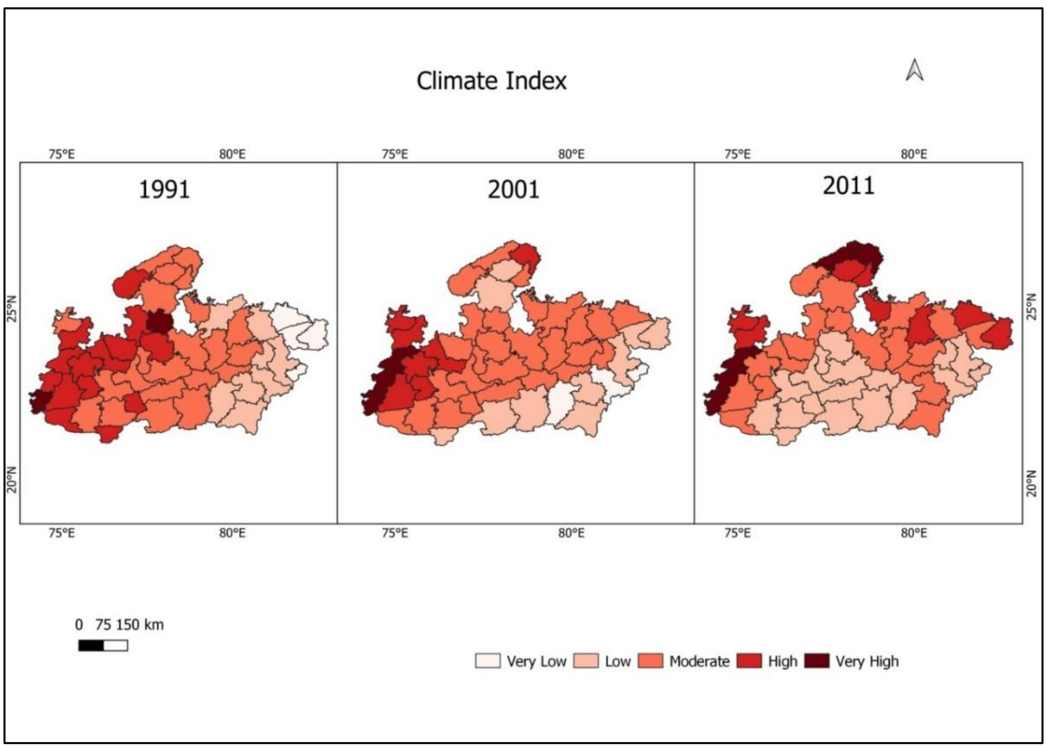
Source: Author's calculation

Note: Figures in parenthesis indicate the percentage of rural/urban population of Madhya Pradesh under each level

Table 5b.15 Districts under very high category of climate index

1991	2001	2011
Alirajpur	Alirajpur	Bhind
Ashoknagar	Jhabua	Alirajpur
	Ratlam	Morena
		Jhabua
		Ratlam

Source: Author's calculation



Source: Prepared by authors using QGIS

Fig5b.5. Climate Index (district)

Alirajpur district continues to possess a very high CI throughout the study period, mainly due to the higher variation in rainfall in this district. Ratlam, Jhabua, and Mandsaur also remain high or very high vulnerable in all decades. A clear shift in the pattern of the climate index is evident in figure 5b.5. The CI scores of Singrauli and Rewa increased from very low in 1991 to high in 2011 due to the high increase in maximum temperature. Though the mean CI in 2001 was less than in 1991, it significantly increased in 2011, as compared to the past decades (1991 and 2001), as evident from the ANOVA of CI for three decades (Table 5b.19)

The number of districts with very high CI was found to be higher in 2011 due to the high rate of change in temperature and higher rainfall variation in the 30 years associated with 2011 (Tables 5b.14 and 5b.15). The population share in the very high CI category also increased from 2% to 9% from 1991 to 2011. Alirajpur district continues to possess a very high CI throughout the study period, mainly due to the higher variation in rainfall in this district. Ratlam, Jhabua, and Mandsaur also remain high or very high vulnerable in all decades. A clear shift in the pattern of the climate index is evident in figure 5b.5. The CI scores of Singrauli and Rewa increased from very low in 1991 to high in 2011 due to the high increase in maximum temperature. Though the mean CI in 2001 was less than in 1991, it significantly increased in 2011, as compared to the past decades (1991 and 2001), as evident from the ANOVA of CI for three decades (Table 5b.19).

5b.4.2.5 Changes in pattern of Climate Vulnerability

Table 5b.16 Number of districts under each level of CVI

CVI	Rural			Urban		
	1991	**2001**	**2011**	**1991**	**2001**	**2011**
Very Low	2(5)	0(0)	1(2)	3(1)	3(7)	0(0)
Low	13(29)	15(31)	16(32)	11(33)	13(33)	18(50)
Moderate	22(42)	28(56)	20(39)	22(46)	19(41)	18(32)
High	11(22)	4(9)	9(20)	12(18)	12(16)	10(12)
Very High	2(3)	3(5)	4(7)	2(1)	3(2)	4(6)
Total	50(100)	50(100)	50(100)	50(100)	50(100)	50(100)

Source: Author's calculation.

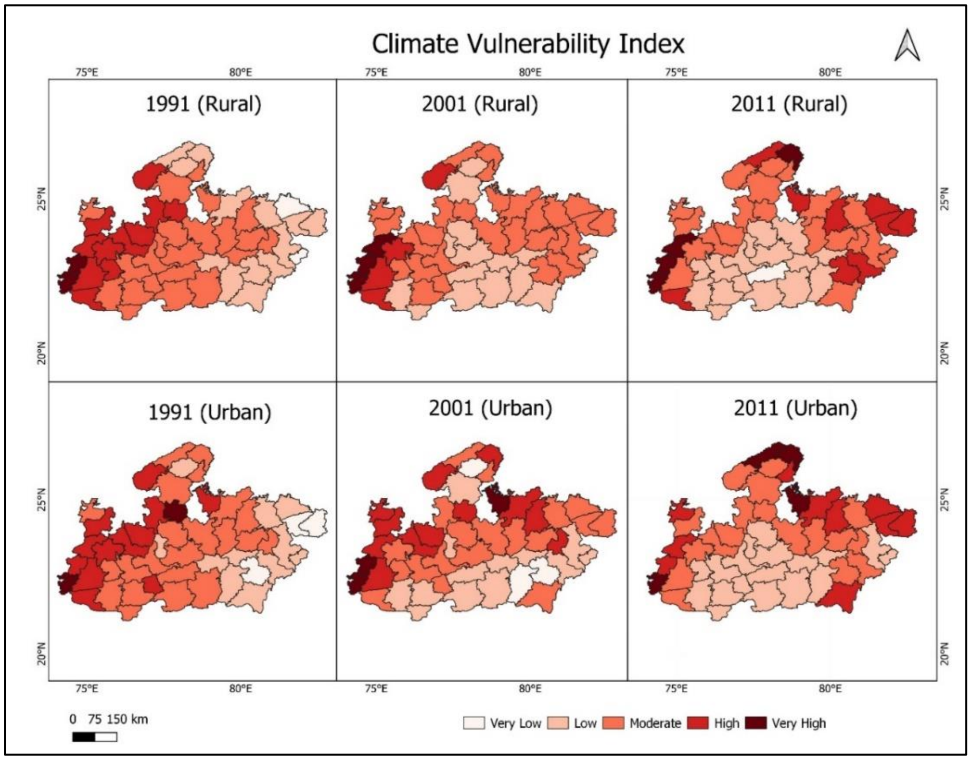
Note: Figures in parenthesis indicate the percentage of rural/urban population of Madhya Pradesh under each level

Table 5b.17. Districts under very high category of CVI

Rural			Urban		
1991	**2001**	**2011**	**1991**	**2001**	**2011**
Alirajpur	Alirajpur	Alirajpur	Alirajpur	Alirajpur	Bhind
Jhabua	Jhabua	Jhabua	Ashoknagar	Jhabua	Alirajpur
	Ratlam	Bhind		Tikamgarh	Morena
		Ratlam			Tikamgarh

Source: Author's calculation

The number of rural and urban areas under very high vulnerability to climate change has increased from 1991 to 2011. The share of very highly vulnerable rural as well as urban population has increased during the same period (Table 5b.16). Rural Alirajpur and Jhabua remain very high vulnerable in all decades due to their very high social vulnerability as well as very high climate exposure (Table 5b.17). Rural areas with very high vulnerability increased from 2 to 4 as rural Ratlam and Bhind became very highly vulnerable to climate change over the decades, mainly due to their very high climate index (Figures 5b.5 & 5b.6). Hence the share of the rural population very highly vulnerable to climate change also increased from 3% to 7% (Table 5b.16). The number of rural areas under high vulnerability has decreased from 11 to 9. The rural population under this category has also decreased. Like rural areas, the number of urban areas under very high vulnerability also increased from 2 to 4 over the decades. The rural population under the very high category increased from 1% to 6%. Urban Alirajpur has remained very highly vulnerable to climate change for decades due to the very high climate index and the high or moderate social vulnerability in urban areas. Rural Ashoknagar had a very high vulnerability to climate change in 1991 due to the very high climate index and moderate social vulnerability. Though the social vulnerability position worsened to high, the reduction in the climate index score over time led to its shift to high vulnerability to climate change. As the climate index values increased for Jhabua, Morena and Bhind over the decades, they became very highly vulnerable to climate change. However, the social vulnerability possessed is high or moderate. At the same time, the very high social vulnerability and high climate index contribute to very high vulnerability to climate change in urban Tikamgarh. Like rural areas, the number of urban areas under high vulnerability to climate change also decreased, and the share of the urban population highly vulnerable also decreased.



Source: Prepared by authors using QGIS

Figure 5b.6. Climate Vulnerability Index (Rural & Urban)

ANOVA results show that CVI in both rural and urban areas significantly decreased from 1991 to 2001. However, the decrease from 1991 to 2011 is not significant (Tables 5b.18 & 5b.19). Also, the index scores significantly increased from 2001 to 2011, which is attributed to increased CI in the recent decade. The rural areas possess significantly high vulnerability to climate change, as evident from the ANOVA analysis of all 300 observations (rural and urban together) of CVI.

Table 5b.18. Results of rural-urban wise ANOVA analysis of all decades

Row Mean- Column Mean	SeVI	IVI	CSVI	CVI
	Rural	Rural	Rural	Rural
Urban	-1.26* (0.00)	-1.80* (0.00)	-1.44* (0.00)	-0.86* (0.00)
Equal mean test across regions	987.4* (0.00)	1312.51* (0.00)	1443.42* (0.00)	597.38* (0.00)
Equal variance test across regions	35.48* (0.00)	21.5* (0.00)	0.30 (0.58)	0.56 (0.45)

Source: Prepared by authors

Table 5b.19. Results of ANOVA analysis of rural and urban indices of all decades

Row mean- column mean	SeVI				IVI				CSVI				CI		CVI			
	Rural		Urban		Rural		Urban		Rural		Urban		District		Rural		Urban	
	1991	2001	1991	2001	1991	2001	1991	2001	1991	2001	1991	2001	1991	2001	1991	2001	1991	2001
2001	-0.10 (0.30)		-0.21* (0.00)		-0.36* (0.00)		-0.61* (0.00)		-0.19* (0.00)		-0.34* (0.00)		-0.36* (0.01)		-0.26* (0.00)		-0.35* (0.00)	
2011	-.058* (0.00)	-0.48* (0.00)	-0.46* (0.00)	-0.26* (0.00)	-0.36* (0.00)	-0.006 (0.99)	-0.85* (0.00)	-0.24* (0.004)	-0.51* (0.00)	-0.32* (0.00)	-0.59* (0.00)	-0.25* (0.00)	0.62* (0.00)	0.98* (0.00)	-0.06 (0.62)	0.2* (0.004)	-0.11 (0.12)	0.24* (0.00)
Equal mean test across regions	43.56* (0.00)		93.15* (0.00)		24.48* (0.00)		77.81* (0.00)		48.84* (0.00)		101.7* (0.00)		35.98* (0.00)		10.36* (0.00)		23.88* (0.00)	
Equal variance test across regions	1.41 (0.5)		3.15 (0.21)		20.86* (0.00)		0.007 (0.1)		4.07 (0.13)		1.18 (0.55)		2.15 (0.34)		0.20 (0.9)		1.43 (0.5)	

Source: Prepared by authors

5b.5 Discussion of results

The vulnerability of a place to climate change is determined not only by its exposure to varying climate but also by its inherent vulnerability characterised by the demographic constitution, access to basic infrastructure and the relative socioeconomic development of the areas. Rural areas in most Indian states are highly dependent on natural resource-intensive sectors and possess relatively less socioeconomic development than urban areas. These differences may accentuate their vulnerability to climate change, even if they are exposed to the same variation in climate. Though vulnerability studies conducted outside India have identified disparities in social vulnerability among rural and urban areas (Ge et al.,2017; Ge et al.,2021; Wang et al.,2022), these studies have not considered the biophysical dimension of vulnerability. These disparities are not addressed in the Indian situation, even if there is a widespread belief that the rural population in India is more vulnerable to climate change. This objective attempted to fill this gap by assessing rural-urban disparities in Madhya Pradesh. It also tried to address the gap in spatiotemporal studies on climate change vulnerability by assessing the spatiotemporal pattern of climate change vulnerability of rural and urban areas for three decades. The segregation of social vulnerability to socioeconomic vulnerability and infrastructural vulnerability and capturing its temporal nature over the decades facilitated an effective assessment of vulnerability, adding to the novelty of the study.

The study found that rural areas in Madhya Pradesh possess significantly higher vulnerability to climate change than their urban counterparts. The significant differences among values of the social vulnerability index and its subindices between rural and urban areas have contributed to this difference in overall vulnerability to climate change. This result matches the findings of Ge et al. (2021) and Patri et al. (2022) that urbanisation reduces vulnerability.

The social vulnerability index and its subindices of rural and urban areas have significantly decreased over the decades of study. It aligns with the findings of Das et al. (2021), Vittal et al. (2020), and Yenneti et al. (2016) that social vulnerability decreases over time in India. The Climate Index scores in the study found a significant decrease between 1991 and 2001. However, the mean CI in 2011 is significantly higher than in its former decades, indicating increased climate exposure in the recent decade. This result matches the increasing probability of hydroclimatic hazards noted by Vittal et al. (2020). Vittal et al. (2020) also noted that this probability of occurrence of hydroclimatic hazards resulted in an increased risk of hydroclimatic events in India despite the decreasing social vulnerability from 2001 to 2011. Similarly, our study found a significant increase in climate vulnerability in rural and urban areas from 2001 to 2011. Hence, the decrease in CVI scores in rural and urban areas in 2011 from 1991 was not significant, though the mean CVI scores in 2001 were significantly less than in 1991.

Vittal et al. (2020) found a decrease in mortality to hydroclimatic hazards in India over decades despite the increased probability of occurrence of hazards. They attribute this decrease in mortality to the reduction in social vulnerability. As our study also found an increase in climate index as the main contributor to the increase in climate vulnerability index in recent decades, and the variation in climate is predicted to increase in Madhya Pradesh by different studies, more reduction in social vulnerability is the best possible solution to reduce overall vulnerability to climate change in the coming decades. Therefore, policy efforts should be directed towards reducing socioeconomic and infrastructural vulnerability, the two major dimensions of social vulnerability.

The study identified that a decrease in the share of children, improvement in overall literacy rate and reduction of the gender gap in literacy, decreased dependence on the agriculture sector, and increased access to infrastructure have resulted in a reduction in socioeconomic and infrastructural vulnerability of both rural and urban areas over the decades. The lesser shares of children in urban population, higher literacy rates and low gender gaps in literacy, low agriculture dependence and better access to infrastructure in urban areas resulted in lower socioeconomic and infrastructural vulnerability than urban counterparts. Further improvements in access to education and livelihood diversification, especially among women and marginalised sections, can reduce socioeconomic vulnerability to an extent in the coming decades. The government of Madhya Pradesh has initiated schemes like Ladli Laxmi Yojana, Beti-Bachao, Beti-Padhao scheme, and scholarships to girls to improve access to female education in the state (GoMP,2023). These schemes could improve the literacy rate of women and reduce child marriages to an extent, as reflected in the latest National Family Health Survey (NFHS-5).

Further strengthening of these programmes will enable a better reduction of the gender gap in education. The reduction in child marriages can lead to a reduction in childbirth. The reduction in family size and economic dependence can also reduce socioeconomic vulnerability.

The increasing share of marginal workers due to income losses from agriculture and forest products also contributes to higher socioeconomic vulnerability. The number of marginal workers also increased due to climate change-induced migration, as unskilled migrants from rural areas could not find a proper position in the job market in urban areas (Subramanian, 2015; Motkuri & Naik,2016; Bhagat, 2017; Pradhan & Narayanan, 2020; Pradhan & Narayanan, 2022). Agriculture dependence and employment as marginal workers are high among the marginalised communities and women. Along with improving education, skill training and livelihood diversification schemes should be strengthened to reduce the higher share of marginal workers. Strengthening the existing programmes for livelihood diversification like MGNREGA (Mahatma Gandhi National Rural Employment Guarantee Program) and skill development programs of state government like Mukhya Mantri Kaushalya Yojana, Mukhya Mantri

Kaushal Samvardhan Yojana can reduce the share of marginal workers. The government has also initiated livelihood diversification schemes targeting marginalised communities like SC and ST. Strengthening these schemes and ensuring their reach to people in need could reduce socioeconomic vulnerability. Though government schemes have improved access to basic facilities, regional and rural-urban disparities are still high. Ensuring their proper reach to people in need can reduce infrastructural vulnerability and enhance the overall human development in the state.

The spatial pattern of the climate vulnerability index and its subindices notes a concentration of vulnerability among rural and urban areas in southwestern, eastern and northern parts of the state. Though rural and urban areas in western Madhya Pradesh were highly vulnerable to climate change, they gradually shifted to lower vulnerability positions. The rural and urban areas in peripheral districts dominated by scheduled tribes became more vulnerable to climate change. The studies on regional disparities in Madhya Pradesh (Dutta et al.,2020; Shevalkar,2020; Singh et al.,2018; Shankar,2005) also point towards the backwardness in tribal areas and higher development in districts in western and central Madhya Pradesh. Hence, the interventions for improving access to infrastructure, livelihood diversification, and access to education should target more tribal areas of the state.

This study advances from the earlier approaches to climate change vulnerability by analysing rural and urban areas at the district level in Indian states. The spatiotemporal analysis of climate vulnerability indices and their subindices over three decades aids in the identification of the dominant vulnerability dimension, which will also facilitate targeted policy interventions **(**Mazumdar & Paul, 2016). Despite these advantages, this study also suffers from certain limitations. The geographic size of rural and urban areas has changed over the study period. Demographic indicators like the share of the elderly population, disabled population, and houseless population are identified as essential socioeconomic indicators. The lack of data for these variables at the town/ village level of the 1991 population census constrained its usage in this analysis. The lack of rural-urban data of certain districts in 1981 constrained the calculation of the population growth rate for 1981-91 and thus omitted this variable. Due to the delays in conducting the decadal population census in 2021, the study could use data only up to 2011. However, the study can be updated further after the latest available data.

5b.6 Conclusion

This study assesses the vulnerability to climate change patterns over three decades in rural and urban Madhya Pradesh. It also tried identifying the dimension to which each spatial unit is more vulnerable. Based on the results, it is found that rural areas in Madhya Pradesh possess higher vulnerability to climate change than urban areas. Though social vulnerability has decreased over decades, overall climate vulnerability significantly increased in 2011 compared to 2001, resulting from increased climate change exposure as indicated by the CI score. These findings suggest that appropriate policy measures should be taken to reduce social vulnerability at disaggregate levels in rural and urban Madhya Pradesh. Strengthening policy measures for increasing access to education, livelihood diversification, skill development, infrastructural facilities, etc., in rural areas focusing on women and marginalised sections can reduce vulnerability to climate change in Madhya Pradesh.

Chapter 6

Spatiotemporal pattern of Vulnerability of Agriculture Sector to Climate Change

Madhya Pradesh has, around 70% of its population depends on the agricultural sector, who are mainly marginal and small landholders. Chapter 5 points out the dependence on the agricultural sector as one of the significant factors contributing to the vulnerability of the population in Madhya Pradesh. From chapters 4 and 5, it is clear that reducing the overall vulnerability of the population to climate change requires reducing the vulnerability of the agriculture sector and its dependents. Hence, this chapter attempted to study the spatiotemporal pattern of the vulnerability of the agriculture sector in the state and the leading factors. The first section (6.1) points out the need to assess the vulnerability of the agriculture sector to climate change in Madhya Pradesh. The following section, 6.2, provides details about the sources of data. Section 6.3 details the research methods, 6.4 provides the analysis results,6.5 discusses the results and recommends policy measures, and 6.6 concludes the chapter.

6.1 Relevance of assessing vulnerability of agriculture sector to climate change

The agriculture sector is known as the backbone of the Indian economy. Though the share of national income from agriculture has decreased over the years, dependence on this sector for livelihood has not decreased to that extent. The agriculture sector plays a major role in feeding a larger population and alleviating poverty and malnutrition. It acts as an input provider to other industries, and the income from this sector will trigger the demand for other sectors of the economy (Gulati et al., 2021). Climate change can significantly impact this sector (as detailed in section 1.4), which may reduce the income of its dependents (Kumar, 2009; Kumar & Parikh, 2001; Mendelsohn, 2014; Saravanakumar,2015). The abundance of small and marginal cultivators and agricultural labourers who possess limited coping capacity (CLRA, 2009) adds to the higher vulnerability of this sector to climate change. It is necessary to identify the extent to which this sector is vulnerable to climate change and the major factors contributing to it, which will facilitate targeted interventions to reduce the likely impacts on the sector and the population depending on it.

Unlike other states of India, Madhya Pradesh has had a spectacular performance in the agriculture sector in the recent decade (the 2010s) because of an increase in irrigated area, increased power supply for agriculture, increased agricultural mechanization, development of road network, effective procurement mechanism and Minimum Support Price for wheat (Gulati et al., 2021). Though the overall performance of the state is high, the growth in the agriculture sector is uneven across the state, as evidenced by the literature. Regional disparities in land distribution, land use patterns, cropping patterns, access to inputs like fertilizers, irrigation, and mechanization, as well as increased government support towards commercialization, have resulted in the uneven development of this sector. (Singh et al.,2018; Dutta et al.,2020; Shevalkar,2020). The state is moving towards crop specialization, with three crops, wheat, chickpea, and soyabean, occupying a significant share (62 per cent in 2008-17) (George & Sharma,2023). The increasing specialization due to the high return and increased government support led to the development of regions like Malwa, which are prominent in these crops. At the same time, regions with more production of coarse cereals, like Sorghum, suffer from disparities in access to fertilizers, irrigation, mechanization, power supply, and government support for the marketing of crops. The agriculture sector in the state also suffers from increased fragmentation of landholdings, which leads to an increase in the number of operational holdings[15] but decrease in area under each (GoI,2020).

[15] *An operational holding is defined as "all land which is used wholly or partly for agricultural production and is operated as one technical unit by one person alone or with others without regard to the title, legal form, size or location" (GoI, 2020).*

These existing issues, if compounded with changes in climatic parameters and their extremes, will adversely impact the agriculture sector and the livelihood of its dependents. Assessment of the differential vulnerability to climate change spatially among the districts with differences in agricultural characteristics and understanding changes in their vulnerability over time is essential for reducing losses due to climate change.

Studies on agricultural vulnerability in India and other countries have generally used the IPCC approach (section 2.4.1) to assess this sector's vulnerability to climate change. The vulnerability assessments in the agriculture sector have identified a high rate of change in maximum and minimum temperature and high intensity and variability of rainfall as significant contributors to exposure (Sehgal et al., 2013; Srivastava,2015). Whereas landholding size, the yield of crops, cropping intensity, commercialization of agriculture, diversification to livestock, and access to inputs like irrigation, fertilizer, roads, electricity, etc. contribute to the sensitivity and adaptive capacity of the agriculture sector (Raju et al., 2017; Sehgal et al.,2013; Srivastava, 2015; Antwi-Agyei et al., 2012; Das,2013; Choudhary & Sirohi,2022). State-level and district-level studies on the vulnerability of the agriculture sector in India have categorized the state of Madhya Pradesh and some of its districts as highly vulnerable due to their higher sensitivity and lower adaptive capacity. Das (2013) classified the agriculture sector of Madhya Pradesh as highly vulnerable due to the higher socioeconomic vulnerability, though the biophysical vulnerability of the state was low. O'Brien et al. (2004b) have classified the districts in Madhya Pradesh as vulnerable to climate change and globalization due to their high climate sensitivity, import sensitivity and low adaptive capacity. Among the 115 districts identified as very high agriculturally vulnerable by Rao et al. (2013), 14 belong to Madhya Pradesh due to their high or very high exposure and sensitivity and low adaptive capacity. The projected increase in drought years and the projected rise in minimum temperature contributed to high exposure. High net sown area, low rainfall, high drought-prone area, and low water holding capacity contributed to high sensitivity and low net irrigated area and low groundwater availability contributed to the low adaptive capacity of high and very highly vulnerable districts in Madhya Pradesh (Rao et al., 2013). MPSKMCCC (2018) classified 9 districts as very high agriculturally vulnerable in Madhya Pradesh, due to the low yield of food grains, low irrigation rate and fertilizer consumption, low net sown area and higher share of wasteland. From the above literature, it is understood that the IPCC approach will be more suitable for assessing the vulnerability of the agriculture sector in Madhya Pradesh, as it will identify which component contributes more to vulnerability, and interventions can be targeted accordingly.

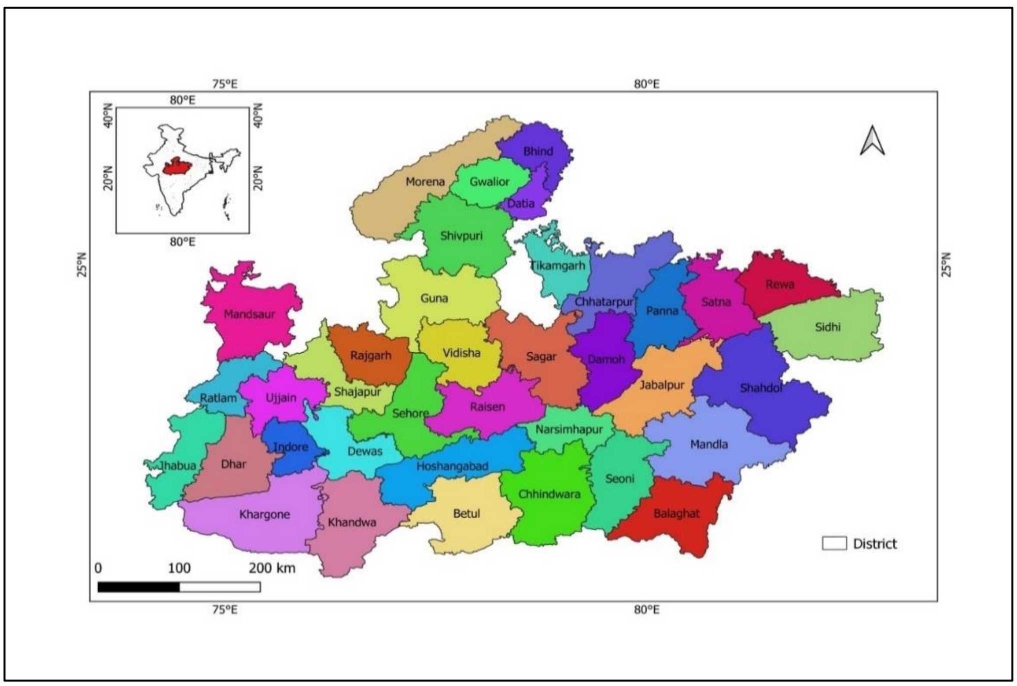
Though most of the studies on agriculture sector vulnerability use the IPCC framework, the methods used for providing weightage to indicators and their aggregation to composite index differ in each study. Studies like Rao et al. (2013) and Sehgal et al. (2013) constructed subindices of exposure, sensitivity and adaptive capacity as weighted means of their respective indicators. Later, the subindices are combined to form a composite vulnerability index by applying their respective weights. Weights were assigned based on literature, expert opinion or the Analytic Hierarchy process. Choudhary and Sirohi (2022) and Raju et al. (2017) used Principal Component Analysis to construct agricultural vulnerability. PCA facilitates a weighted index aggregation and hence is the most suitable method for constructing the Agriculture Vulnerability Index. It also facilitates the identification of the major factors contributing to exposure, sensitivity and adaptive capacity, as done by Jha & Gundimeda (2019). Identifying the factors contributing to each subcomponent will facilitate more targeted policy-making to reduce vulnerability.

The studies on the vulnerability of the agriculture sector to climate change are generally static, as they discuss vulnerability at only one point in time (Das,2013; Rao et al.,2013; Sehgal et al.,2013; Raju et al., 2017). Very few studies, like Varadan & Kumar (2015), used instability and change over a period as a variable to detect the change over time. Palanisami et al. (2008) attempted to assess the vulnerability of agroclimatic regions in Tamil Nadu for three decades: 1980-81,1990-91, and 2000-01. However, the index is constructed separately for each decade, and the results show only the ranking of each zone in each year of study. As the index is constructed by simple averaging, there is no attempt to identify the significant contributors of vulnerability. This study tries to overcome these gaps through a spatiotemporal assessment of vulnerability in the agriculture sector. It tries to capture the dynamic nature of vulnerability by assessing the spatial and temporal vulnerability of the district-level agriculture sector for five decades using data from 1970 to 2015. Identifying a spatiotemporal pattern of components of vulnerability to understand how their temporal or spatial change contributes to the changes in overall vulnerability adds novelty to this study. Identifying the major factors contributing to each component of the vulnerability of the agriculture sector adds further novelty to the study.

Thus, the objective of the study is to assess the spatiotemporal pattern of the vulnerability of the agricultural sector in Madhya Pradesh to climate change at the district level by preparing a composite agricultural vulnerability index out of indicators representing the change in climatic variables, demographic dependence on the sector, land use pattern, productivity of major crops, technological advancement, diversification practices, etc. It tries to identify the most vulnerable districts in each decade and also captures the spatial and temporal changes in the vulnerability of the sector over five decades. Identifying the level of each component of vulnerability and the major factors leading to their particular level helps in targeted policy interventions for reducing vulnerability in each district.

6.2 Source of data and scale of analysis

The study in this chapter also uses the same data sources as the previous two chapters. The data for rainfall is collected from India WRIS, and the temperature and agriculture sector-related variables are collected from the ICRISAT district level database. In objective 2, the districts were considered as existing in 2011. Unlike that, this chapter considers data from 1970 onwards. The district level database of ICRISAT is available from 1966. ICRISAT has apportioned the data of new districts formed after 1966 to older districts from where it is carved out to provide time series data. Hence, the number of units in this study is only 37, which includes data from 52 districts existing in 2023. Figure 6.1 shows the district map as of 1966, and Table 6.1 shows the names of districts formed after 1966, whose data is apportioned to older districts. The original database of ICRISAT is available from 1966 to 2017. However, due to the lack of most of the variables used in the study from 1966 to 1969 and after 2015, the study period is restricted to 1970-2015.



Source: Authors' preparation using QGIS

Figure 6.1 Districts of Madhya Pradesh as of 1966

Table 6.1 Districts used in the study and new districts merged to it

Sl.No.	District as on 1966	District as on 2023
1	Balaghat	Balaghat
2	Mandla	Mandla, Dindori
3	Shahdol	Shahdol, Anuppur, Umaria
4	Panna	Panna
5	Rewa	Rewa
6	Satna	Satna
7	Seoni	Seoni
8	Jabalpur	Jabalpur, Katni
9	Sidhi	Sidhi, Singrauli
10	Sagar	Sagar
11	Damoh	Damoh
12	Vidisha	Vidisha
13	Sehore	Sehore, Bhopal
14	Raisen	Raisen
15	Guna	Guna, Ashoknagar
16	Gwalior	Gwalior
17	Bhind	Bhind
18	Datia	Datia
19	Morena	Morena, Sheopur
20	Shivpuri	Shivpuri
21	Tikamgarh	Tikamgarh, Niwari
22	Chhatarpur	Chhatarpur
23	Chhindwara	Chhindwara
24	Betul	Betul
25	Hoshangabad	Hoshangabad, Harda
26	Narsimhapur	Narsimhapur
27	Dewas	Dewas
28	Shajapur	Shajapur
29	Rajgarh	Rajgarh
30	Ujjain	Ujjain
31	Indore	Indore
32	Ratlam	Ratlam
33	Mandsaur	Mandsaur, Neemuch
34	Dhar	Dhar
35	Khargone	Khargone, Barwani
36	Khandwa	Khandwa, Burhanpur
37	Jhabua	Jhabua, Alirajpur

Source: ICRISAT district level database

The data of agriculture sector-related variables like poultry, livestock and area under marginal, small and total operational holdings are collected officially once every 5 years. Data of cultivators and agricultural labourers are collected once every 10 years. The other agriculture sector variables are available in an annual format. So, these variables are converted to annual format by interpolation and extrapolation of available data. After obtaining the 46-year data of agricultural sector variables, they are segregated into five decades[16]: 1970-79, 1980-89, 1990-99, 2000-09 and 2010-15 to represent the vulnerability situation of 1970s, 80s, 90s,2000s and 2010s respectively.

Then, the decadal averages of each indicator are calculated in order to avoid yearly fluctuations in the data. The district-level rainfall data collected from IWRIS (India Water Resources Information System) has data for 50 districts of Madhya Pradesh. The annual and seasonal rainfall of new districts is averaged with that of older districts to obtain the annual and monsoon rainfall of combined districts. Later, they are segregated into five decades, and the coefficient of variation in each decade is assessed. The district-level monthly temperature data is collected from ICRISAT for 51 districts. The highest monthly maximum temperature among the old district and new districts carved out from it is considered the monthly maximum temperature of the old district. In the same way, the monthly minimum temperature of the old district is the lowest monthly minimum among the old and new districts carved out from it. After finding the monthly maximum (minimum) temperatures of 37 districts of all years, the monthly values are averaged to obtain the annual mean maximum temperature (annual mean minimum temperature). Like rainfall and agricultural sector variables, the annual temperature data is classified into five decades. Then, the slope of the annual mean maximum and annual mean minimum temperatures are calculated for each decade.

[16] *Though the last period of study has only 6 years, it is also referred as decade as it represents 2010s.*

6.3 Methodology

This study follows an integrated approach to assess the vulnerability of the agriculture sector by using both biophysical and socioeconomic aspects in the agriculture sector. Therefore, it follows the definition of the IPCC approach and classifies indicators into three components of vulnerability. Figure 6.2 provides the steps involved in the assessment of the vulnerability of the agriculture sector to climate change in Madhya Pradesh. The proxy variables for each indicator are selected based on literature and the availability from 1970. The variables collected from the two databases are grouped under three components of vulnerability: Exposure, Sensitivity and Adaptive Capacity, according to classification in earlier studies on vulnerability to climate change.

Exposure consists of changes in temperature and variations in rainfall. To indicate the increase in temperature, the rate of change in annual mean maximum and annual mean minimum temperature in each decade is used. The coefficient of variation in annual rainfall and monsoon rainfall in each decade is used to indicate the variation in rainfall. As monsoon rainfall contributes about 90 % of annual rainfall in Madhya Pradesh (Mishra et al., 2016), its variation is also included in the study.

Sensitivity includes the indicators for demographic dependence, net cropped area and yield of major crops. Demographic dependence includes the indicators for dependence on the agriculture sector and marginalisation of holdings. The total working population in the agricultural sector (cultivators and agricultural labourers) per net cropped area indicates the dependence on the agriculture sector. The percentage of holdings operated by small and marginal farmers to total operational holdings indicates the marginalisation of holdings. Wheat, rice, soyabean, and chickpea account for more than 5 % of the gross cropped area of the state. Soyabean occupies around 25% of the gross cropped area of the state (Gulati et al., 2017), but its data was not available till 1982. So instead of Soyabean, the study uses the yield of oilseeds which includes soyabean, rapeseed and mustard, groundnut, linseed, sesamum, niger seeds etc. So, this study considers the yield of wheat, rice, chickpea and oilseeds and assumes that an increase in the yield of these crops will bring more returns to the sector, thereby reducing sensitivity. The percentage of net cropped area is obtained by dividing it by the total geographical area of the district. The net cropped area represents the total land area used for cultivation at least once a year. It is an essential indicator of the status of agricultural development in the state. Expanding net cropped areas will help meet the food requirements of the growing population and thus reduce the sensitivity to climate change.

Adaptive capacity contains indicators like cropping intensity, major inputs used in this sector and the extent of diversification methods practised in the study units. Cropping intensity indicates the number of times land is cultivated in a crop year. It is calculated as the percentage of gross cropped area in net cropped area. The Gross Cropped Area represents the total area sown more than once. The availability of adequate inputs like irrigation, fertiliser, farm mechanisation etc., can increase cropping intensity. Irrigation and fertiliser consumption are the two major inputs used in agriculture. Irrigation intensity is the percentage of net irrigated area out of the net cropped area. The total consumption of fertilisers includes the consumption of nitrogen, phosphorus and potassium fertilisers. The diversification of agriculture to livestock and poultry rearing and diversification among the crops cultivated can increase the adaptive capacity of farmers by providing additional income. The Crop Diversification Index of each district was constructed using Simpson's Diversity Index (Simpson, 1949).

Using the formula,

$$CDI = 1 - \sum (pa_{xt})^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where pa_{xt} indicates the proportion of area under a particular crop in a district in a particular year. The value of this index ranges from 0 (high crop specialization) to 1 (High crop diversification). Like other variables, CDI is also averaged for each decade to avoid yearly fluctuations.

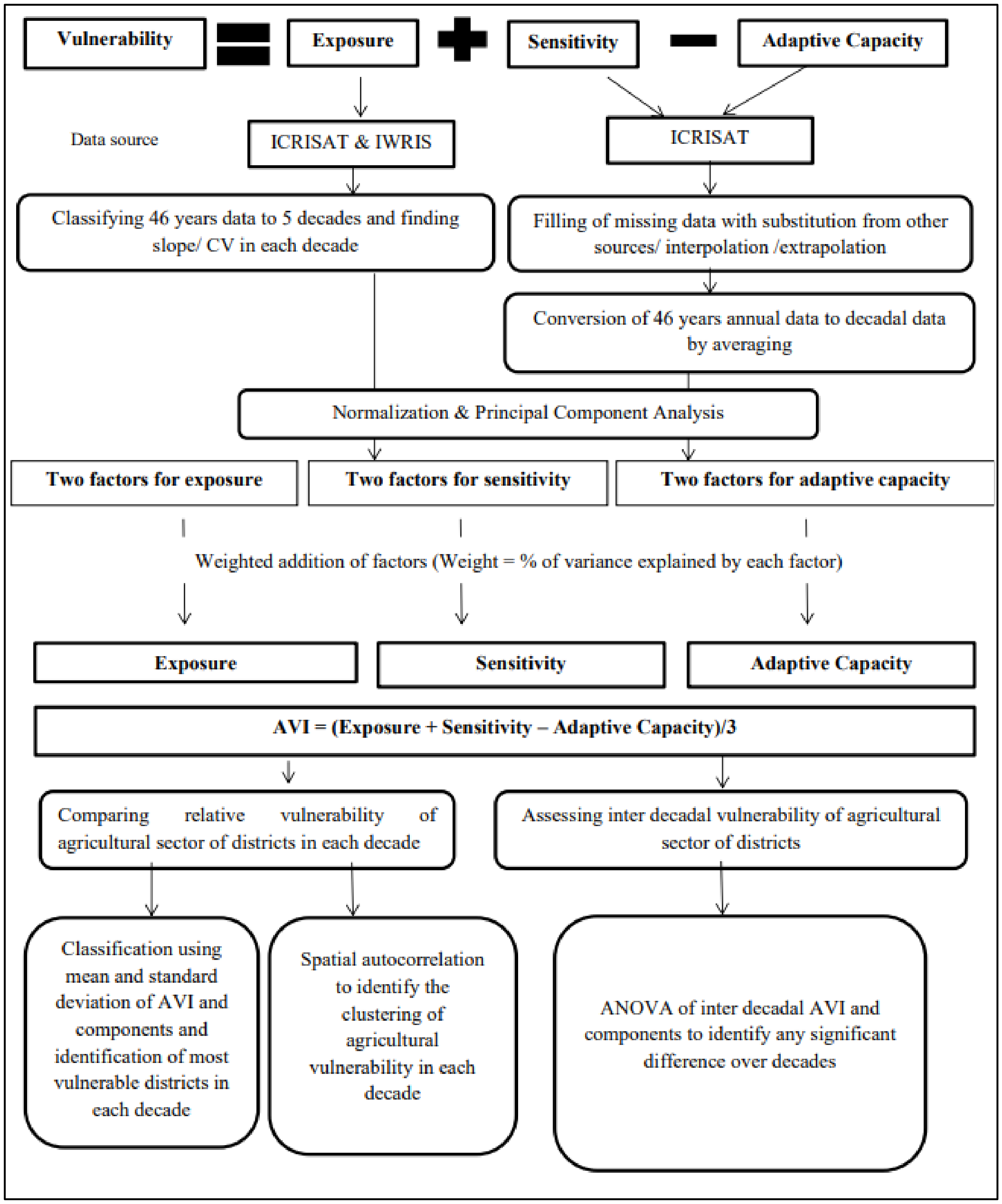
The variables are normalised to facilitate spatiotemporal comparison over the decades, and so the maximum and minimum values are selected from the pooled dataset of 185 observations (37 districts *5 decades). All the indicators were normalised using the following equation: For variables of exposure and adaptive capacity and variables of demographic dependence in sensitivity,

$$\text{Normalised value} = \frac{(\text{Value of indicator} - \text{Minimum value})}{(Maximum\ value - Minimum\ value)} \ldots (2)$$

For indicators that have negative relation with sensitivity, like the yield of major crops and percentage of net cropped area, the equation used is,

$$\text{Normalised value} = \frac{(\text{Maximum value} - \text{Value of indicator})}{(Maximum\ value - Minimum\ value)} \ldots (3)$$

The normalised values of each variable range from 0 to 1. Principal Component Analysis is conducted for each vulnerability component to identify the most vulnerable districts to climate change. Following Siagian et al. (2014), the variables with communality extracted less than 0.5, such as the Crop Diversification Index and yield of rice, are removed from the analysis. The final variables selected for the analysis and their direction to vulnerability assigned in the literature are provided in table 6.2 and their descriptive statistics is provided in table 6.3. Table 6.4 shows the results of statistical tests for developing AVI.



Source: Authors' preparation

Figure 6.2 Steps involved in creation of AVI

Table 6.2 Variables used for preparation of AVI

Concept	Description of variable	Variable Name	Relation with vulnerability	Source of variable
		Exposure		
Increase in temperature	Rate of change in mean maximum temperature	TMAX	Positive	Choudhary& Sirohi (2022)
	Rate of change in mean minimum temperature	TMIN	Positive	Choudhary& Sirohi (2022)
Variation in rainfall	Coefficient of variation in annual rainfall	ANNUALV	Positive	Hiremath & Shiyani (2013)
	Coefficient of variation in SWM rainfall	MONSOONV	Positive	Hiremath & Shiyani (2013)
		Sensitivity		
Demographic dependence	Number of agricultural dependents (cultivators and agricultural labourers) per ha of NCA	AGRIDEP	Positive	Hiremath & Shiyani (2013)
	Percentage of holdings of small and marginal farmers	MARGH	Positive	Sendhil et.al (2018)
Land use	Percentage of Net Cropped Area to total geographical area	NCA	Negative	Rao et al. (2013), Sehgal et al (2013)
Yield	Yield of Wheat	WHEAT	Negative	MPSKMCCC (2018)
	Yield of Chickpea	CHICKPEA	Negative	MPSKMCCC (2018)
	Yield of Oilseeds	OILSEEDS	Negative	-
		Adaptive Capacity		
Land use	Cropping Intensity (Net cropped area/Gross cropped area *100)	CI	Positive	Sehgal et al (2013), Hiremath & Shiyani (2013)
Inputs	Irrigation Intensity (Net Irrigated Area/ Net Cropped Area *100)	II	Positive	Das (2013), Hiremath & Shiyani (2013)
	Total consumption of fertilizer per ha of GCA	FERTILIZER	Positive	Rao et al. (2013)

Livestock population per ha of GCA	LIVESTOCK	Positive	Hiremath & Shiyani (2013)
Poultry population per ha of GCA	POULTRY	Positive	MPSKMCCC (2018)

Source: Combined from Various sources

Table 6.3 Descriptive Statistics of the Variables Used

Selected Variables	No. of cases	Min	Max	Range	Mean	S. D.	CV
Exposure							
TMAX	185	-0.2	0.1	0.3	0.0	0.1	503.8
TMIN	185	-0.1	0.1	0.3	0.0	0.1	226.9
ANNUALV	185	8.2	40.1	31.9	23.3	6.5	27.9
MONSOONV	185	8.9	42.2	33.3	25.0	7.0	28.1
Sensitivity							
AGRIDEP	185	0.4	2.7	2.3	1.1	0.4	41.8
MARGH	185	2.7	57.3	54.6	22.7	11.9	52.5
NCA	185	0.3	0.8	0.5	0.5	0.1	25.7
WHEAT	185	393.6	3977.9	3584.2	1605.1	781.6	48.7
CHICKPEA	185	345.4	1887.5	1542.1	785.5	250.7	31.9
OILSEEDS	185	138.5	1508.5	1370.0	631.3	288.0	45.6
Adaptive Capacity							
CI	185	101.1	190.4	89.3	127.9	18.9	14.8
II	185	0.9	100.1	99.3	31.3	22.4	71.5
FERTILIZER	185	0.7	169.6	168.9	40.1	35.4	88.3
LIVESTOCK	185	0.7	3.6	2.9	1.9	0.6	32.9
POULTRY	185	0.0	4.7	4.6	0.4	0.6	146.2

Source: Author's computation

Table 6.4 Results of Statistical Tests used for PCA

Statistical Tests		Exposure	Sensitivity	Adaptive Capacity	Criteria
Correlation Matrix	**Determinants**	0.07	0.022	0.122	>.00001, No multicollinearity issue
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	**KMO value**	0.52	0.71	0.64	< 0.50 = unacceptable
Bartlett's Test of Sphericity	$\chi^2_{(DF)}$	$472.4^{***}_{(6)}$	$693.2^{***}_{(15)}$	$381.7^{***}_{(10)}$	Significant, not an identity matrix
Communalities	**Average**	0.8	0.8	0.75	>.7, Good

Components retained	**Component**	2	2	2	Eigen value>1
Variance Explained	**% of variance**	81	80	75	>60%, Acceptable

Source: Author's findings; Table format adapted from: Das et al. (2021)

All the components of vulnerability have Kaiser-Meyer-Olkin Measure (KMO) value greater than 0.5, denoting sampling adequacy. Bartlett's test of Sphericity of all the components has p-value less than 0.05 (significant), indicating the appropriateness of data (Mavhura et al., 2017). The variables also lack multicollinearity, as indicated by the determinant of correlation matrices (determinant greater than 0.00001) (Das et al., 2021). The Principal Component Analysis with Varimax rotation produced two subcomponents each for Exposure, Sensitivity and Adaptive Capacity with variances 81, 80.5 and 74.9 %, respectively. The rotated component matrices for the three indices are provided in tables 6.5 to 6.7.

Table 6.5 Rotated Component Matrix of PCA for Exposure Index

Variable Name	**Components**	
	1	**2**
MONSOONV	.971	
ANNUALV	.964	
TMIN		.787
TMAX		.713

Extracted method: Principal Component Analysis. Rotation method: Varimax with Kaiser normalization. Rotation converged in 3 iterations. Suppress small coefficients (absolute value below .40)

Table 6.6 Rotated Component Matrix of PCA for Sensitivity Index

Variable Name	**Components**	
	1	**2**
OILSEEDS	.875	
WHEAT	.850	
CHICKPEA	.789	
NCA	.683	.488
AGRIDEP		.917
MARGH		.897

Extracted method: Principal Component Analysis. Rotation method: Varimax with Kaiser normalization. Rotation converged in 3 iterations. Suppress small coefficients (absolute value below .40)

Table 6.7 Rotated Component Matrix of PCA for Adaptive Capacity Index

Variable Name	Components	
	1	2
II	.911	
FERTILIZER	.897	
CI	.870	
POULTRY		.826
LIVESTOCK		.672

Extracted method: Principal Component Analysis. Rotation method: Varimax with Kaiser normalization. Rotation converged in 3 iterations. Suppress small coefficients (absolute value below .40)

Weighted indices are calculated for exposure, sensitivity, and adaptive capacity by adding the factors' scores to the weightage. The weights assigned are the percentage of variance explained by each factor. The three subindices for exposure, sensitivity and adaptive capacity are combined to form a vulnerability index using the IPCC formula, Vulnerability = Exposure+ Sensitivity – Adaptive Capacity. The IPCC's original formula is constructing vulnerability without weightage. However, this study uses weightage as it facilitates the vulnerability index to be in the range of 0 to 1, the same as its subindices and thus facilitates easy comparison. Here, equal weights are used as the number of factors extracted from PCA is the same for each subindex. The weight provided is 2/6. 6 is the sum of factors extracted for all subindices.

To identify the spatial pattern of vulnerability in each decade, AVI and its subindices of each decade are classified into five levels of vulnerability based on their respective mean and standard deviation, as done by Frigerio et al. (2018). ANOVA analysis is conducted with indices of all decades to identify the changes in AVI and its subindices over the decades. The spatial autocorrelation of AVI in each decade is assessed using Univariate Local Moran's I and Univariate LISA in GeoDa software with 999 randomizations and a 0.05 significance filter (Frigerio et al., 2018).

6.4. Results

6.4.1 Major factors contributing to agriculture sector vulnerability

Table 6.8 Major components in AVI

Component number	Description	Variance explained (%)	Cumulative Variance (%)
Exposure			
1	Variation in rainfall	52.8	52.8
2	Increase in temperature	28.2	81.1
Sensitivity			
1	Yield of major crops and net cropped area	44.7	44.7
2	Demographic dependence	35.8	80.5
Adaptive Capacity			
1	Input availability and cropping intensity	51.5	51.5
2	Diversification from agriculture	23.4	74.9

Source: Authors' Computation

Table 6.8 shows the major factors obtained from the Principal Component analysis. Three dimensions of vulnerability got two components each, and they are named based on the indicators constituting that component.

6.4.1.1 Variation in rainfall

Variations in annual rainfall and Southwest monsoon rainfall constitute the first component. It explains around 53% of the variation in exposure. The variability in rainfall is increasing in Central India, including Madhya Pradesh. Low and moderate rainfall decreases significantly, whereas heavy and intense rainfall trends increase (Guhatakurta et al.,2011). About 72% of the cultivation in Madhya Pradesh is rainfed, and the monsoon's failure and its erratic and uncertain nature affect agricultural growth in Madhya Pradesh (GoMP,2018). Rainfall deficit can affect water availability for irrigation, and intense rain may damage crops due to waterlogging. Excessive rain for a short period can intensify soil erosion, leading to the loss of nutrient-rich soil (Kim,2012). Excess rainfall can affect the yield of rice and sorghum (Saravanakumar, 2015), while a decline in rainfall can affect the yield of food grains (Prasanna,2014). Delays in the onset of monsoon can affect the crop cycle, leading to less productivity in the agriculture sector and food insecurity (Ranuzzi & Srivastava, 2012). So, the districts with higher variation in rainfall will possess more exposure.

6.4.1.2 Increase in temperature

This component consists of an increase in mean maximum temperature and mean minimum temperature, which explains around 28% variation in exposure. According to Duhan & Pandey (2013), the maximum and minimum temperatures in the state increased by 0.6 and 0.62 ºC over 102 years from 1901 to 2002. It is projected that 30% of the area of the state will experience more than 2ºC warming by 2050 under the RCP 8.5 scenario (Mishra et al.,2016). The rise in temperature will increase evapotranspiration, leading to soil moisture depletion. It increases the need for irrigation among crops, affects grain filling, and the yield of crops like wheat, rice, soyabean, mustard, and horticultural crops (GIZ,2011, Mall et al., 2016; Lobell et al., 2012; Challinor et al.,2014). It can also cause heat stress among crops, livestock, and poultry, affecting productivity (Aggarwal,2009). The increase in extremes like heatwaves put further pressure on the agriculture and water sectors (Rao et al., 2019). So, the districts with higher maximum and minimum temperature increases will have more exposure.

6.4.1.3 Yield of major crops and net cropped area

This component explains the 45% variation in sensitivity, and it consists of the yield of major crops like wheat, chickpea and oilseeds and the percentage of net cropped area. These two variables could reduce sensitivity; thus, the districts with a low yield of these crops and low net cropped areas are highly vulnerable. Though studies like Rao et al. (2013) and Sehgal et al. (2013) have assumed that an increase in the net sown area will increase the vulnerability of the agricultural sector, our analysis found that the yield of major crops and net cropped area is positively correlated. The districts with low net cropped areas are highly correlated with districts with lower wheat, chickpea, and oilseed yields. Vishwakarma (2016) found that the net cropped area of Madhya Pradesh has increased by 3.15 per cent from 1990-91 to 2011-12 due to an increase in irrigation facilities. The study also found that crop productivity positively correlates with the net cropped area. So, districts with fewer net cropped areas and lower yields of major crops will be more sensitive to climate change.

6.4.1.4 Demographic dependence

This component constitutes around 36% of the variation in sensitivity. The percentage of the population depending on the agriculture sector as cultivators and marginal labourers and the share of marginal and small operational holdings to total holdings contribute to this factor. According to GoMP (2018), 67% of the farming population is small and marginal, having extremely less per capita land holding. Small and marginal farmers use less capital intensive technologies and possess limited capacity to cope with climate change (Sehgal et al., 2013). Limited options for diversifying livelihood and poverty threaten the farmers in arid and semi-arid regions of India. Due to a lack of a fixed source of income, they tend to migrate when economic activities get disrupted by weather conditions (Keshri & Bhagat,2012; Pradhan & Narayanan,2020). So, the districts with more agricultural dependence and more share of small and marginal landholders will be more sensitive to climate change.

6.4.1.5 Input availability and cropping intensity

This factor consists of 52% of the variation in adaptive capacity and includes cropping intensity, irrigation intensity and fertilizer usage. Improved irrigation infrastructure and more equitable water distribution can increase productivity and income from the agricultural sector and save crops from dry spells or droughts (Sehgal et al., 2013; Raju et al., 2017; Rao et al., 2013). Fertilizer application (balanced application of nitrogen, phosphorus and potassium) also plays a vital role in improving the yield of crops. Fertilizer consumption has increased in Madhya Pradesh due to a shift in cropping pattern from food grains to cash crops and due to growth in irrigation facilities (GoMP,2018). Higher cropping intensity indicates that more crops are cultivated in a year. High cropping intensity indicates greater land use efficiency and better soil moisture retention capacity (Raju et al., 2017; Das, 2013). The districts with more irrigation facilities, fertilizer consumption and mechanization possess more cropping intensity (Raju et al., 2017). Therefore, districts with higher cropping intensity, irrigation intensity, and fertilizer consumption will possess a high adaptive capacity.

6.4.1.6 Diversification from agriculture

This component consists of a 23% variation in adaptive capacity and constitutes livestock population per hectare of gross cropped area and poultry population per hectare of the gross cropped area. Livestock can be considered the best insurance against drought, famine and other natural calamities. It serves as a sustainable source of income for the rural population, supplements the energy needs of croplands, and also contributes significantly to state income (GoMP,2018; Srivastava,2015). Poultry also serves as a livelihood diversification measure, but in Madhya Pradesh, it is generally done on a small scale in backyard areas. Integrated farming with livestock and poultry can increase the adaptive capacity of farmers to climate change.

6.4.2 Identification of most vulnerable districts in each decade

The scores of the components mentioned in section 6.4.1 produced through PCA are added with weightage to produce indices of Exposure, Sensitivity and Adaptive Capacity. Later, the Agricultural Vulnerability Index (AVI) is constructed from these indices using the formula, Vulnerability = Exposure + Sensitivity- Adaptive Capacity. Each index is multiplied by 2/6 while constructing AVI. Table 6.9 lists the number of districts under each level of AVI and its subindices in each decade, and table 6.10 lists the districts in the very highly vulnerable category in each case. Figures 6.3 to 6.6 plot the spatial distribution of each sub-indices and the AVI.

Table 6.9 Districts under different levels of AVI and subindices

Level	1970-79	1980-89	1990-99	2000-2009	2010-15
Exposure					
Very Low	2	1	3	3	3
Low	10	12	11	9	9
Moderate	11	14	11	15	16
High	14	7	10	6	5
Very High	0	3	2	4	4
Sensitivity					
Very Low	2	2	1	2	1
Low	10	12	14	12	14
Moderate	10	12	10	9	10
High	13	8	8	10	8
Very High	2	3	4	4	4
Adaptive Capacity					
Very Low	1	2	1	0	1
Low	11	10	12	13	14
Moderate	17	17	10	16	13
High	6	4	13	5	7
Very High	2	4	1	3	2
AVI					
Very Low	1	2	2	3	3
Low	10	10	10	9	8
Moderate	18	14	14	11	13
High	3	9	9	11	11
Very High	5	2	2	3	2

Source: Author's computation

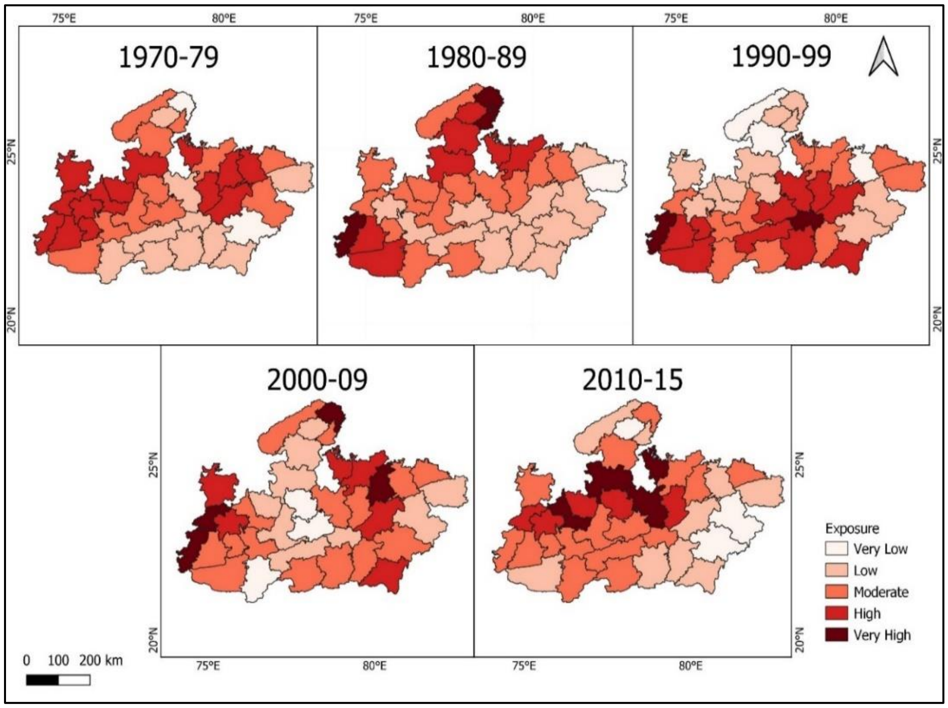
Table 6.10 Districts under very high vulnerability in 5 decades

1970-79	1980-89	1990-99	2000-09	2010-15
Exposure				
Nil	Bhind	Jhabua	Ratlam	Tikamgarh
	Jhabua	Narsimhapur	Bhind	Sagar
	Datia		Panna	Shajapur
			Jhabua	Guna
Sensitivity				
Balaghat	Balaghat	Balaghat	Balaghat	Balaghat
Sidhi	Sidhi	Sidhi	Sidhi	Sidhi
	Shahdol	Shahdol	Shahdol	Shahdol
		Mandla	Mandla	Mandla
Adaptive Capacity (Very Low)				
Vidisha	Vidisha	Guna	Nil	Mandla
	Guna			
AVI				
Panna	Jhabua	Balaghat	Balaghat	Tikamgarh

Damoh	Panna	Sidhi	Mandla	Sagar
Guna			Panna	
Satna				
Jabalpur				

Source: Author's computation

6.4.2.1 Exposure



Source: Authors' preparation using QGIS

Figure 6.3 Exposure Index for 5 decades

Table 6.11Results of ANOVA of Exposure Index for five decades

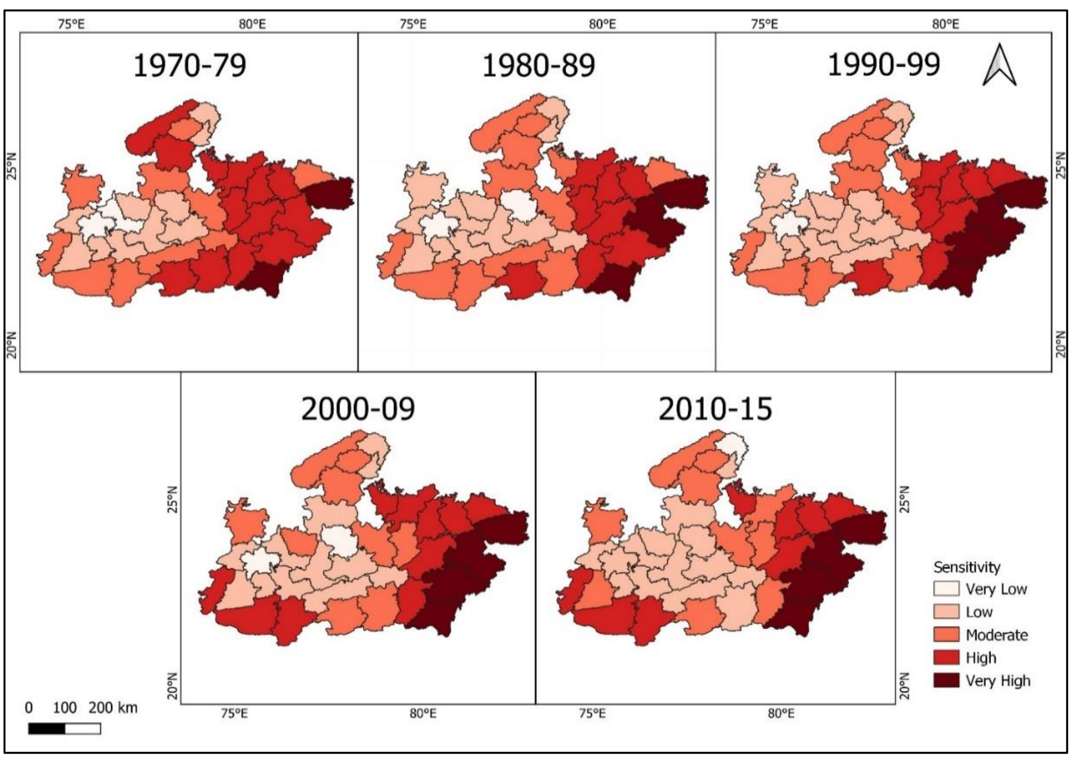
Row mean-column mean	1970-79	1980-89	1990-99	2000-09
1980-89	-1.143*			
	(0.000)			
1990-99	-1.046*	0.097		
	(0.000)	(0.975)		
2000-09	-0.348	0.794*	0.696*	
	(0.188)	(0.000)	(0.000)	
2010-15	-0.869*	0.274	0.177	-0.520*
	(0.000)	(0.431)	(0.809)	(0.009)
Equal mean test across regions	24.45* (0.000)			
Equal variance test across regions	11.548* (0.021)			

Source: Author's computation

The districts under very high exposure are found to increase over the decades from 0 in the 1970s to 4 in the 2010s (Table 6.9). The spatial pattern differs in each decade, as indicated by figure 6.3, as temperature changes and rainfall variation change over time in each district. Jhabua district possessed very high climatic exposure in three decades of study, whereas in the 2010s, the exposure was low in Jhabua (Table 6.10 and figure 6.3). In 2010-15, it was found to be concentrated in the northern and central districts of Madhya Pradesh (Figure 6.3).

ANOVA analysis conducted for the exposure component of all decades (table 6.11) shows that mean exposure in 1970-79 was significantly higher than in all decades. 1980-89 is found to have the lowest mean exposure, and 1990-99 had a mean exposure only higher than 1980-89 and is lower than all other decades, though not significant. Exposure of 2000-09 is also significantly higher than in other decades except 1970-79. The recent decade, 2010-15, has significantly less exposure than 1970-79 and 2000-09 but higher but not significant mean exposure than the 1970s and 1980s.

6.4.2.2 Sensitivity



Source: Authors' preparation using QGIS

Figure 6.4 Sensitivity Index for 5 decades

Unlike exposure, the sensitivity component, which is the internal property of the agriculture sector, the state shows an almost similar spatial pattern in all decades (Figure 6.4). The eastern part of the state exhibits high sensitivity to climate change due to higher rice cultivation and low production of the major crops considered in our study. Balaghat and Sidhi remained very highly sensitive throughout the study period, and Shahdol and Mandla became highly sensitive during the study period (Table 6.10). Indore was very low sensitive until the 2000s and became relatively low in 2010-15. The ANOVA analysis indicates that the sensitivity to climate change has not significantly changed in the state over the study period (Table 6.2). The main reason behind this is the unchanging concentration of high sensitivity in the eastern parts of the state.

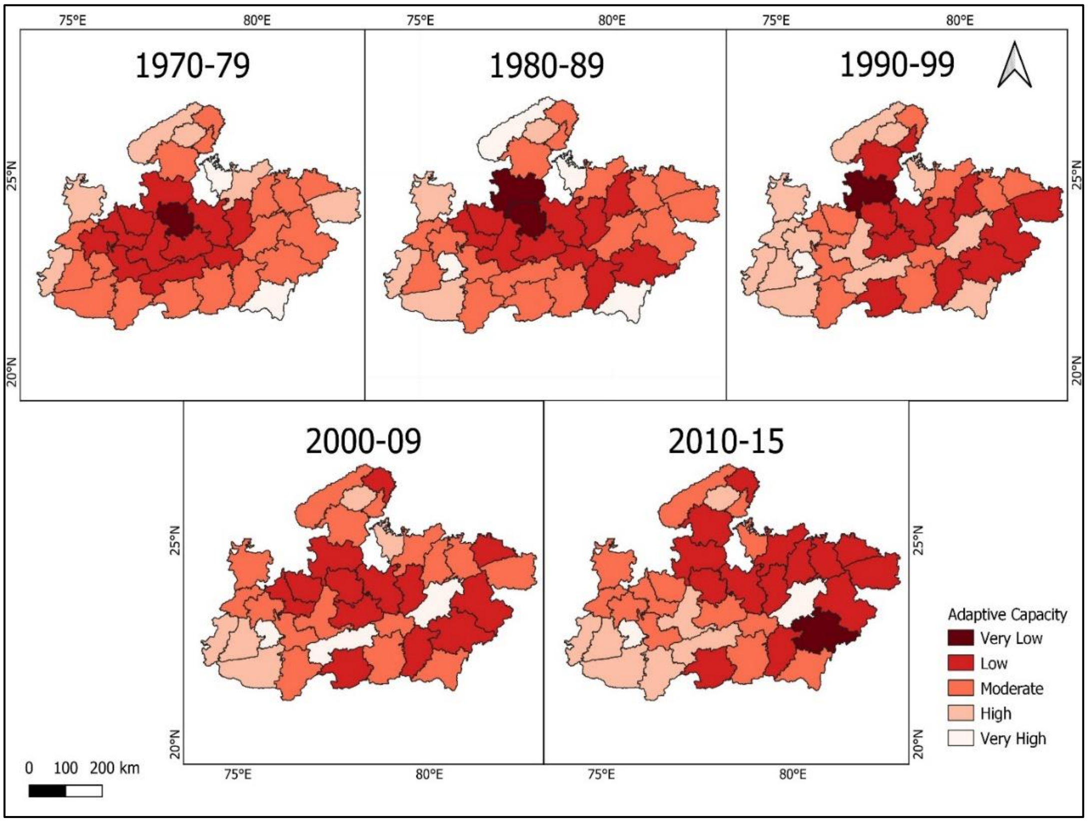
Table 6.12 Results of ANOVA of Sensitivity Index for five decades

Row mean-column mean	**1970-79**	**1980-89**	**1990-99**	**2000-09**
1980-89	-0.089 (0.99)			
1990-99	-0.32 (0.443)	-0.23 (0.744)		
2000-09	-0.012 (1.000)	0.078 (0.994)	0.308 (0.482)	
2010-15	-0.046 (0.999)	0.043 (0.999)	0.273 (0.602)	-0.035 (1.00)
Equal mean test across regions	1.26 (0.28)			
Equal variance test across regions	7.22 (0.125)			

Source: Author's computation

6.4.2.3 Adaptive Capacity

Figure 6.5 shows that the spatial pattern of adaptive capacity changed over the decades. Districts in northern and northeast parts, which possessed relatively higher adaptive capacity in the 1970s, gradually reduced to low adaptive capacity in the 2010s. Whereas some districts in central and western parts of the state gradually improved their position from relatively low adaptive capacity in the 1970s to relatively high adaptive capacity in the 2010s**.** Mandla, which had a high adaptive capacity in the 70s, possessed a very low adaptive capacity in the 2010s. In contrast, Indore had a very high adaptive capacity from the 1980s onwards.



Source: Author's preparation using QGIS

Figure 6.5 Adaptive Capacity Index for 5 decades

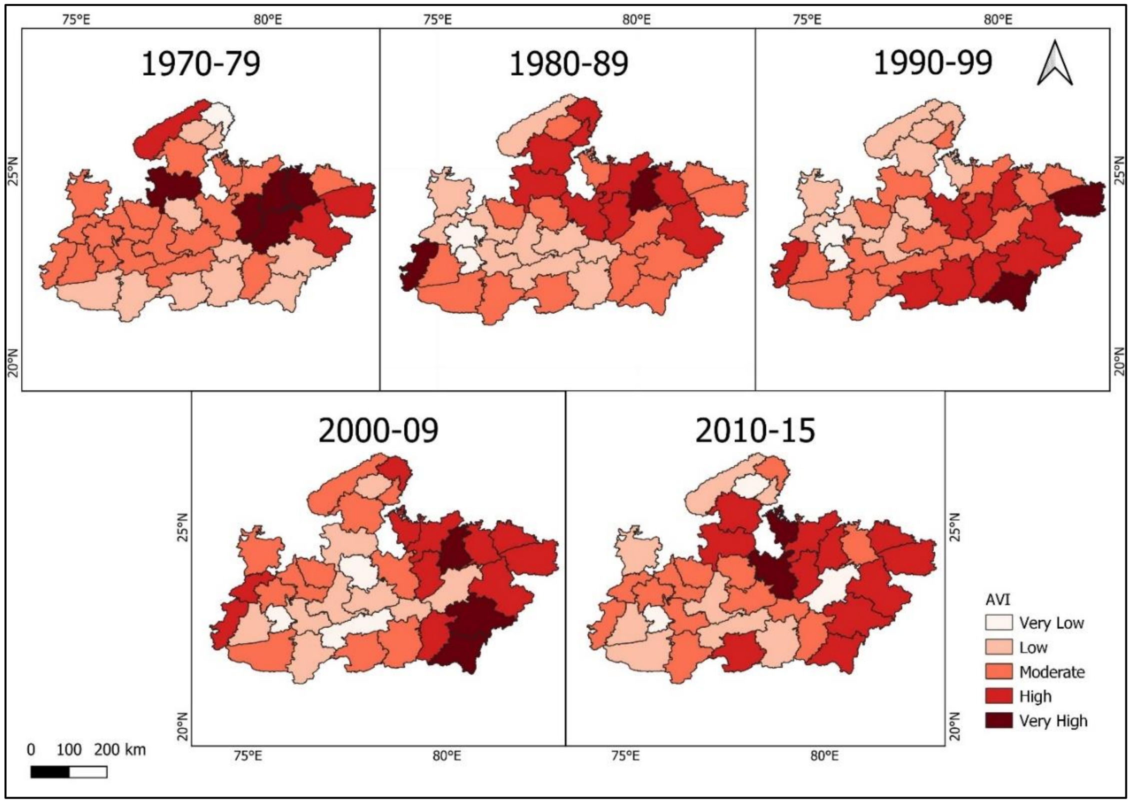
Table 6.13 Results of ANOVA of Adaptive Capacity Index for five decades

Row mean-column mean	1970-79	1980-89	1990-99	2000-09
1980-89	0.257 (0.270)			
1990-99	0.729* (0.000)	0.473* (0.002)		
2000-09	1.09* (0.000)	0.833* (0.000)	0.36* (0.04)	
2010-15	1.63* (0.000)	1.38* (0.000)	0.90* (0.000)	0.544* (0.000)
Equal mean test across regions	67.63* (0.00)			
Equal variance test across regions	45.7* (0.000)			

Source: Author's computation

The mean adaptive capacity has improved significantly over the decades, and the 2010s possess the highest mean adaptive capacity among all the decades (Table 6.13).

6.4.2.4 Agricultural Vulnerability Index



Source: Author's preparation using QGIS

Figure 6.6 Agricultural Vulnerability Index for 5 decades

Due to the changes in the spatiotemporal pattern of components, as indicated by figures from 6.3 to 6.5, the pattern of the agriculture vulnerability index has also changed over the decades. Districts in the eastern, northern and northeastern parts of the state remain high or very highly vulnerable in most of the decades. Meanwhile, western districts except Jhabua remain low or moderately vulnerable, and Indore has been very low in vulnerability since the 1980s. Panna, Damoh, Satna, and Jabalpur in eastern Madhya Pradesh and Guna in northern parts were very high vulnerable in 1970-79. These districts possessed high exposure, high sensitivity and high or moderate adaptive capacity in 70-79 relative to other districts. The AVI value of these districts decreased in the preceding decades. However, the AVI of Balaghat and Mandla increased from 1990-99 due to very high sensitivity, a decrease in adaptive capacity, and an increase in exposure. These districts shifted to a high vulnerability category in the recent decade as the AVI of Sagar and Tikamgarh became high due to very high exposure and high or moderate sensitivity and adaptive capacity.

Table 6.14 Results of ANOVA of AVI for five decades

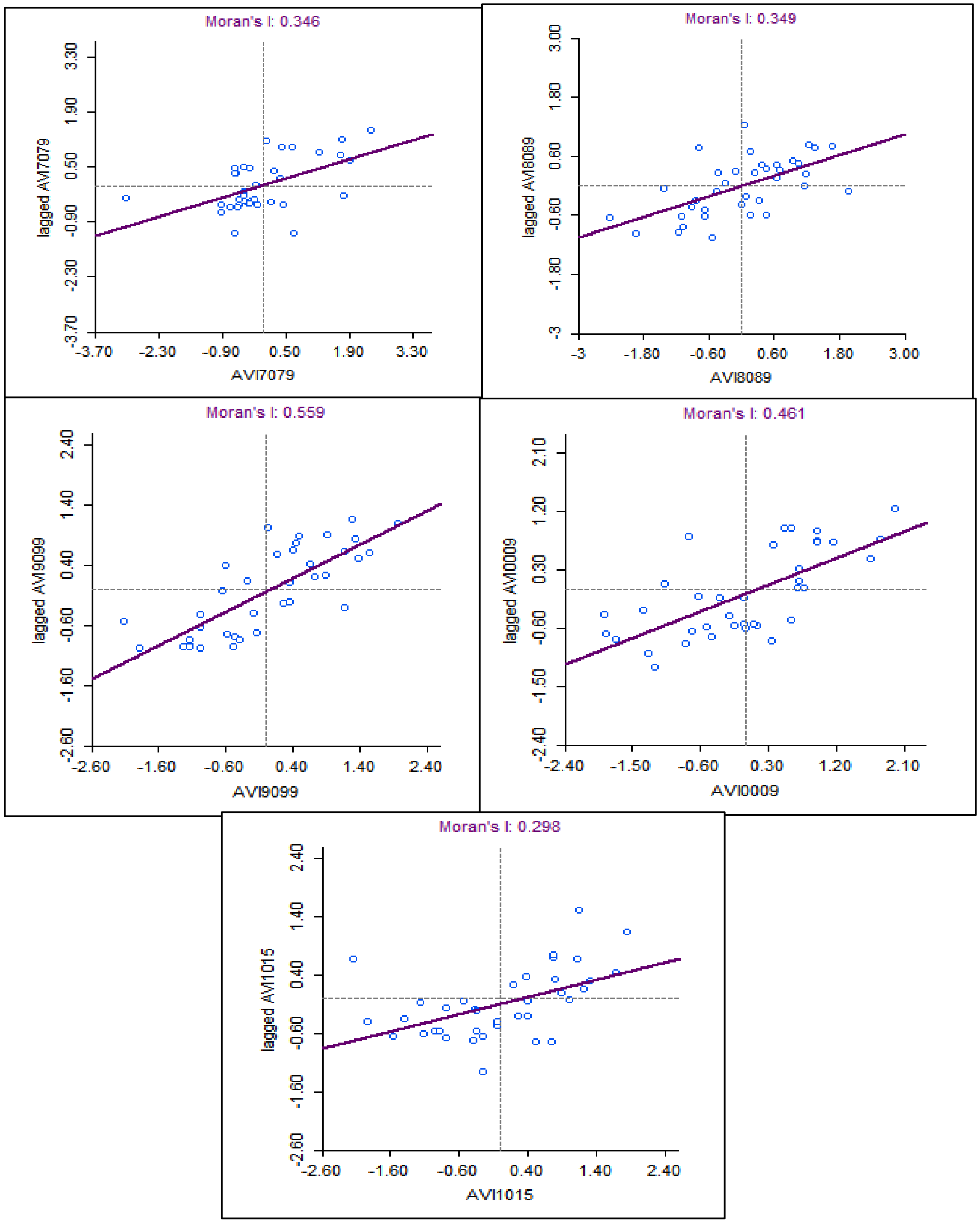
Row mean-column mean	1970-79	1980-89	1990-99	2000-09
1980-89	-0.496^{*} (0.000)			
1990-99	-0.7^{*} (0.000)	-0.20 (0.114)		
2000-09	-0.483^{*} (0.000)	0.013 (1.000)	$0.215^{\#}$ (0.078)	
2010-15	-0.85^{*} (0.000)	-0.354^{*} (0.000)	-0.152 (0.374)	-0.367^{*} (0.000)
Equal mean test across regions	38.2^{*} (0.00)			
Equal variance test across regions	33.10^{*} (0.000)			

Source: Author's computation

The ANOVA analysis shows that AVI in 2010-15 significantly decreased from all decades except 1990-99. 1970-79 possessed a significantly high mean AVI, and 2000-09 had the second-highest mean AVI. This may be due to the high mean exposure in 2000-09, as table 6.8 notes. 2010-15 possess the lowest mean AVI among all the decades (Table 6.14). Though it had higher exposure than 1980-89 and 1990-99 (Table 6.11), the significantly high adaptive capacity (Table 6.13) led to lower AVI than these decades.

6.4.3 Spatial autocorrelation of AVI

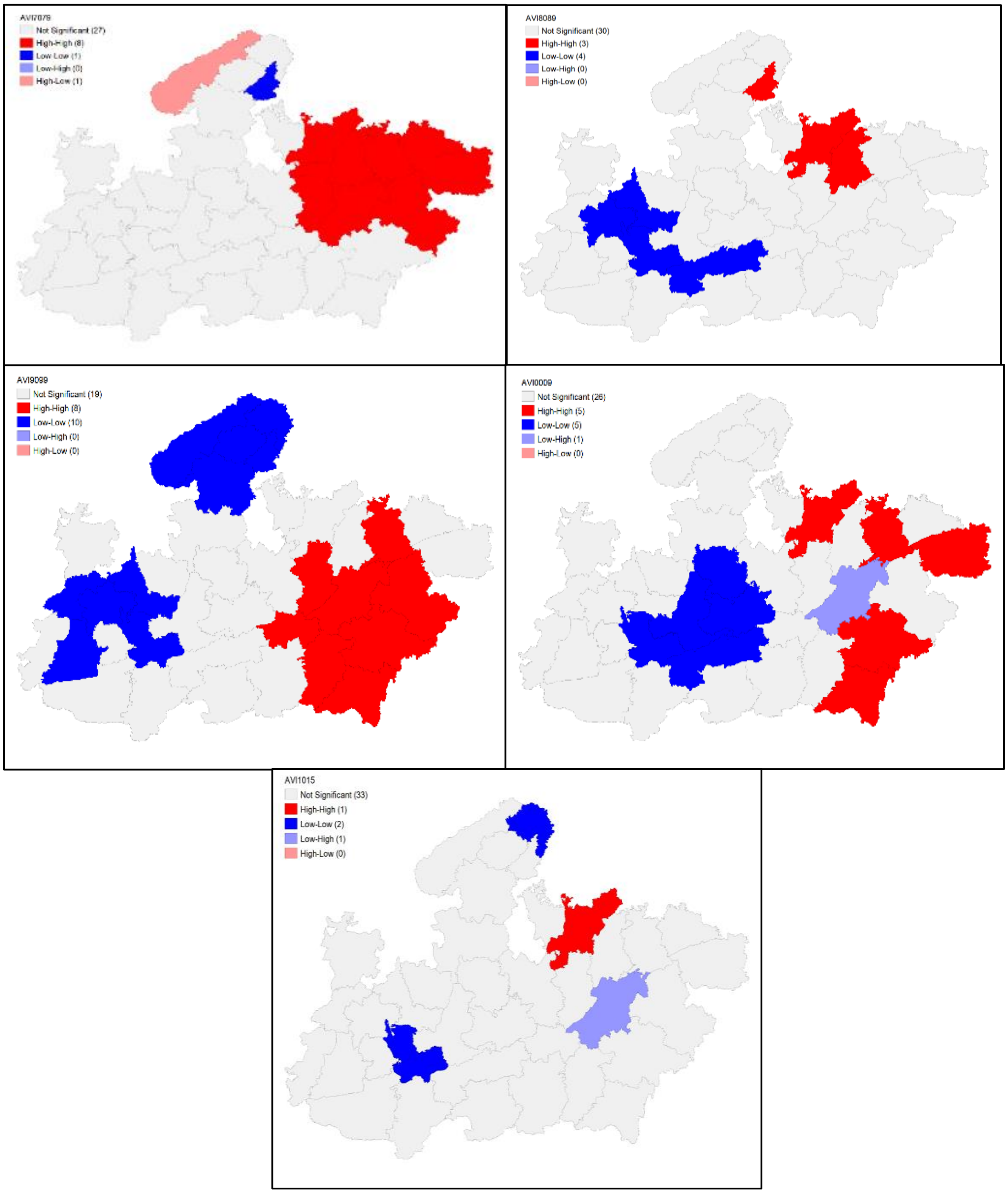
Figure 6.7 shows the results of Moran's I and LISA cluster maps produced for AVI.



Source: Author's preparation using GeoDa

Figure 6.7 Scatterplot and Moran's I statistics of AVI of 5 decades

The figures show that the clustering is not significant in many districts. Moran's I value was around 0.35 in the first two decades, indicating positive spatial autocorrelation. It increased to .6 in 90-99 and decreased in the later decades.



Source: Author's preparation using GeoDa

Figure 6.8 LISA cluster maps of AVI of 5 decades

In 70-79, 8 districts in the east were identified as a high-high cluster. In 80-89, the number of high-high clusters decreased, and the number of low-low clusters increased in western Madhya Pradesh due to less AVI of western districts. The clustering was highest in 1990-99 as both low-low and high-high clusters increased in number. It started decreasing in 2000-10 with more developments in the agriculture sector in the state. By 2010-15, the clustering was not significant in about 33 districts out of 37, as the spatial pattern of AVI changed in this decade. Districts in the eastern parts possessed less relative vulnerability in 2010-15, whereas districts like Sagar and Tikamgarh possessed high vulnerability due to high exposure in the recent decade. It is also interesting to note that Jabalpur, included in the high-high cluster in 1970-79 and 1990-99, became an outlier from 2000-09 as its vulnerability reduced from very high in 1970-79 to very low in 2010-15. Sagar district has remained high-high in most of the decades, as neighbours surrounding it have high or very high AVI.

6.5 Discussion of results

This study was an attempt to understand the spatiotemporal pattern of the vulnerability of the agriculture sector in Madhya Pradesh to climate change. Though studies are available assessing the vulnerability of the agriculture sector in India and other countries, they generally possess a static nature. i.e., vulnerability is assessed for only one point in time. We attempted to overcome this issue by analysing the temporal and spatial pattern of agriculture sector vulnerability. The study period is classified into five decades, and AVI is calculated. Along with temporal changes in AVI, the temporal changes in each component are also discussed to identify the variation in which subindex leads to variation in AVI. The study uses the IPCC framework used by other agricultural vulnerability studies. However, it modifies from their approach by identifying the major factors contributing to each component, as done by Jha & Gundimeda (2019). Using Principal Component Analysis to construct each subindex helps identify the factors contributing to variation in each subindex. This study also advances from previous studies by assessing the spatial autocorrelation of AVI for five decades, which will aid in understanding the changes in the clustering pattern of AVI.

The study identified variation in rainfall as the major contributor to variation in exposure. The yield of major crops and net cropped area contributes the most to sensitivity and input availability, and cropping intensity contributes the most to adaptive capacity. The study found that exposure in the most recent decade (2010-15) is significantly less than its previous decade but higher than in the eighties and nineties. 2000-09 also had higher mean exposure than previous decades except for the 1970s. This indicates a chance for an increase in exposure, as predicted by studies like MPSKMCCC (2018). The study found no significant change in sensitivity over the years. The reason is the increase in demographic dependence and higher marginalisation of holdings despite the increase in yield of major crops and net cropped area. Though net cropped area and yield of major crops are increasing at the state level, the higher disparities prevailing among the districts also contribute to the lack of changes in the sensitivity component.

Moreover, the very high sensitivity of districts like Balaghat and Mandla remains unchanged, whereas western and central districts possess low sensitivity throughout the study period. However, the mean adaptive capacity significantly increased over the decades, mainly due to the availability of inputs and cropping intensity. The study also found that the districts with very high relative AVI in each decade are changing as the districts with very high exposure and adaptive capacity have changed over the decades. The exposure component changes over time as variations in rainfall and temperature increases have changed over the decades. So, future planning of cropping pattern and other developments in the agriculture sector should be conducted in accordance with the climatic projections by Mishra et al. (2016) and others. Early warning of extreme climate events, access to insurance, providing appropriate relief for losses, adjusting planting timing, breeding crops suitable for changed climatic conditions, etc., can reduce the impacts of high exposure.

The districts like Balaghat and Mandla have been identified as the most sensitive districts throughout the decades. These districts follow the monocropping of paddy, and so other crops like wheat, oilseeds, and chickpea are less in these districts. Moreover, they are tribal districts with a high share of small and marginal farmers. Though the mean adaptive capacity has increased over decades, a high regional disparity in technological interventions exists among districts (Dutta et al.,2020; Shevalkar,2020). Madhya Pradesh stands second in states with the largest share of regions with disadvantaged agriculture (Chand & Srivastava, 2016). The study found that the mean AVI was lowest in 2010-15, though its mean exposure was higher than in 1980-89 and 1990-99. The higher adaptive capacity compared to other decades led to reduced AVI. As exposure is projected to increase, policy efforts should be directed towards increasing adaptive capacity. It requires a decrease in disparities among districts in access to fertiliser, irrigation, etc., the development of agriculture-related infrastructure like roads, markets, and storage, and the encouragement of diversification to allied sectors. It is also noted that the sensitivity has not changed over the decades. Cooperative farming or similar policy measures to consolidate land and farming at a large scale could reduce the marginalisation of holdings. Diversifying livelihood through skill training and education can also reduce the excessive dependence on agriculture. A balanced development of the agriculture sector in the districts of Madhya Pradesh is essential to reduce its vulnerability to climate change.

Differences exist in the indicators used, time of analysis and number of districts assessed in the previous studies on district-level agriculture vulnerability and this study. Hence, the high vulnerability category districts do not precisely match this study. However, the districts under very high AVI, like Mandla, Balaghat, and Sidhi, and the new districts formed from them are classified as very high agriculturally vulnerable by SKMCCC (2018). The other districts identified as having very high AVI in this study, like Panna, Damoh, Guna, and Satna, are also classified as highly vulnerable by Rao et al. (2013). Sagar is identified as one of the flood and drought hotspots in Madhya Pradesh, and Tikamgarh as one of the flood hotspots by Mohanty & Wadhawan (2021). Thus, all the very high AVI districts identified by our study match the findings of similar studies, and hence the results are valid.

This study has the following limitations: Though there are many other variables available in the literature that can affect the vulnerability of the agriculture sector, like mechanisation, roads, markets, etc., they could not be added to this study due to a lack of data. The study can be updated further once more data on variables are available. It can also be updated once data from other years are available.

6.6. Conclusion

Though the agriculture sector in Madhya Pradesh attained double-digit growth in recent years and contributes significantly to the state gross value added, the sector's development remains highly skewed. The higher disparities in sector development among different districts make the backward districts more prone to stressors like climate change. This study tried to ascertain the spatial and temporal vulnerability of the sector to climate change at the district level using an agricultural vulnerability index. The agricultural vulnerability index is prepared for five decades (1970s to 2010s) using the IPCC approach. It locates very highly agriculturally vulnerable districts and districts with very high exposure and sensitivity and very low adaptive capacity. Using spatial autocorrelation also helped identify the clusters of vulnerability and their change over time. The study found high variation in rainfall, low yield of major crops low, net cropped area low, input availability and low cropping intensity as the major contributors to agricultural vulnerability in the state. The districts identified as very high vulnerable match the results of previous studies and thus validate our results. The study advocates for early warning, adjustment of planting times, development of breeds suitable for the projected climate, skill training and more access to education for livelihood diversification and reduction in disparities in access to inputs like irrigation and fertilizer as major interventions required to reduce the vulnerability of agriculture sector in the state. It also advocates for a balanced development of the agriculture sector in the districts to reduce the vulnerability to climate change.

Chapter 7

Vulnerability of Social Groups to Climate Change

From the assessment of vulnerability to climate change in Madhya Pradesh in the fifth chapter, it is clear that agriculture dependence and a higher share of marginalised groups, along with low infrastructure access, contributed mainly to the vulnerability to climate change in the state. Reducing the vulnerability of the agriculture sector and of marginalised social groups can bring about an overall reduction of vulnerability. A detailed study was undertaken regarding vulnerability in the agriculture sector in the sixth chapter, and the major factor contributing to the vulnerability of that sector is understood. In this chapter, the differential vulnerability of different social groups in Madhya Pradesh was assessed to understand what contributed to the vulnerability of marginalised groups. The first section (7.1) points out the need to assess climate change vulnerability among social groups of Madhya Pradesh. Section 7.2 of this chapter deals with data sources, 7.3 explains the research methods, and 7.4 provides the analysis results. 7.5 discusses the results, validates the results with previous studies, and specifies the limitations, while 7.6 concludes the study.

7.1 Relevance of climate change vulnerability assessment among social groups

The potential impacts of climate change on a population vary depending on their inherent vulnerability, characterised by their social or political identities, access to basic facilities, assets and other entitlements, place of residence, and demographic characteristics. The inherent social stratification prevailing in economies, especially agrarian economies, can lead to differentiated vulnerability to climate change. Marginalised sections of an economy are generally more vulnerable to climate change due to their political and social identities, excessive dependence on natural resource-dependent sectors and limited access to basic facilities. The higher dependence on agriculture, forestry, increasing landlessness and lack of access to development programmes among these sections, when compounded with adverse climate, may result in acute poverty, food insecurity, high proneness to diseases, unemployment, the shift from agriculture to wage labour and distress migration (Chakravarty &Dand, 2005; Bhawan & Marg, 2010; Karat & Rawal, 2014; GoI,2011; GoI,2020).

Madhya Pradesh is commonly known as the tribal state of India, as it has the highest share of the tribal population in India (14.64% as per GoI (2011)). 21% of the state population belongs to Scheduled Tribes (ST), and 16% to Scheduled Castes (SC). Agriculture constitutes the primary source of livelihood for these social groups, but their agricultural practices remain mostly rainfed, and they undertake monocropping. The areas dominated by tribals were more engaged in millet cultivation. To diversify the cropping systems and to increase farmers' income, the government schemes promoted the cultivation of wheat and oilseeds. This changing pattern of cropping led to a change in consumption patterns. Less intake of nutrient-rich millet led to increased malnutrition among the tribal communities (GoMP,2016). The new schemes could not succeed in the tribal areas due to the higher cost of inputs endured, constraints in marketing, etc. The technology uptake in tribal areas is weak due to the poor reach of extension mechanisms to these farmers. The share of net cropped area and net irrigated area in tribal-dominated districts remains relatively low compared to other districts of the state (GoI,2020; GoMP,2016; Singh et al.,2018). These districts also possess the major share of small and marginal landholders in the state (GoI,2020). The primitive modes of agriculture, along with the high concentration of poverty, low educational attainments, low infrastructural access, etc., may increase the vulnerability of tribal areas to climate change. Literacy rate, access to electricity, drinking water, and sanitation for the ST populations remains the lowest in the state compared to other social groups. In addition, the dependence on agriculture for livelihood and marginalisation among workers is highest in the ST population. On the other hand, the SC populations are also highly vulnerable because they form the highest proportion of the population with small and marginal land holdings. Besides, the SC population was observed to be facing steep inequalities in literacy rates among different genders. Thus, the available literature and other statistics point out that each social group's socioeconomic conditions, infrastructural facilities, and agricultural characteristics differ. If these adverse socioeconomic conditions compound the historical and projected changes in climate in the state, it might lead to loss of livelihood and income and may result in acute poverty. This necessitates the identification of the vulnerability of these social groups to climate change and the formulation of policy measures to reduce it.

Though studies on vulnerability in India have identified districts with more marginalised sections as highly vulnerable to climate change (Azhar et al.,2017; Mishra,2015; Bahinipati,2014), a study specifically on these social groups has not been conducted yet. In global vulnerability literature and Indian literature, the vulnerability of specific communities, like farmers, fishing communities, etc., are addressed (Sahana et al.,2021; Huynh& Stringer,2018; Morzaria-Luna et al.,2014). However, the differentiated vulnerability among social groups has not been attempted, as per the authors' knowledge. This comparison is necessary in states like Madhya Pradesh, where disparities among social groups are very high. Therefore, this study focuses on *assessing the vulnerability of different social groups (SC, ST and Non SC/ST) in Madhya Pradesh to climate change in the context of increasing climate change exposure and differential socioeconomic characteristics among different social groups. It tries to identify the most vulnerable districts for each social group and the most vulnerable social group in each district so that vulnerability reduction efforts can be targeted towards them.*

As climate change is an external stressor and social or contextual vulnerability is the internal property of the social groups, a separate assessment of both dimensions and the assessment of integrated vulnerability by combining both dimensions is suitable for this study. Hence, the study adapts a place-based vulnerability model for constructing the Climate Vulnerability Index (CVI), similar to the sixth chapter. CVI is constructed as an aggregate of two separate indices: The climate change Index (CI), which represents biophysical vulnerability and the Composite Social Vulnerability Index (CSVI), which represents social or contextual vulnerability. As social vulnerability is multidimensional, it is constructed as an aggregate of three subindices: Socioeconomic, Infrastructural and Agricultural Vulnerability. This segregation will facilitate the identification of the dimension of vulnerability that makes each group more vulnerable. The study also tries to identify which social group is more vulnerable in each district so that social group-specific policy measures can be framed at the district level. The study also tries to conduct social group-wise ANOVA of vulnerability indices to identify whether any significant difference exists among the scores.

7.2 Sources of data and scale of analysis

The data for socioeconomic and infrastructural variables for the social groups are collected from the Census of India, 2011, as the data on these variables have not been available in recent years**.** Though the agriculture census was conducted in 2015-16, this study used Agricultural Census (2010-11) data for agriculture-related variables to maintain consistency in the time of the study. The annual mean maximum temperature, annual mean minimum temperature and annual mean temperature are computed from the monthly maximum and minimum temperature of districts collected from the ICRISAT district level database. The annual and monsoon rainfall of each district is computed by averaging 0.25*0.25 gridded data from IMD.

7.3 Methodology

This objective follows the same methodology as the second objective (Chapter 5). The Climate Vulnerability Index (CVI) is constructed as an aggregate of the Climate Index (CI) and Composite Social Vulnerability Index (CSVI). In Chapter 5, the Composite Social Vulnerability Index has two subindices, SeVI and IVI. In this objective, one more subindex is constructed, viz. Agricultural Vulnerability Index. Hence, CSVI in this objective is an aggregate of three sub-indices: Socioeconomic

Vulnerability Index (SeVI), Infrastructural Vulnerability Index (IVI) and Agricultural Vulnerability Index (AVI). CI, SeVI, IVI and AVI are constructed using the indicator approach and CSVI, and CVI are constructed by aggregating the subindices with weightage.

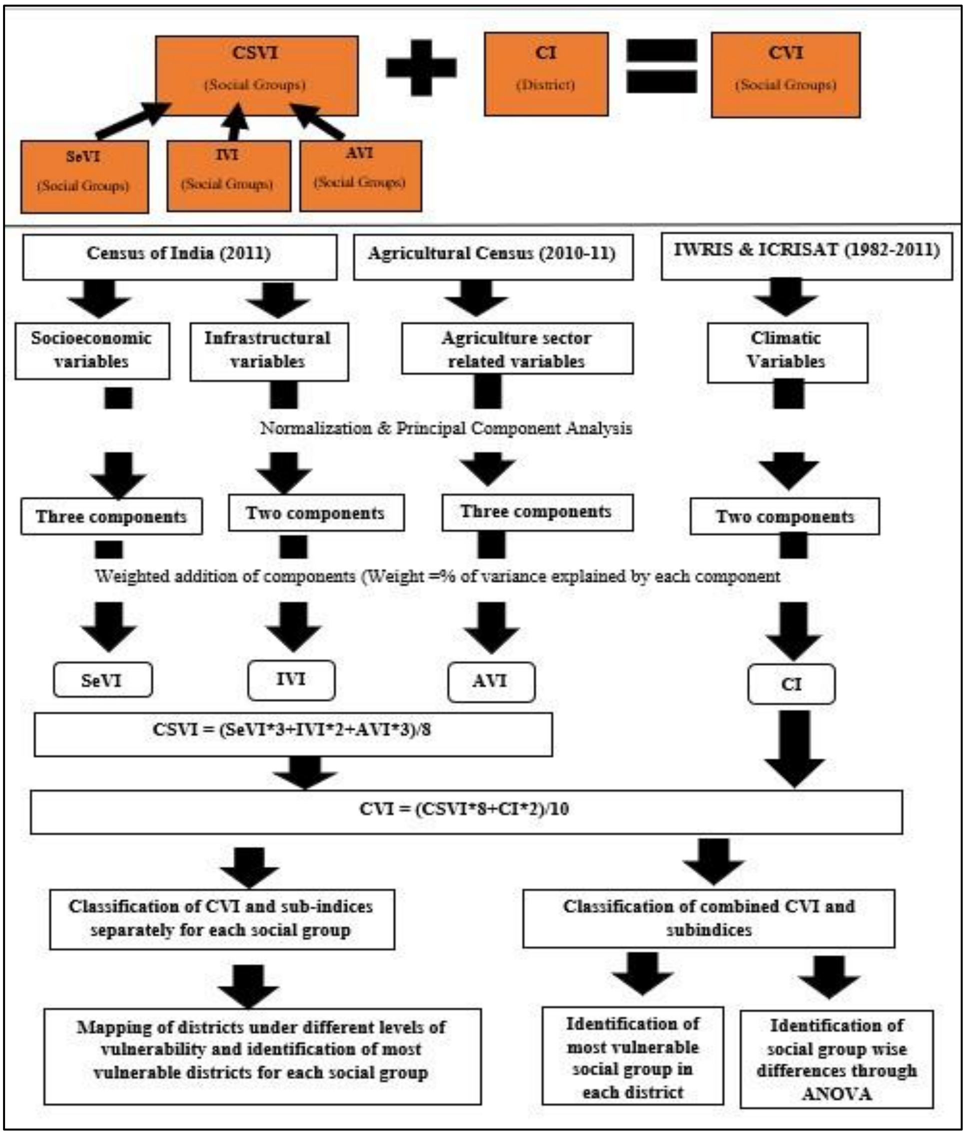


Figure 7.1 Steps used for construction of CVI

Source: Prepared by authors

Figure 7.1 shows the steps used for creating the index. The proxy variable selection for each indicator is based on the literature on climate change vulnerability, social vulnerability, agricultural vulnerability and data availability for the social groups. Table 7.1 lists the variables used in the study.

Table 7.1 Variables used in SeVI, IVI, AVI and CI

Concept	Variable Description	Variable Name	Relation with vulnerability	Source of variable
		Socioeconomic variables		
Decadal change in population	Population growth rate (2001-2011)	POPGR	Positive	Mazumdar & Paul (2016)
Dependent population	% of children (0-6) and elderly (60 or above) to total population	DEPPOP	Positive	Azhar et.al. (2017)
Special needs population	% of disabled population to total population	DISABLED	Positive	Mazumdar & Paul (2016)
Education	Literacy rate of male	LRM	Negative	Adapted from Maiti et al. (2015)
	Literacy Rate of female	LRF	Negative	Acosta-Michlik et al. (2005)
Employment	Male Work Participation Rate	WPRM	Negative	Morzaria – Luna et al. (2014)
	Female Work Participation Rate	WPRF	Negative	Cutter et al. (2003)
		Infrastructural Variables		
Infrastructure and lifelines	% of households having access to electricity as source of light	LIGHT	Negative	Mazumdar & Paul (2016)
	% of households having access to clean fuel	FUEL	Negative	Mavhura et al. (2017)
	% of households having access to drinking water within premises	DWPREM	Negative	Maiti et al.(2017)
	% of households having access to latrine within premises	LATRINE	Negative	Letsie & Grab (2015)
	% of households with dilapidated housing condition	DILAPID	Positive	Maiti et al. (2015)
	% of households having access to banking services	BANK	Negative	Mazumdar & Paul (2016)
Socioeconomic Status	% of households having access to television	TV	Negative	de Sherbinin & Bardy (2015)
	% of households having access to radio	RADIO	Negative	Mazumdar & Paul (2016)
	% of households having access to mobile phone	MPHONE	Negative	Vincent (2004)
	% of households having access to two-wheeler	TWOWL	Negative	Romero-Lankao et al. (2016)

	% of households having access to four-wheeler	FOURWL	Negative	Romero-Lankao et al. (2016)
Agriculture sector related variables				
Marginalisation	Average size of landholding	LSIZE	Negative	Sehgal et al. (2013)
	% of small and marginal holdings to total holdings	MARGH	Positive	Sendhil et.al (2018)
Rights to land	% of holdings self-owned and operated to total holdings	OWNH	Negative	Thangaraj, M. (1994).
	% of female operated holdings to total holdings	FEMH	Negative	Thangaraj, M. (1994).
Technological efficiency of land	Cropping intensity	CI	Negative	Sehgal et al (2013), Hiremath & Shiyani (2013)
	% of net irrigated area to area under total holdings	IRRIGAT	Negative	Thangaraj, M. (1994).
Climatic Variables				
Increase in temperature	Rate of change in mean maximum temperature	TMAX	Positive	Choudhary& Sirohi (2022)
	Rate of change in mean minimum temperature	TMIN	Positive	Choudhary& Sirohi (2022)
Variation in rainfall	Coefficient of variation in annual rainfall	ANNUALV	Positive	Hiremath & Shiyani (2013)
	Coefficient of variation in SWM rainfall	MONSOONV	Positive	Hiremath & Shiyani (2013)

Source: Collected from various sources

Table 7.1 lists the variables used in the study. The variables used are grouped into Socioeconomic, Infrastructural, Agriculture sector related, and Climatic variables. Socioeconomic variables are related to the demographic characteristics of each social group, such as decadal change in population, economic dependence, education, employment and population with special needs. Infrastructure variables denote access to necessities such as drinking water, electricity, sanitation, clean fuel, banking services and housing conditions. It also includes access to assets, including communication devices and transport. Variables related to the agriculture sector include characteristics related to the operational holdings of three social groups. Access to land has always been considered an indicator of socioeconomic status, and the variables include lack of rights to land, its marginalisation, and disparities in the technological efficiency of land; variables for climate change include changes in annual mean maximum and minimum temperature and variation in annual and monsoon rainfall, as an increase in temperature and variation in rainfall are the major indicators of climate change. Table 7.2 shows the descriptive statistics of the variables used in the study.

Table 7.2 Descriptive Statistics of variables used

Variables	No. of cases	Min.	Max.	Range	Mean	S.D.
			Socioeconomic Vulnerability Index (SeVI)			
POPGR	150	-11.82	65.54	77.35	21.45	9.95
DEPPOP	150	19.55	29.37	9.82	23.31	2.05
LRM	150	38.22	91.60	53.38	74.06	12.16
LRF	150	26.74	79.84	53.10	53.99	12.21
WPRM	150	46.75	58.56	11.81	53.23	2.77
WPRF	150	7.86	55.38	47.52	35.61	10.09
DISABLED	150	1.28	3.81	2.53	2.18	0.46
			Infrastructural Vulnerability Index (IVI)			
LIGHT	150	12.97	97.58	84.61	63.44	20.11
LATRINE	150	2.14	85.82	83.69	22.13	18.21
DWPREM	150	1.67	56.58	54.91	19.04	13.33
FUEL	150	0.56	75.28	74.72	13.64	14.48
DILAPID	150	1.24	14.77	13.53	5.38	3.13
BANK	150	15.58	81.91	66.33	42.14	14.87
RADIO	150	3.52	35.97	32.45	12.53	5.11
TV	150	2.63	81.24	78.62	26.15	17.30
MPHONE	150	9.41	78.10	68.69	37.46	16.28
TWOWL	150	1.36	54.35	52.99	13.85	10.77
FOURWL	150	0.09	14.49	14.40	1.64	2.08
			Agricultural Vulnerability Index (AVI)			
LSIZE	149	0.59	4.00	3.41	1.60	0.50
FEMH	149	0.34	26.26	25.93	9.90	4.76
MARGH	149	39.23	95.43	56.20	75.01	10.35
OWNH	149	81.95	100.00	18.05	99.54	1.72
IRRIGAT	149	0.53	95.30	94.77	40.57	21.68
CI	149	105.61	197.40	91.79	141.15	22.00
			Climate Index (CI)			
TMAX	50	0.02	0.04	0.02	0.03	0.00
TMIN	50	0.02	0.05	0.03	0.03	0.01
ANNUALV	50	16.83	37.17	20.35	23.36	3.60
MONSOONV	50	17.34	39.59	22.25	24.69	4.10

Source: Author's calculation

To facilitate intergroup comparison, values of socioeconomic and infrastructural variables are normalised using maximum and minimum values of each variable calculated from 150 observations (50 districts*3 social groups). AVI is calculated for only 149 observations due to the lack of agriculture census data for the ST of Bhind district. As climatic variables are available only at the district level, it has only 50 observations. For the variables that have a positive relationship with vulnerability, the formula used for normalisation is as follows:

$$Normalized\ value = \frac{(\text{Value of indicator} - \text{Minimum value})}{(Maximum\ value - Minimum\ value)} \ldots\ldots\ldots (1)$$

The direction of variables which have negative relation with vulnerability is reversed using the formula,

$$Normalized\ value = \frac{(\text{Maximum value} - \text{Value of indicator})}{(Maximum\ value - Minimum\ value)} \ldots\ldots (2)$$

The Principal Component Analysis (PCA) with varimax rotation is conducted separately for each category of variables after normalisation. Table 7.3 shows the results of PCA for each category of variables.

Table 7.3. Results of Statistical Test for PCA

Statistical Tests		SeVI	IVI	AVI	CI	Criteria
Correlation Matrix	**Determinants**	0.004	0.000	0.043	0.072	>.00001, No multicollinearity issue
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	**KMO value**	0.7	0.8	0.5	0.5	< 0.50 = unacceptable
Bartlett's Test of Sphericity	$\chi^2_{(DF)}$	791.18*** (21)	2268.04*** (55)	455.11*** (15)	123.17*** (16)	Significant, not an identity matrix
Communalities	**Average**	0.86	0.81	0.75	0.77	>.7, Good
Components retained	**Component**	3	2	3	2	Eigen value>1
Variance Explained	**% of variance**	86	81	75	77	>60%, Acceptable

Source: Author's calculation

The values of the determinants of correlation matrices are greater than 0.00001 in all cases, indicating the lack of multicollinearity (Das et al., 2021). The Kaiser-Meyer-Olkin Measure (KMO) value was detected as 0.5 or more in all cases, indicating sampling adequacy. Bartlett's

Sphericity test was highly significant, with $p < 0.05$ for all cases. The communalities extracted for each variable were greater than 0.5 (Siagian et al., 2014), and the average communality of variables in each case was greater than 0.7 (Das et al.,2021). It indicates that the principal components best explain the variance of each variable. PCA with varimax rotation produced three principal components for SeVI and AVI and two principal components for IVI and CI.

Table 7.4 Rotated Component Matrix of PCA for SeVI

Variable Name	Components		
	1	2	3
LRF	.951		
LRM	.936		
DEPPOP	.830		
WPRF	-.725	.634	
WPRM		.908	
GR	.419	.508	.499
DISABLED			.867

Extracted method: Principal Component Analysis. Rotation method: Varimax with Kaiser normalization. Rotation converged in 8 iterations. Suppress small coefficients (absolute value below .40)

Table 7.5 Rotated Component Matrix of PCA for IVI

Variable Name	Components	
	1	2
TV	.941	
LATRINE	.938	
FUEL	.912	
TWOWL	.899	
DWPREM	.879	
LIGHT	.849	
MPHONE	.820	
FOURWL	.763	.493
RADIO		.835
DILAPID		.831
BANK		.680

Extracted method: Principal Component Analysis. Rotation method: Varimax with Kaiser normalization. Rotation converged in 3 iterations. Suppress small coefficients (absolute value below .40)

Table 7.6 Rotated Component Matrix of PCA for AVI

Variable Name	Components		
	1	2	3
MARGH	.986		
LSIZE	.984		
IRRIGAT		.827	
CI		.733	
OWNH			.810
FEMH		-.425	.618

Extracted method: Principal Component Analysis. Rotation method: Varimax with Kaiser normalization. Rotation converged in 4 iterations. Suppress small coefficients (absolute value below .40)

Table 7.7 Rotated Component Matrix of PCA for CI

Variable Name	Components	
	1	2
ANNUALV	.981	
MONSOONV	.980	
TMIN		.807
TMAX		.660

Extracted method: Principal Component Analysis. Rotation method: Varimax with Kaiser normalization. Rotation converged in 3 iterations. Suppress small coefficients (absolute value below .40)

The rotated component matrices for all the indices are provided in tables 7.4 to 7.7. The components are labelled based on strongly loaded variables (correlation greater than 0.5). The weighted addition of the rotated component scores of respective variables forms SeVI, IVI, AVI and CI. The weightage is provided to give more importance to the dominant determinants in each vulnerability dimension. The weight assigned is the percentage of cumulative variance explained by each component extracted.

The SeVI, IVI and AVI are aggregated with weightage to construct a Composite Social Vulnerability Index to represent the social vulnerability of the districts. Following Hahn et al. (2009), the number of components extracted from PCA for each sub-index is used as the weight for the subindices.

CSVI= (SeVI*3+IVI*2+AVI*3)/8……. (1)

Where 3, 2 and 3 are the number of components extracted from PCA of socioeconomic, infrastructural, and agriculture sector-related variables, respectively. 8 represents the total number of components. The CSVI is aggregated with CI to construct the Climate Vulnerability Index (CVI).

CVI= (CI*2+CSVI*8)/10…. (2)

Where 2 is the number of components extracted from PCA for climatic variables, 8 is the total number of components extracted from PCA for socioeconomic, infrastructural and agriculture sector related variables, and 10 represents the total number of components.

Following Frigerio et al. (2018), the CVI scores and their sub index score for each decade are classified using the mean and standard deviation of index scores in the particular decade. The classification is as follows: Very Low (<Mean-1.5 S.D.), Low (Mean -1.5 S.D. to Mean-0.5 S.D.), Moderate (Mean -0.5 S.D. to Mean+0.5 S.D.), High (Mean +0.5 S.D. to and Mean+1.5 S.D.) and Very High (> Mean+1.5 S.D.). The spatial maps of the districts at different vulnerability levels for each social group are plotted using QGIS software. To identify the inter-group changes in CVI and its subindices, the index scores of all observations are considered together, and ANOVA is conducted.

7.4 Results

7.4.1 Components of Principal Component Analysis

This section explains the major components of vulnerability derived from PCA, including socioeconomic, infrastructural, agriculture sector related, and climatic variables (Table 7.8). 86% of the variance in the socioeconomic vulnerability index is explained by three components derived from seven socioeconomic variables. 11 infrastructural variables explain 81% of the variance in the infrastructural vulnerability index. Three components from 6 agriculture sector related variables explain 75% of the variance in the agricultural vulnerability index, and 2 components derived from four climatic variables explain 77% of the variance.

Table 7.8 Major determinants of vulnerability of social groups to climate change

Component number	Description	Variance explained (%)	Cumulative Variance (%)
Socioeconomic Vulnerability Index			
1	Access to education, dependence and employment of female	47.5	47.5
2	Employment and Decadal change in population	23.3	70.8
3	Special needs population	15.3	86.2
Infrastructural Vulnerability Index			
1	Access to assets and infrastructure	57.2	57.2
2	Access to radio, banking and housing condition	24.1	81.3
Agricultural Vulnerability Index			
1	Size of holdings	32.8	32.8
2	Technological efficiency	25.0	57.8
3	Ownership of holdings	17.4	75.2
Climate Index			
1	Variation in rainfall	49.9	49.9
2	Change in temperature	27.3	77.2

Source: Rotated component Matrix with Varimax Rotation and Kaiser Normalization for SeVI and CI and unrotated component matrix and Kaiser Normalization for IVI.

7.4.1.1 Access to education, dependence and female employment

This component explains 47% of the variance in SeVI. Lack of access to education and the share of dependent population load positively and female employment load negatively in this component. It indicates that lack of access to education, higher share of dependent population and female employment increases vulnerability. Among the social groups where access to education is less, childbirth will be high, and hence, the share of the dependent population will be higher. Children and the elderly are economically dependent on others, increasing their vulnerability. Also, their proneness to diseases and lack of mobility during climatic extremes increases their vulnerability. Families with more dependents often have limited financial resources, reducing their coping capacity (Siagian et al., 2014). Lack of education leads to more employment in agriculture, which is highly impacted by climate change. Female work participation in agriculture is high in Madhya Pradesh, especially among the marginalised sections. Though the lack of employment is assumed to be increasing vulnerability in literature, it is found to decrease vulnerability here. In the second objective (Chapter 5), the gender gap in employment is also found to decrease vulnerability. Chatterjee et al. (2018) found that women with lower education have more labour force participation in agriculture and allied sectors. In contrast, women from higher castes or with high family status are reluctant to work in the agriculture and allied sectors, which will reduce their overall work participation. Access to education leads to more employment diversification and knowledge enhancement and reduces the share of the dependent population through proper birth control measures, thereby enhancing adaptation to climate change. This component is found to be highest among ST and lowest among Non SC/ST.

7.4.1.2 Employment and decadal change in population

This component explains 23% of the variation in SeVI. The lack of work participation among males and females and decadal change in population loads positively in this component. The working population can recover quickly from the impacts of climate change. The higher growth rate in population limits access to resources, making the population vulnerable to the impacts of climate change, like food insecurity and diseases. The higher growth rate also increases the dependent population's share and reduces the working population's coping capacity. This component is the highest among all social groups of northern districts, as these districts generally have lower work participation. However, it is found to be the lowest among all social groups in eastern districts, which generally possess higher work participation.

7.4.1.3 Special needs population

This component explains about 15% of the variation in SeVI. The share of the population with disability loads highly in this component. Decadal change in population also loads positively with less loading. The disabled population is found to be highly vulnerable to climate change, especially during extreme climate events. This component is higher among SC and lower among ST and Non SC/ST.

7.4.1.4 Access to Infrastructure and assets

This component explains about 57% of the variation in IVI. The lack of access to basic infrastructural facilities like electricity, sanitation, drinking water, clean fuel, communication devices like television, mobile phone and transport like two-wheeler and four-wheeler loads positively in this component. Access to electricity, drinking water, clean fuel, and toilets improves living conditions for the population. Access to drinking water and toilet facilities reduces the chances of diseases like diarrhoea (Kumar & Das,2014), reduces death and productivity loss and saves time and expenses for health maintenance (Ghosh & Cairncross, 2014). Access to electricity as a light source improves productivity and saves time for education and employment, especially among women (IEA et al., 2022). The use of inefficient fuel is one of the leading causes of indoor air pollution, risking health and leading to premature deaths among women and children. It is also one of the sources of greenhouse gases like carbon dioxide (IEA et al.,2022). Thus, increasing access to clean fuel is beneficial for adaptation as well as mitigation efforts to climate change. Access to communication facilities like television and telephone helps in warning during climatic extremes. Access to transport facilitates easy evacuation during extreme events. The asset status of people is an indicator of their quality of life, and those with improved quality of life are generally found to be less socially vulnerable. This component is found higher among ST and lower among Non SC/ST.

7.4.1.5 Access to radio, banking and housing condition

This component explains about 24% of the variation in IVI. Radio serves as an effective means of communication in rural areas by disseminating weather forecasts and early warning messages of extreme events. It also serves as an effective instrument for extension services by government departments to the primary sector. Access to banking services builds their coping capacity with the impacts of climate change. Dilapidated houses are found to be highly vulnerable to damage during extreme climatic events. This component is higher among ST and SC and lower among Non SC/ST.

7.4.1.6 Size of holdings

This component explains about 32% of the variation in AVI. The average size of holdings and share of small and marginal holdings load positively in this component. The direction of the average size of holdings was reversed before PCA. Hence, in this component, the low average size of holdings is loaded in the same direction with the share of small and marginalised holdings. The average size of holdings is decreasing in the state due to the decrease in the size of land available for cultivation and the increase in population over time. This fragmentation also leads to an increase in small and marginal farmers. Small and marginal farmers are found to be highly vulnerable to climate change due to limited access to technology and extension services. This component is highest among SC and lowest among Non SC/ST.

7.4.1.7 Technological efficiency

This component explains about 25% of the variation in IVI. Low cropping intensity and low share of irrigated area load highly in this component. Cropping intensity indicates the number of times a land is cultivated in a crop year. High cropping intensity indicates greater land use efficiency and better soil moisture retention capacity (Raju et al., 2017; Das, 2013). A high cropping intensity can meet increased demands for food due to population growth. It is possible through irrigation, fertilizers, crop rotation, mechanization, plant protection measures, etc. Thus, the higher cropping intensity indicates effective adaptation of technology. Improved irrigation infrastructure and more equitable water distribution can increase productivity and income from the agricultural sector and save crops from dry spells or droughts (Sehgal et al., 2013; Raju et al., 2017; Rao et al., 2013). Increasing cropping intensity and irrigation can increase the adaptive capacity of the exposed population. This component is found highest among all the social groups in the tribal dominant districts like Jhabua, Burhanpur, Anuppur, etc. It is found to be the lowest among all social groups in districts like Harda, which are relatively agriculturally developed districts.

7.4.1.8 Ownership of holdings

This component accounts for 17% of the variation in the Agricultural Vulnerability Index. The direction of ownership of holdings and the share of female owned holdings were reversed before conducting PCA. These variables loaded positively in the component, indicating that a lower share of owned holdings and a lower share of holdings owned by females increase vulnerability to climate change. Land ownership facilitates access to credit and technology and thus increases adaptive capacity to climate change. As females constitute a major share of the workforce in the agriculture sector, ownership of land in their names will increase their adaptive capacity to climate change. This component is found highest in all social groups of districts like Jhabua, Alirajpur, Rajgarh, etc. and is found lowest in all social groups of Burhanpur, Panna, Ujjain, Indore, etc.

7.4.1.9 Variation in rainfall

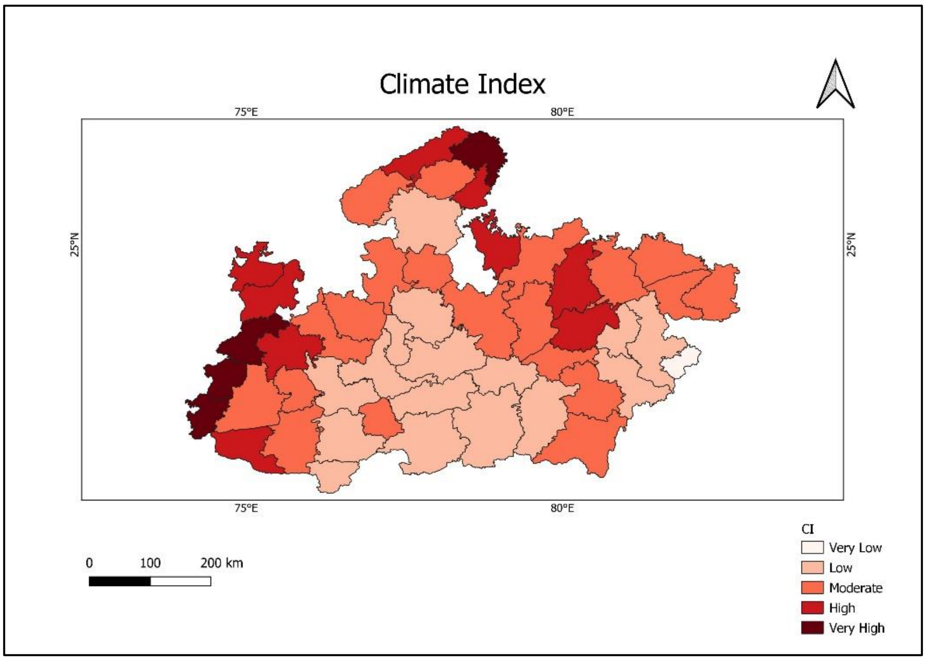
Variations in annual rainfall and Southwest monsoon rainfall constitute the first component. It explains around 50% of the variation in climate index. The variability in rainfall is increasing in Central India, including Madhya Pradesh. Low and moderate rainfall decreases significantly, whereas heavy and intense rainfall trends increase (Guhatakurta et al.,2011). The extreme events associated with rainfall, like drought, flood, etc., can lead to higher economic losses, morbidities, mortalities, livelihood loss, forced migration, etc. (Pradhan & Narayanan, 2020; Pradhan & Narayanan, 2022). This component is highest in southwestern districts like Alirajpur, Jhabua, and Barwani and northern districts like Bhind, Morena, etc. It is the lowest in Eastern districts like Shahdol, Anuppur, etc.

7.4.1.10. Change in temperature

This component explains 27% of the variation in temperature. The rate of change in annual mean maximum temperature and annual mean minimum temperature loads positively in this component. The maximum and minimum temperatures in the state have increased by 0.6 and 0.62 ºC over 102 years from 1901 to 2002 (Duhan & Pandey,2013). It is projected that 30% of the area of the state will experience more than 2ºC warming by 2050 under the RCP 8.5 scenario (Mishra et al.,2016). The increase in temperature can affect all social groups through its effects on health, productivity, livelihood, income, etc. Increased temperature can lead to increased transmission of vector-borne diseases and loss of productivity due to heat stress, heat waves, etc. The impact of high temperatures on yield and the increased occurrence of pests and diseases in the agriculture and allied sectors can affect the livelihood and income of the population, especially the marginalised sections.

7.4.2 Climate Index (CI) at district level

Figure 7.2 shows the Climate Index prepared at the district level. Climate Index is found to be very high in Alirajpur, Bhind, Jhabua and Ratlam mainly due to the higher variation in annual as well as monsoon rainfall.



Source: Prepared using QGIS

Figure 7.2 Climate Index at district level

7.4.3 Identification of most vulnerable districts for each social group

The CVI and its sub-indices of each social group are categorised into five levels based on their respective mean and standard deviation. Table 7.9 lists the number of districts and table 7.10 lists the percentage of each social group under each vulnerability level. Table 7.11 lists the most vulnerable districts of each social group. Figures 7.3 to 7.5 plot the districts under different levels of vulnerability for each social group.

Table 7.9 Districts under different levels of vulnerability for each social group

Level	SeVI			IVI			AVI			CSVI			CVI		
	SC	ST	N	SC	ST	N	SC	ST	N	SC	ST	N	SC	ST	N
Very Low	5	4	1	5	3	5	1	1	2	2	2	4	3	2	4
Low	7	12	16	8	4	8	16	11	12	14	13	11	11	13	12
Moderate	21	16	18	18	27	18	16	27	19	21	20	16	20	19	19
High	12	16	12	19	16	19	14	7	15	10	11	17	12	13	13
Very High	5	2	3	0	0	0	3	3	2	3	3	2	4	2	2
Total	50	50	50	50	50	50	50	49	50	50	49	50	50	49	50

Source: Author's calculation

Table 7.10 Percentage of each social group under different levels of vulnerability

Level	SeVI			IVI			AVI			CSVI			CVI		
	SC	ST	N	SC	ST	N	SC	ST	N	SC	ST	N	SC	ST	N
Very Low	6.1	3.1	3.8	14.6	2.2	13.5	0.8	1.0	2.5	2.2	0.8	12.2	6.6	0.8	12.2
Low	13.7	28.9	26.7	9.3	3.2	15.9	36.7	19.3	29.5	30.3	26.6	23.0	22.6	31.9	27.0
Moderate	47.0	27.4	36.4	34.5	73.0	34.4	35.6	57.2	39.3	46.3	44.0	27.0	38.4	34.8	29.9
High	26.9	38.6	27.6	41.5	21.6	36.2	22.2	14.4	27.9	15.3	19.3	34.8	27.4	22.4	26.4
Very High	6.3	2.0	5.5	0.0	0.0	0.0	4.7	8.1	0.8	5.9	9.3	2.9	4.9	10.1	4.4
Total	100.0	100.0	100.0	100.0	100.0	100	100.0	100.0	100	100.0	100.0	100.0	100.0	100.0	100.0

Source: Author's calculation

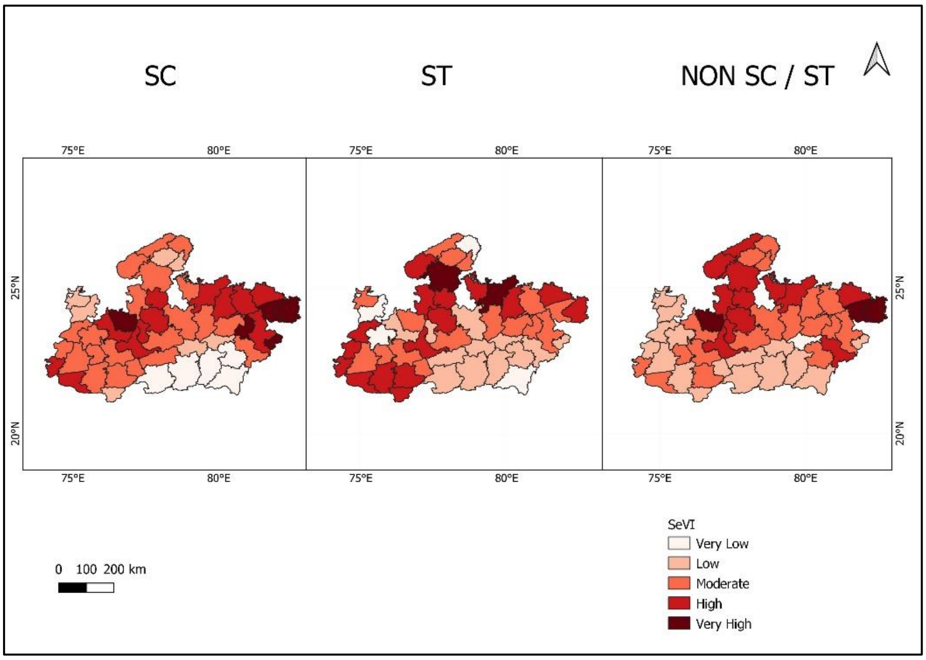
Table 7.11 Very high vulnerable districts identified for each social group

SeVI			AVI			CSVI			CVI		
SC	**ST**	**N**	**SC**	**ST**	**N**	**SC**	**ST**	**N**	**SC**	**ST**	**N**
Umaria	Shivpuri	Rajgarh	Jhabua	Jhabua	Anuppur	Sidhi	Jhabua	Sidhi	Alirajpur	Jhabua	Bhind
Rajgarh	Chhatarpur	Sidhi	Sidhi	Rewa	Alirajpur	Rewa	Shivpuri	Singrauli	Sidhi	Alirajpur	Sidhi
Sidhi		Singrauli	Rewa	Mandsaur		Singrauli	Rewa		Rewa		
Singrauli									Jhabua		
Anuppur											

Source: Author's calculation

7.4.3.1 Socioeconomic Vulnerability Index (SeVI)

SC and Non SC/ST in Rajgarh, Sidhi and Singrauli possess very high socioeconomic vulnerability. SC in the other two districts (Umaria and Anuppur) has also been found to be very socioeconomically vulnerable. ST in 2 districts (Shivpuri and Chhatarpur) have very high socioeconomic vulnerability (Table 7.11). The number of districts where ST possess very high vulnerability is less than SC and Non SC/ST. When high and very high vulnerability are considered together, the number of districts and percentage of the social groups under high and very high is more for ST, i.e.,18 districts and 40% share of ST have a high or very high socioeconomic vulnerability (Tables 7.9 &7.10). Figure 7.3 shows the spatial distribution of SeVI for each social group.

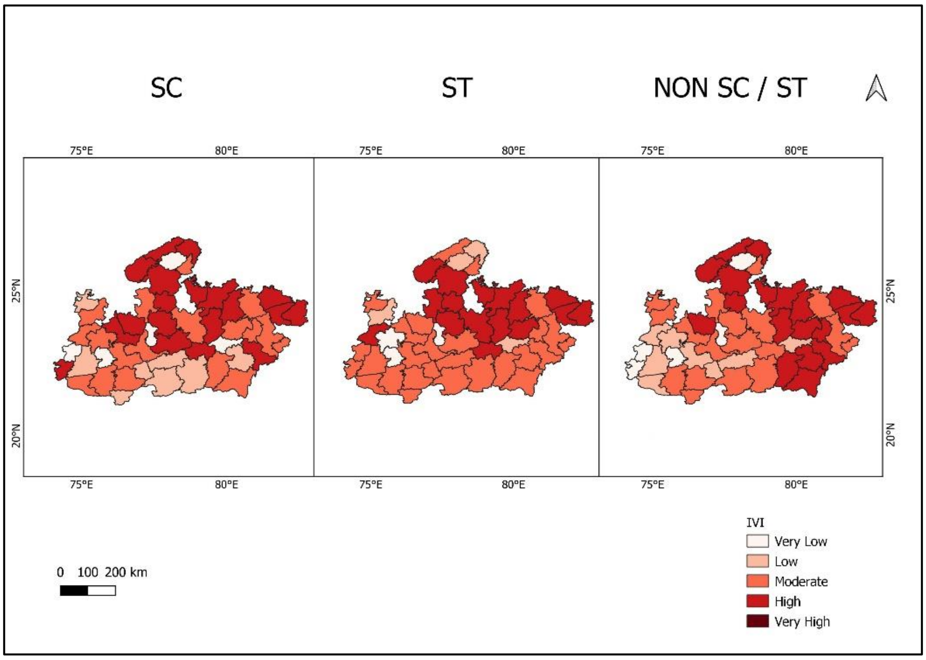


Source: Prepared using QGIS

Figure 7.3 Socioeconomic Vulnerability Index

7.4.3.2 Infrastructural Vulnerability Index

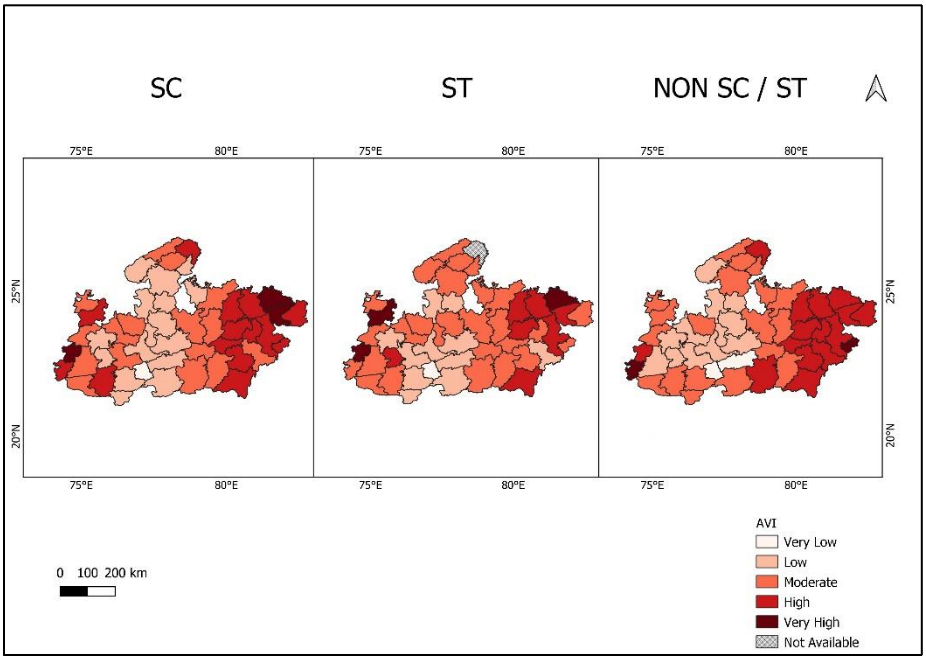
The study could not identify very high infrastructural vulnerability in any social groups. However, SC and Non SC/ST are high infrastructurally vulnerable in 19 districts, and ST are high infrastructurally vulnerable in 16 districts (Table 7.9). The population share under high infrastructural vulnerability is higher for SC and lowest for ST (Table 7.10). Figure 7.4 shows the spatial distribution of IVI for each social group.



Source: Prepared using QGIS

Figure 7.4 Infrastructural Vulnerability Index

7.4.3.3 Agricultural Vulnerability Index



Source: Prepared using QGIS

Figure 7.5 Agricultural Vulnerability Index

SC and ST of Jhabua and Rewa possess very high agricultural vulnerability. SC of Sidhi and ST of Mandsaur are also very high agriculturally vulnerable. Non SC/ST possess very high agricultural vulnerability in Anuppur and Alirajpur (Table 7.11). The share of the population under very high agricultural vulnerability is more for ST. Figure 7.5 shows the spatial distribution of AVI for each social group.

7.4.3.4 Composite Social Vulnerability Index

CSVI is prepared by aggregating SeVI, IVI and AVI. SC & Non SC/ST of Sidhi and Singrauli and SC & ST of Rewa possess very high social vulnerability. ST in Jhabua and Shivpuri also possess very high social vulnerability (Table 7.11). Though SC and ST possess only one more district in the very high vulnerable category than Non-SC/ST, the population share under the very high category in ST is thrice that of Non-SC/ST, and that of SC is twice that of Non-SC/ST (Tables 7.9 & 7.10). Figure 7.6 shows the spatial distribution of CSVI for each social group.

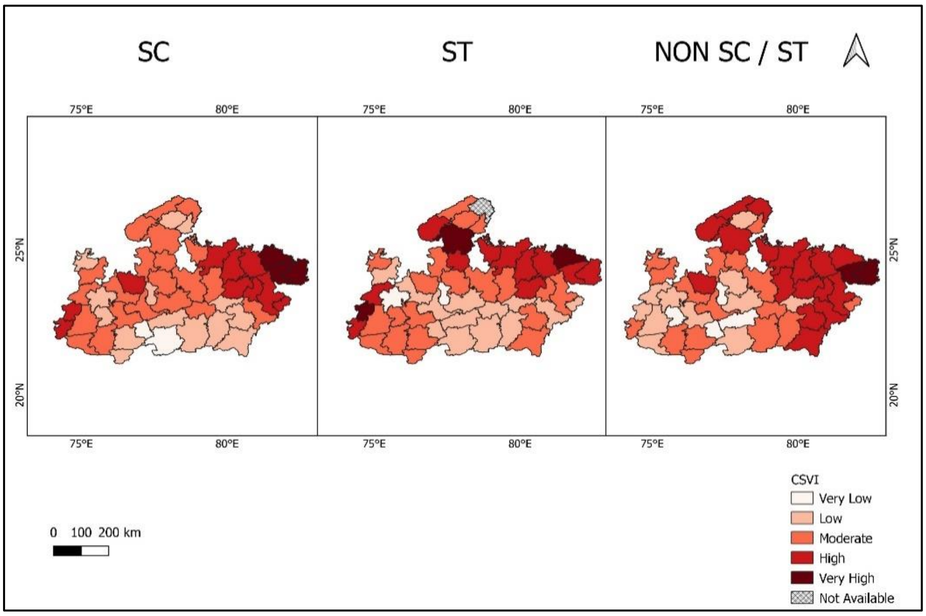


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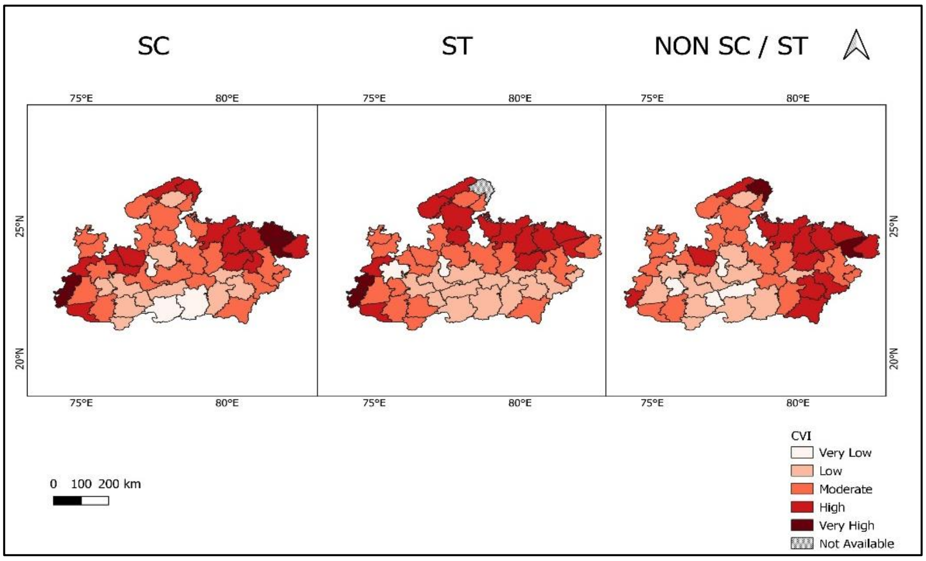
Figure 7.6 Composite Social Vulnerability Index

7.4.3.5 Climate Vulnerability Index



Source: Prepared using QGIS

Figure 7.7 Climate Vulnerability Index

The Climate Vulnerability Index of each social group is prepared by aggregating the Composite Social Vulnerability Index of each social group with the district level Climate Index. SC and ST of Jhabua and Alirajpur and SC & Non SC/ST of Sidhi are very high vulnerable to climate change. Rewa of SC also possesses very high climate vulnerability (Table 7.11). Though SC possesses very high vulnerability in more districts than ST, the share of the ST population with very high vulnerability is twice that of SC (Tables 7.9 & 7.10). Figure 7.7 shows the spatial distribution of CVI for each social group.

7.4.4 Most vulnerable social groups in Madhya Pradesh

In section 7.4.3, each social group is individually considered, and classification is done by calculating the mean and standard deviation separately for each social group. In this section, mean and standard deviation are calculated by considering all social groups together, and each index is classified using all observations. Table 7.12 identifies the social groups under very high combined vulnerability in each dimension of social vulnerability.

Table 7.12 Social groups in very high vulnerability in CVI and subindices

Combined SeVI		Combined IVI		Combined AVI		Combined CSVI		Combined CVI	
District	**Caste**	**District**	**Caste**	**District**	**Caste**	**District**	**Caste**	**District**	**Caste**
Shivpuri	ST	Nil	Nil	Jhabua	ST	Jhabua	ST	Jhabua	ST
Chhatarpur	ST			Jhabua	SC	Sidhi	SC	Alirajpur	SC
Jhabua	ST			Sidhi	SC	Shivpuri	ST	Alirajpur	ST
Ashoknagar	ST			Rewa	ST	Rewa	ST	Ratlam	ST
Sheopur	ST			Mandsaur	ST			Rewa	ST
Umaria	SC			Rewa	SC			Sidhi	SC
Burhanpur	ST							Panna	ST
Guna	ST								
Barwani	ST								
Rajgarh	SC								
Khargone	ST								
Khandwa	ST								

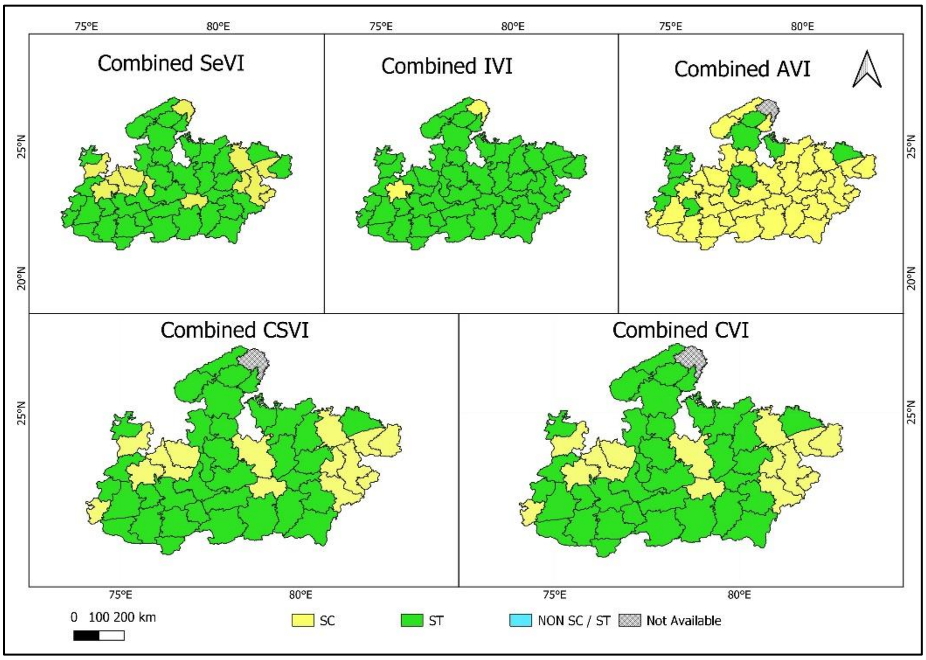
Source: Author's calculation

Table 7.13 Social groups in very low vulnerability in each dimension of vulnerability

Combined SeVI		Combined IVI		Combined AVI		Combined CSVI		Combined CVI	
District	**Caste**	**District**	**Caste**	**District**	**Caste**	**District**	**Caste**	**District**	**Caste**
Jabalpur	Non SC/ST	Indore	Non SC/ST	Harda	Non SC/ST	Harda	Non SC/ST	Harda	Non SC/ST
Jhabua	Non SC/ST	Bhopal	Non SC/ST	Hoshangabad	Non SC/ST	Indore	Non SC/ST	Indore	Non SC/ST
Balaghat	Non SC/ST	Alirajpur	Non SC/ST	Vidisha	Non SC/ST	Bhopal	Non SC/ST	Bhopal	Non SC/ST
Anuppur	Non SC/ST	Jhabua	Non SC/ST	Ujjain	Non SC/ST	Hoshangabad	Non SC/ST	Hoshangabad	Non SC/ST
Betul	Non SC/ST	Gwalior	Non SC/ST	Bhopal	Non SC/ST	Ujjain	Non SC/ST	Dewas	Non SC/ST
Balaghat	SC	Jabalpur	Non SC/ST	Guna	Non SC/ST	Dhar	Non SC/ST	Betul	Non SC/ST
Narsimhapur	Non SC/ST	Harda	Non SC/ST	Indore	Non SC/ST	Dewas	Non SC/ST	Dhar	Non SC/ST
Chhindwara	Non SC/ST	Dhar	Non SC/ST	Dewas	Non SC/ST	Gwalior	Non SC/ST	Ujjain	Non SC/ST
		Ujjain	Non SC/ST	Sehore	Non SC/ST	Jabalpur	Non SC/ST	Vidisha	Non SC/ST
		Indore	SC	Raisen	Non SC/ST	Ratlam	Non SC/ST	Gwalior	Non SC/ST
		Hoshangabad	Non SC/ST	Harda	ST	Betul	Non SC/ST	Raisen	Non SC/ST
		Ratlam	Non SC/ST						
		Barwani	Non SC/ST						
		Bhopal	SC						
		Dewas	Non SC/ST						

Source: Author's calculation

ST of Shivpuri, Chhatarpur, Jhabua, Ashoknagar, Sheopur, Burhanpur, Guna, Barwani, Khargone and Khandwa and SC of Umaria and Rajgarh possess very high combined socioeconomic vulnerability. ST of Jhabua, Rewa and Mandsaur and SC of Jhabua, Sidhi and Rewa possess very high combined agricultural vulnerability. ST of Jhabua, Shivpuri and Rewa and SC of Sidhi possess very high combined social vulnerability. ST of Jhabua, Alirajpur, Ratlam, Rewa and Panna and SC of Alirajpur and Sidhi possess very high combined vulnerability to climate change. At the same time, Non SC/ST in most districts possess very low combined vulnerability in CVI and subindices (Table 7.13). SC in Balaghat possess very low combined socioeconomic vulnerability. SC of Indore and Bhopal possess very low combined infrastructural vulnerability, while ST of Harda possess very low combined agricultural vulnerability. However, in combined composite social vulnerability and combined climate vulnerability, only Non SC/ST possess very low vulnerability.



Source: Prepared using QGIS

Figure 7.8 Most vulnerable social group in each district

Figure 7.8 identifies the most vulnerable caste in each district. CSVI is highest among ST in 38 districts and SC in 12 districts.

On the other hand, combined IVI is highest among ST in 48 districts and SC in 2 districts, Bhind and Ujjain. Combined AVI is highest among SC in 38 districts and ST in 11 districts. The Composite Social Vulnerability and overall climate vulnerability are highest among ST in 35 districts and SC in 14 districts.

Table 7.14. Results of social groups wise ANOVA of vulnerability scores

Row mean-Column mean	Combined SeVI		Combined IVI		Combined AVI		Combined CSVI		Combined CVI	
	Non SC/ST	SC	Non SC/ST	SC	Non SC/ST	SC	Non SC/ST	SC	Non SC/ST	SC
SC	0 .71* (0.00)		0.866* (0.000)		0.622* (0.00)		0.717* (0.00)		.57* (0.00)	
ST	1.05* (0.00)	0.33* (0.00)	1.373* (0.00)	0.51* (0.00)	0.4* (0.00)	-0.22 (0.126)	0.896* (0.00)	0.179* (0.04)	.71* (0.00)	0.13 (0.14)
Equal means test across social groups	65.21* (0.00)		91.6* (0.00)		17.05* (0.00)		93.5* (0.00)		60.89* (0.00)	
Equal variance test across social groups	14.04* (0.001)		42.44* (0.00)		6.06* (0.048)		1.81 (0.404)		0.89 (0.64)	

*Source: Authors' calculation; Note: * indicates significance at 5%.*

To understand whether any significant difference exists among the vulnerability of social groups, ANOVA has been conducted with scores of combined CVI and subindices.

Table 7.14 illustrates that Non SC/ST possess the lowest combined vulnerability to climate change and is significantly different from SC and ST. ST significantly differs from SC in combined socioeconomic, infrastructural and composite social vulnerability. Whereas, for the combined climate change vulnerability of ST, the difference from SC is not significant. Though SC possesses higher combined agricultural vulnerability, the difference from ST is not significant. Thus, the study identified that ST possesses the highest vulnerability to climate change than other social groups.

7.5. Discussion of results

Vulnerability to climate change differs among social groups in a population owing to their socioeconomic characteristics, access to infrastructure, employment, etc. Though district wise studies are available on social vulnerability assessments to climate change or disasters in India, social group wise vulnerability has not been attempted yet. This objective tried to overcome this gap by conducting a vulnerability assessment for each social group in Madhya Pradesh to climate change. It also attempted to compare the vulnerability of all social groups to identify the most vulnerable social group state wise and in each district. The climate vulnerability index is a function of the climate change index and composite social vulnerability index. The composite social vulnerability index is a weighted average of three subindices: Socioeconomic Vulnerability, Infrastructural Vulnerability, and Agricultural Vulnerability. Identifying the most vulnerable in overall CVI and each subdimension helps to understand the dimension where more focus is required for reducing the vulnerability to climate change for each social group.

The study found that access to education, dependence and employment of females contributed more to the socioeconomic vulnerability of social groups. Access to assets and infrastructure contributed more to infrastructural vulnerability, and the size of holdings contributed more to agricultural vulnerability. The districts with a very high vulnerable population under different indices differ for each social group. SC of Sidhi possesses very high SeVI, AVI, CSVI and CVI. ST of Jhabua possess very high AVI, CSVI and CVI. Non SC/ST of Sidhi possess very high SeVI, CSVI and CVI. ST has the highest share of population percentage under high and very high socioeconomic vulnerability and population percentage under high infrastructural vulnerability. They also have the highest share of the population percentage under very high AVI, CSVI and CVI. ST also possesses significantly higher vulnerability than other social groups in SeVI, CSVI, and CVI. Though the mean IVI of ST is higher than SC, the difference is not significant. SC possessed a higher mean than ST only in AVI, but the difference was not significant. It is also found that ST has the highest vulnerability in all dimensions except AVI in most districts. AVI is found to be the highest in SC in most of the districts. The lower access to education, high share of dependent population, decadal change in population and employment contribute to the high socioeconomic vulnerability, and it can be reduced by improving access to education, control of the population by birth control measures, skill training, etc. Increased literacy and skill training can increase employment and job diversification in sectors other than agriculture. Though female employment is expected to reduce vulnerability, it is found to increase vulnerability due to the high share of women as agricultural workers. The reluctance among women of higher castes to work in low paid jobs and the agriculture sector lowers the work participation of women among Non SC/ST. These findings also stress the need for increasing access to education and skill development among social groups.

Access to basic infrastructure and assets is lower among STs due to the remoteness of their places of residence. Hence, proper measures should be undertaken to enhance their access to these facilities. The increased fragmentation of holdings contributes to the reduction in the average size of holdings, and thus, the share of small and marginal holders is increasing. The limited access of marginal and smallholders to extension services and the lack of ownership constrained the access to extension services, resulting in low cropping intensity and irrigated areas. Agricultural vulnerability can be reduced by consolidating small and marginal holdings and collective farming, which will facilitate the reach of extension services, improvement of cropping intensity and irrigation access to the land. The Climate Vulnerability Index is very high for Jhabua, Alirajpur and Ratlam, as the higher social vulnerability compounds with high climate exposure in these districts.

As the state is highly exposed to climate change, as indicated by the literature as well as our analysis, the overall climate vulnerability can be reduced only by reducing the social vulnerability in the state. This reduction is possible only if more focus is provided on the most vulnerable sections. Socioeconomic and Infrastructural vulnerability is found more among ST, so interventions to reduce it should focus more on this social group. Though agricultural vulnerability is found more among SC, the difference is not significant. Hence, interventions to reduce agricultural vulnerability should focus on both social groups.

As there are no studies available on vulnerability to climate change among different social groups, the results of this study will not match precisely with the findings of others. However, the vulnerable districts identified by this study for different social groups match those identified by MPSKMCCC (2018). MPSKMCCC (2018) assessed the district-level vulnerability of different sectors to climate change in Madhya Pradesh. Jhabua, Alirajpur, Sidhi, Rewa and Bhind, identified as very high climate vulnerable districts for different social groups, are included in the 8 districts identified as very high climate vulnerable by MPSKMCCC (2018). This validates our identification of vulnerable districts for each social group. The study identifies that the vulnerability of SC and ST significantly differs from Non SC/ST. Though there are no direct vulnerability assessments to prove its validity, the findings in government reports like GoMP (2016), GoI (2020), and GoI (2011) on disparities of these groups from Non SC/ST supports our results.

Though the study could address the gap in vulnerability analysis of social groups in a population, it suffers from certain limitations due to data constraints. The Non SC/ST groups include information about several population groups, including the social groups other than SC and ST and religious minorities in India. Generally, the surveys conducted by the National Sample Survey Organization and other agencies collect data from Other Backward Caste (OBC) groups, who possess higher socioeconomic backgrounds than SC and ST but lower than the position of upper caste Hindus. OBC represent a middle caste category comprising several individual castes that vary in their social advantage or disadvantage (Farnworth et al.,2022). As the data of OBC is not available separately in the Census of India (2011), this study could not identify whether the vulnerability of OBC to climate change differs from other social groups. The study can be advanced further if a data source with separate data for SC, ST, OBC, and others is used. Though the Bhind district is classified as very high in the climate change index, the CVI of ST in that district could not be calculated due to the lack of data for AVI variables. The CVI of this social group can be calculated once the data becomes available. The enumeration of the population census of 2021 was delayed due to COVID. The government of India has initiated efforts to conduct a population and agriculture census for this decade. This study can be updated after the release of new data. Also, there is scope for temporal study using multiple rounds of census data.

7.6. Conclusion

This study was undertaken to compare the vulnerability of social groups to climate change in Madhya Pradesh. To compare vulnerability among the social groups, a composite index for the social vulnerability of each social group is prepared out of three subindices: socioeconomic, infrastructural, and agricultural. The composite vulnerability index is then combined with the climate change index at the district level. The study found that social groups possess different levels of vulnerability to climate change in districts of Madhya Pradesh due to differences in composite social vulnerability characterized by differences in socioeconomic characteristics, infrastructural access and agricultural characteristics. Intergroup comparison using combined indices and their ANOVA indicates the significant differences among social groups in vulnerability index scores. Non SC/ST was found to be the least vulnerable among all groups, and ST was the highest in overall climate vulnerability and composite social vulnerability. The study advocates for reducing social vulnerability in the context of high exposure to climate change. Reducing social vulnerability is possible by identifying the dominant dimension of the vulnerability of each social group in particular districts and targeting interventions to reduce it. Also, policy measures at the district level for reducing vulnerability to climate change have to be implemented, focusing more on the most vulnerable social groups in the particular district. The results identified are valid as the climate vulnerability correlates with its subindices and matches the literature. This study can find wide applications in climate change vulnerability assessment of other Indian states and developing countries with similar socioeconomic and demographic characteristics.

Chapter 8

Major findings, Conclusion and Policy suggestions

The main objective of this thesis is to assess the vulnerability of the Madhya Pradesh population to climate change. The study is conducted at multiple scales for a comprehensive assessment of the vulnerability of the state population. The first objective tried to compare the generic social vulnerability of the population with the population of other states and union territories of India. The second objective assessed the spatiotemporal pattern of vulnerability to climate change by integrating indicators representing climate change and social vulnerability. As the rural-urban disparity is very high among the population of Madhya Pradesh, a study on the spatiotemporal pattern of the vulnerability of rural and urban areas is also conducted. The assessment of the vulnerability of the state population has identified agriculture sector dependence as one of the main drivers of vulnerability. The vulnerability is also found to be higher among the tribal-dominated districts. These two led to an in-depth study of agriculture sectoral vulnerability and differences in vulnerability among different social groups of the state.

Chapter 2 of this thesis explains the concept of vulnerability, definitions that evolved in various disciplines, the evolution of different models, the application of vulnerability in climate change discipline, its assessment and how the earlier studies have attempted the assessment of vulnerability. Chapter 3 gives a detailed note on the study area, ie. The state of Madhya Pradesh, research methodology, variables used, data sources, etc. Chapters 4 to 7 explain the study conducted with four objectives. The present chapter summarizes the major findings from the study, provides a general conclusion and suggests the required policy measures to reduce the vulnerability of the Madhya Pradesh population to climate change. Section 8.1 explains the major findings from the thesis, 8.2 suggests the policy measures, 8.3 lists the contributions of this study and 8.4 lists the limitations of the thesis and the future direction of research. The final section, 8.5, concludes the thesis.

8.1 Major findings of thesis

8.1.1 Objective 1

The national vulnerability assessments have attributed social vulnerability as the major reason for vulnerability to different stressors in Madhya Pradesh. However, there was no consensus regarding drivers of vulnerability, as the context differs in each study. Moreover, a detailed analysis of factors contributing to the social vulnerability of the population is required, as it is an internal property of a population irrespective of the stressor to which it is exposed. Hence, in objective 1, a comparison of the social vulnerability of the Madhya Pradesh population compared to the population of other states and union territories of India is attempted. The literature review on vulnerability assessments shows that social vulnerability assessment covering all Indian districts is limited. Though Vittal et al. (2020) and Yenneti et al. (2016) attempted social vulnerability assessments at the national level, limited coverage of variables constrained their study. The social vulnerability assessments also suffer from aggregating all dimensions to one index, which masks the areas where actual focus is required, leading to improper targeting of interventions. Following Borden et al. (2007), Holand et al. (2011) and Mazumdar & Paul (2016), a composite social vulnerability index consisting of the socioeconomic vulnerability index and infrastructural vulnerability index was constructed. The study also used spatial autocorrelation techniques to identify the clusters of social vulnerability.

The study identified agriculture and allied sector dependence, low education and employment levels, high population growth, and a larger share of socially and economically dependent populations as the major factors contributing to socioeconomic vulnerability and lower access to basic assets and infrastructure as the major factors contributing to infrastructural vulnerability. It found that more districts in India possess socioeconomic vulnerability than infrastructural vulnerability. Madhya Pradesh is identified as an exceptional case, with more districts possessing higher infrastructural vulnerability than socioeconomic vulnerability. It also found that the socioeconomic and infrastructural vulnerability of India is concentrated more in bigger states, especially the Empowered Action Group States, to which Madhya Pradesh belongs. A larger share of the population in EAG states, combined with their relative socioeconomic backwardness, contributes to the very high vulnerability of these states. The ANOVA analysis identified the Central Zone, where Madhya Pradesh is located, as the second most vulnerable socioeconomic and infrastructural zone in India. The districts from Madhya Pradesh identified as very highly vulnerable, socioeconomic as well as infrastructural, are mainly tribal dominated, which calls for tribal-focused adaptations. Identifying higher dependence on the agricultural and allied sectors and illiteracy as the dominant factors contributing to socioeconomic vulnerability and limited access to infrastructure and assets as major drivers of infrastructural vulnerability necessitate appropriately targeted interventions. Proper adaptation measures in the agricultural sector, livelihood diversification, and skill development improved access to education, especially among women, strengthening of employment assurance and food security programs, increasing the infrastructural quality and increasing the asset status are advocated as the intervention measures required to reduce the social vulnerability of this population. The results of this study match with the social vulnerability hotspots identified by previous studies like Yenneti et al. (2016), Azhar et al. (2017), Das (2013), Sendhil et al. (2018), etc., conducted in different contexts using different datasets and methodologies. The hotspots identified by these studies also belong to Central, eastern and northern states, especially the districts in EAG states and hence, the results from objective 1 are found valid.

8.1.2 Objective 2 (a)

National-level studies on vulnerability to climate change in India have identified Madhya Pradesh, as well as its districts, as highly vulnerable to climate change due to several climatic, demographic and socioeconomic factors. The increasing impacts of climate change and the prevailing socioeconomic backwardness in the state make identifying the pattern of vulnerability to climate change in Madhya Pradesh a necessity, which is attempted in objective 2 (a). As the approaches usually used, such as IPCC and LVI, have their own limitations, this study tried to apply place-based vulnerability in the context of climate change. By following Borden et al. (2007), Mazumdar & Paul (2016) and Torok et al. (2021), an integrated climate vulnerability index is prepared using a Climate Index and a Composite Social Vulnerability Index, which is further bifurcated into Socioeconomic Vulnerability Index and Infrastructural Vulnerability Index. Though spatiotemporal assessments of vulnerability are attempted in India as well as other countries to identify the dynamic nature of vulnerability (Cutter & Finch,2008; Frigerio et al.,2018; Santos et al.,2022; Yenneti et al.,2016; Das et al.,2021), they are constrained by the omission of climatic variables. The study under this objective brought a dynamic nature to the climate vulnerability index through a spatiotemporal assessment of the district-level climate change vulnerability. It used the Climate Vulnerability Index, an aggregate of the Climate Index and Composite Social vulnerability index. The Composite Social Vulnerability Index, in turn, consists of socioeconomic and infrastructural vulnerability indices.

It found that social vulnerability to climate change in Madhya Pradesh has decreased over the decades (1991 to 2011), attributed to decreased socioeconomic and infrastructural vulnerability. However, overall climate vulnerability has increased, though not significantly, in the most recent decade due to a significant change in climate in the recent 30-year period. Similar to the result of the first objective, infrastructural vulnerability is more prominent than socioeconomic vulnerability in Madhya Pradesh. The number of districts and percentage of the population with high or very high infrastructural vulnerability is twice that of the population with high or very high socioeconomically vulnerable. Similar to objective 1, the peripheral districts dominated by marginalised sections like SC and ST are identified as highly vulnerable.

The higher share of a marginalised population, low access to education, high agriculture sector dependence, the high growth rate in population, a large share of dependent population, limited access to infrastructure, etc., together with high climatic exposure, contributed to very high vulnerability of districts like Alirajpur and Jhabua. Whereas, high access to education, low dependence on the agriculture sector, a lower share of children and marginalised communities and higher access to basic infrastructure contributed to low climate change vulnerability among districts like Indore, Bhopal, Gwalior, and Jabalpur, despite their high or moderate exposure to climate change in the study period. The findings by Patri et al. (2022) and Ge et al. (2021) that urbanisation can significantly reduce vulnerability and losses from disaster and the findings by Azhar et al. (2017) that tribal districts possess high vulnerability validate the results of this study. The findings of Yenneti et al. (2016) and Vittal et al. (2020) that social vulnerability decreases over time also supports the results of this study. The vulnerable districts in Madhya Pradesh identified by different studies on vulnerability to climate change or related disasters in India (Chakraborthy & Joshi, 2016; Azhar et al., 2017; MPSKMCCC, 2018) matches with findings under this objective and thus validate the study.

Objective 2 (b)

Rural areas depend highly on natural resource-intensive sectors and possess relatively less socioeconomic development than urban areas. These differences may accentuate their vulnerability to climate change, even if they are exposed to the same variation in climate. The higher rural-urban disparities prevailing in Madhya Pradesh in access to basic facilities, poverty, literacy rate, etc., can accentuate vulnerabilities of rural areas to climate change. Moreover, the higher emphasis on urban development during economic reforms has resulted in substantial rural-urban disparities in the state regarding livelihood patterns and access to basic amenities like education, health, energy, and infrastructure. These higher disparities and identification of higher vulnerability of both areas in national studies make a spatiotemporal assessment of climate change vulnerability essential in rural and urban areas of Madhya Pradesh, which is attempted under objective 2(b). There is a gap in Indian climate change vulnerability literature on comparative studies of rural and urban areas. Though studies outside India, like Ge et al.,2021 and Wang et al.,2022, attempted a comparison of rural-urban vulnerability to climate change, they are constrained by the lack of climatic variables. Hence, objective 2(b) overcame this gap by attempting a spatiotemporal assessment of vulnerability to climate change in rural and urban areas of Madhya Pradesh using the Climate Vulnerability Index prepared under objective 2 (a). It also tried to address the gap in spatiotemporal studies on climate change vulnerability by assessing the spatiotemporal pattern of climate change vulnerability of rural and urban areas for three decades. The segregation of social vulnerability to socioeconomic vulnerability and infrastructural vulnerability and capturing its temporal nature over the decades facilitated an effective assessment of vulnerability, adding to the novelty of the study.

The study found that rural areas in Madhya Pradesh possess significantly higher vulnerability to climate change than their urban counterparts due to higher values of the social vulnerability index and its subindices. The social vulnerability index and subindices of both areas significantly decreased over the decades. However, the climate vulnerability in rural and urban areas has significantly increased from 2001 to 2011 due to an increased climate index in the recent decade. The study identified that a decrease in the share of children, improvement in overall literacy rate and reduction of the gender gap in literacy, decreased dependence on the agriculture sector, and increased access to infrastructure have resulted in a reduction in socioeconomic and infrastructural vulnerability of both rural and urban areas over the decades. The lesser share of children in urban populations, higher literacy rates, low gender gaps in literacy, low agricultural dependence, and better access to infrastructure in urban areas resulted in lower socioeconomic and infrastructural vulnerability than rural counterparts. The results of this study match the findings of Ge et al. (2021) and Patri et al. (2022) that urbanisation reduces vulnerability. The finding of a significant decrease in the social vulnerability index and its subindices in both areas over the decades aligns with the findings of Das et al. (2021), Vittal et al. (2020), and Yenneti et al. (2016). The increase in the value of the climate index in the most recent decade indicates an increase in climate exposure in the recent decade, which matches the increasing probability of hydroclimatic hazards noted by Vittal et al. (2020). Vittal et al. (2020)'s finding of a decrease in mortality to hydroclimatic hazards in India over decades despite the increased probability of occurrence of hazards, due to reduction in social vulnerability also validates the suggestions put forward by this study to reduce social vulnerability in order to reduce overall vulnerability to climate change in the coming decades.

Objective 3

The agriculture sector of Madhya Pradesh suffers from uneven development of different regions, a high share of rainfed cultivation, high fragmentation of landholding, lower access to credit, low investment capacity and lack of reach of extension services among tribal farmers, despite being a high-performing sector and a significant contributor to the state economy. These issues, together with changes in climatic parameters and their extremes, are increasing the vulnerability of this sector. Hence, the identification of major factors contributing to climate change vulnerability in this sector, as well as the identification of the vulnerability pattern, has become a necessity, which is attempted in objective 3.

The vulnerability assessments in the agriculture sector are generally static in nature (Das,2013; Rao et al.,2013; Sehgal et al.,2013; Raju et al., 2017; MPSKMCCC,2018). Very few studies, like Varadan & Kumar (2015), attempted temporal assessments using 'instability' and 'change over a period' as variables. Though Palanisami et al. (2008) attempted to assess the vulnerability of agroclimatic regions for three decades, the indices were constructed separately for each decade, and only zone-wise rankings were provided in each year of the study. Also, the construction of indices through simple averaging constrained the identification of significant contributors to vulnerability. Jha & Gundimeda (2019) effectively brought an inductive approach to agriculture sector vulnerability and identified factors contributing to exposure, sensitivity, and adaptive capacity, but it again was static. The assessment of the spatiotemporal pattern of vulnerability and its subcomponents may aid in the identification of changes in each subcomponent over time and help identify how far changes in each subcomponent contributed to overall changes in the vulnerability of the agriculture sector. This gap in vulnerability studies in the agriculture sector has been addressed in objective 3 by assessment of spatiotemporal vulnerability patterns in the agricultural sector using the IPCC approach, i.e., agricultural vulnerability as a composite of exposure, sensitivity and adaptive capacity. It also advanced from previous studies by using spatial autocorrelation techniques to identify changes in the clustering pattern of AVI. Variation in rainfall is identified as the major contributor to exposure. The yield of major crops and net cropped area contributes the most to sensitivity and input availability, and cropping intensity contributes the most to adaptive capacity. Increased exposure has been noticed in recent decades, especially 2000-09. Though 2010-15 has a mean exposure less than 2000-09, it is higher than the eighties and nineties. The sensitivity component is found to have no change due to the increase in demographic dependence and higher marginalisation of holdings despite the increase in yield of major crops and net cropped area. The increase in adaptive capacity over the decades is mainly attributed to the availability of inputs and cropping intensity. The agricultural vulnerability decreased in the most recent decade of study due to the higher adaptive capacity despite the increased exposure. The study also identified the prominence of vulnerability in eastern and northern districts, similar to the overall vulnerability of the population in Objective 2 (chapter 5). The increase in exposure in the recent decade (2010-15) identified in the study agrees with the prediction in studies like MPSKMCCC (2018). Also, the districts with very high AVI in the study match with the findings of MPSKMCCC (2018), Rao et al. (2013) and Mohanty & Wadhawan (2021) and hence found valid.

Objective 4

Marginalised sections of an economy are generally more vulnerable to climate change due to their political and social identities, excessive dependence on natural resource-dependent sectors and limited access to basic facilities. The population of Madhya Pradesh state has a higher concentration of Scheduled Tribes (ST) and Scheduled Castes (SC), who are characterised by a high concentration of poverty, low educational attainments, low infrastructural access and primitive modes of agriculture. More than two-thirds of SC and about 93 % of ST live in rural areas with low access to basic social, institutional and infrastructural facilities. When compounded with climate changes, these adverse socioeconomic backgrounds may lead to loss of livelihood and income, eventually resulting in acute poverty. Though studies on vulnerability in India have identified districts with more marginalised sections as highly vulnerable to climate change (Azhar et al.,2017; Mishra,2015; Bahinipati,2014), a study on these social groups has not been conducted in India. The final objective (objective 4), attempted in Chapter 7, addresses this gap by assessing the climate vulnerability index of social groups (SC, ST and Non-SC/ST). It also attempted to compare the vulnerability of all social groups to identify the most vulnerable social group state-wise and in each district. Each social group's CVI index consists of the district-level climate index and the social vulnerability index of that social group. The composite social vulnerability index consists of socioeconomic, infrastructural and agricultural vulnerability index.

The study found that access to education, dependence and employment of females contributed more to the socioeconomic vulnerability of social groups. At the same time, access to assets and infrastructure contributed more to infrastructural vulnerability, and the size of holdings contributed more to agricultural vulnerability. It also found that social groups possess different levels of vulnerability to climate change due to differences in composite social vulnerability characterised by differences in socioeconomic characteristics, infrastructural access and agricultural characteristics. Intergroup comparison using combined indices and their ANOVA indicates the significant differences among social groups in vulnerability index scores. Non SC/ST was found to be the least vulnerable among all groups, and ST has the highest vulnerability in Climate vulnerability and its subdimensions except Agricultural Vulnerability. Agricultural vulnerability is found to be the highest among SC. The vulnerable districts identified by this study for different social groups match those identified by MPSKMCCC (2018). The findings in Yenneti et al. (2016) and in government reports like GoMP (2016), GoI (2020), and GoI (2011) on disparities of SC & ST from Non-SC/ST validate the significant differences in vulnerability identified among social groups under this objective.

8.2 Contributions of the thesis

Though vulnerability to climate change is conducted in India and globally, it mainly assesses the sectoral vulnerability to climate change. The population vulnerability assessments to climate change are generally limited in number. Also, the vulnerability assessments of the population are mainly conducted at the macro level (global or national level comparisons). Microlevel studies focus mainly on particular villages or communities. The meso-level analysis (i.e., analysis at intermediate administrative levels like district, tehsil etc.) is limited due to the constraints in collecting data. If attempted, it will be at the district level only. This study went beyond the district and segregated the district population into rural, urban, and social groups. The study contributes to the existing literature in the following ways:

1. Application of a segregated social vulnerability index for the first time for the Indian population. The segregated social vulnerability index facilitated the identification of the dimension to which each district population in India is vulnerable and will aid targeted policymaking.
2. The grouping of vulnerability indices for each state in objective 1 facilitated identification of where the district stands in over all vulnerability in India and where it stands among its neighbouring districts.
3. Spatiotemporal assessment of vulnerability to climate change for three decades, using an integrated approach for the first time globally.
4. Identifying rural-urban disparity in vulnerability to climate change for the first time in India. This will aid identification of priority areas for targeted interventions.
5. Identification of spatiotemporal pattern of agricultural vulnerability for the first time globally. The pattern of vulnerability and its components is identified to understand where the focus of policymakers is required. The major factors contributing to each dimension of vulnerability are also identified. Usage of spatial autocorrelation techniques help identify the changes in clustering pattern of vulnerability.

6. Identification of vulnerability of social groups within a population for the first time. It identified the most vulnerable social groups in each district and to which dimension of vulnerability they are more vulnerable.

8.3 Limitations of the study and directions for future research

- Lack of data in other databases for rural and urban areas and social groups in a district led to the usage of population census in 3 out of 4 objectives. Population census is the most comprehensive database for a population of a particular area and is the only data source that facilitates a temporal analysis. The delays in collecting the population census 2021 due to COVID-19 restricted the data available up to 2011 only. The study can be updated once the data becomes available.
- The segregation of districts during the study period (1991 to 2011) and the lack of data at lower levels for age groups, disabled population, houseless population etc., constrained its usage in spatiotemporal assessment. However, they are considered as important indicators of vulnerability. Census 1991 has not collected data on assets of households like TV, radio, two wheeler, four wheeler etc. Hence, they are also omitted from the spatiotemporal analysis.
- The lack of data for many essential variables in the agriculture sector, like mechanization, roads, markets etc., led to the omission of these variables. Moreover, the last decade could be calculated only for 6 years (2010-15) due to the non-availability of data for certain variables considered.
- In the fourth objective, the population in each district is grouped into three social groups: SC, ST and Non SC/ST. The Non SC/ST groups include information about several population groups, including the social groups other than SC and ST and religious minorities in India. Generally, the surveys conducted by National Sample Survey

Organization and other agencies collect data from Other Backward Caste (OBC) groups with lower socioeconomic backgrounds than upper caste Hindus. As the data on OBC is not available separately in the Census of India (2011), this study could not identify whether the vulnerability of OBC to climate change differs from other social groups. The study can be advanced further if a data source with separate data for SC, ST, OBC, and others is used.

- The lack of availability of agriculture census data for ST of Bhind constrained the calculation of AVI, CSVI and CVI of ST in this district. Though the district is classified as very high in the climate index, the CVI of ST in that district could not be calculated due to the lack of data for variables of AVI. The CVI of this social group can be calculated once the data becomes available.
- The assessment at the district level gives a clearer picture of vulnerability than state-level aggregated data. It discusses the vulnerabilities within rural and urban areas of districts and social groups within districts. However, it could not accurately represent the ground-level reality at the community or household levels. The aggregation of data at the meso level and the lack of current data necessitates the urgent need for detailed ground-level studies in the highly vulnerable districts of Madhya Pradesh. However, this is beyond the scope of this thesis and can be attempted in future.

8.4 Policy suggestions

As the study found an increase in the climate vulnerability index in recent decades attributed to the increase in climate index, future planning of cropping patterns and other developments in the agriculture sector should be conducted in accordance with the climatic projections by Mishra et al. (2016) and others. Early warning of extreme climate events, access to insurance, providing appropriate relief for losses, adjusting planting timing, breeding crops suitable for changed climatic conditions, etc., can reduce the impacts of high exposure.

As climatic exposure has increased over the years, reducing social vulnerability is the best possible solution to reduce overall vulnerability to climate change in the coming decades. Therefore, policy efforts should be directed towards reducing socioeconomic, infrastructural, and agricultural vulnerability, the three dimensions of social vulnerability mentioned in this study.

The study found the increased population growth rate as an important factor contributing to vulnerability in Madhya Pradesh and other states of India, especially the EAG states. The higher population growth will lead to a shortage of resources and affect public access to education and employment opportunities in an area. The encouragement in the usage of birth control measures by the state and central governments could reduce the population to an extent. Increasing the age of marriage and reducing the gender gap in education could control the growth of the population and will also reduce the burden of economic dependence on the working-age population. NFHS (2015–16) and GOI (2020) found that Indian states having a better sex ratio have more educational and health facility access among women and a higher mean age of marriage and age at first childbirth, leading to less population growth. Hence, the measures to reduce gender gaps in education, work participation and better access to health facilities can reduce this issue to an extent. Controlling population growth can also aid in lowering dependence on the agriculture sector.

The higher morbidity and mortality among the children and elderly during exposure to extreme events makes them more vulnerable to climate change. This could be reduced to an extent by effective penetration of public health insurance among these groups. Improving access to education, especially for women, would help diversify livelihood and increase awareness of climate change. Educated people can be better informed about the impacts of climate change, thus reducing their vulnerability. In addition, their existent vulnerability will be less as they are more prone to be employed in sectors other than agriculture. The government of Madhya Pradesh has initiated schemes such as Ladli Laxmi Yojana, Beti-Bachao, Beti-Padhao scheme, and scholarships to girls to improve access to female education in the state (GoMP, 2023). These schemes could improve the literacy rate of women and reduce child marriages to an extent, as reflected in the latest National Family Health Survey (NFHS-5). Further strengthening of these programmes will enable a better reduction of the gender gap in education. The reduction in child marriages can lead to a reduction in childbirth. Lack of education remains a major constraint in extending agricultural extension activities, especially for tribal farmers. Enhancing access to education among tribal areas could also reduce their social vulnerability.

Higher agriculture sector dependence is the other factor contributing to vulnerability. In recent decades, the share of marginalized communities and the female population among marginal workers has increased. Lack of literacy and the gender gap in literacy are the primary reasons behind the increasing share of marginal workers. The losses in the agriculture sector, as well as forestry and short-term migration to urban areas, also add to this issue. Livelihood diversification policies and increased educational facilities and skills training can somewhat solve this issue. Strengthening programs like MGNREGA (Mahatma Gandhi National Rural Employment Guarantee Program), TPDS (Targeted Public Distribution System), skill development programs of state government like Mukhya Mantri Kaushalya Yojana, Mukhya Mantri Kaushal Samvardhan Yojana and ensuring its reach to the most vulnerable is a necessity.

A balanced development of the agriculture sector in the districts of Madhya Pradesh is essential to reduce its vulnerability to climate change. The districts identified as highly sensitive to climate change, like Balaghat and Mandla, follow the monocropping of paddy, and other crops like wheat, oilseeds, and chickpeas are less in these districts. Moreover, they are tribal districts with a high share of small and marginal farmers. This monocropping leads to groundwater depletion and adds further to the impacts of climate change. Diversification of crops and other agri-allied sectors, such as poultry and animal husbandry, should be promoted to reduce the higher sensitivity of these districts.

The states identified as most vulnerable are found to possess low technological interventions in agriculture (Dutta et al., 2020; Shevalkar, 2020). Madhya Pradesh also stands second in states with the largest share of regions with disadvantaged agriculture. Promoting technological interventions in agriculture in the least developed districts can build adaptive capacity and hence aid in vulnerability reduction. Low access to land is another major factor contributing to the vulnerability of the agriculture sector, especially among the scheduled castes in the state. Cooperative farming or similar policy measures to consolidate land and farming at a large scale could reduce the marginalization of holdings.

Greater attention to crops like wheat and soybean reduces millet cultivation, the staple food of tribal populations in many parts of the state, leading to malnutrition. Moreover, the usage of groundwater, fertilizer, etc, for these crops adds to the impacts of climate change. Encouraging the cultivation of drought-tolerant millets can reduce the problems of malnutrition and food insecurity, and it may aid in the reduction of climate change impacts.

The tribal population depends mainly on forest-based products; hence, the adverse impacts of climate change on forests affect their livelihood and income. The gap in the selling prices for forest products and the buying price of food items is the primary reason for the higher incidence of poverty among forest dwellers. The introduction of adequate marketing facilities for tribal products like NTFPs in collaboration with tribal cooperative societies, skill training for livelihood diversification, etc., can aid livelihood diversification among these groups.

Climate change-induced migration or migration during off-seasons in agriculture contributes to vulnerability, especially the women left behind. Livelihood diversification, skill training for off-season jobs, enabling access to land rights among the women left behind, etc., can reduce vulnerabilities resulting from migration.

Though the studies specifically on Madhya Pradesh (Objectives 2 to 4) indicate that urbanization reduces vulnerability, the national level assessment in objective 1 indicates that the higher population density and higher share of houseless population in urban areas contribute to its vulnerability. The migration from rural areas adds to the stress of cities, so proper policy measures to manage the distress migration should be undertaken.

Increasing the infrastructural quality like housing, access to drinking water, sanitation, and electricity could improve the population's living standard, and increasing the asset status would make them resilient to the impacts of climate change. GoI has been focusing more on infrastructure development through schemes such as the Jal Jeevan mission, PM -Surya Ghar Yojana, Pradhan Mantri Awas Yojana, Pradhan Mantri Ujjwala Yojana, etc. As the Madhya Pradesh population faces higher infrastructural vulnerability than socioeconomic vulnerability, a higher focus is required on enhancing access to this.

The state suffers from disparities in the development of regions, disparities among social groups and gender-wise disparities. Effective coping with climate change can only be possible when effective policy measures are introduced to reduce these disparities. The study has noted a higher concentration of vulnerability among rural and urban areas in southwestern, eastern and northern parts of the state. Policy interventions should be framed to enhance development in these peripheral districts characterized by tribal dominance, high concentration of poverty, low educational attainments, higher mortality rates, low technological interventions, and low access to infrastructure and basic facilities. As the share of women as marginal workers is increasing due to gender disparity in education and land ownership, educational and skill development policies and legislation regarding land access should target women. Targeted policy interventions are essential for improving access to infrastructure, livelihood diversification, and access to education in tribal areas, which have been initiated under various schemes of state and central governments. Effective implementation and proper monitoring of these policy measures are required to ensure that they reach the targeted population quickly.

8.5 Conclusion

The study has identified an urgent need for interventions in socioeconomically backward districts of EAG states, including Madhya Pradesh, mainly located in the eastern and central zones of India. The state of Madhya Pradesh is facing higher exposure to climate change, and more than half of its population is socially vulnerable compared to other states of India. Though social vulnerability is decreasing in the state over the decades, exposure to climate change is significantly increasing. Hence overall vulnerability can be reduced only by reducing socioeconomic and infrastructural vulnerability. The socioeconomic and infrastructural vulnerability can be reduced by focusing more on its main drivers. As agricultural and allied sector dependence is identified as the main driver of socioeconomic vulnerability in India, proper adaptation measures in the agricultural sector, livelihood diversification, and skill development could reduce the excessive dependence in this sector. Strengthening the employment assurance programs, and skill development programs and ensuring its reach to the most vulnerable is a necessity. educational and skill development policies targeted on women and marginalised sections can reduce vulnerability of these sections of society. Increasing the infrastructural quality like housing, access to drinking water, sanitation, and electricity could improve the population's living standard, and increasing the asset status would make them resilient towards climate-related impacts. Effective implementation and proper monitoring of these policy measures are required to ensure that they reach the targeted population quickly. Policy efforts should be also be directed towards decreasing disparities in development of agriculture sector. Thus, the study advocates for reducing social vulnerability of the population in Madhya Pradesh, with a special focus on marginalised sections, in the context of increasing exposure to climate change.

Appendix A

Table A.1 Disparities in socioeconomic characteristics of rural and urban population

Socioeconomic characteristics	Total State population	Rural population	Urban population
Sex Ratio	931	936	918
Literacy rate	69.3	63.9	82.8
Gender gap in Literacy rate	19.5	22.3	12.2
Work Participation Rate	43.5	47.0	34.2
Gender gap in work participation rate	21	15	36.6
Percentage of main workers among total workers	71.9	67.7	87.1
Percentage of marginal workers among total workers	28.1	32.3	12.9
Access to electricity	67.1	58.3	92.7
Access to safe drinking water	72.2	68.9	81.8
Access to latrine within premises	28.8	13.1	74.2

Source: GoI, 2011

Table A.2 Socioeconomic Characteristics of Social Groups in Madhya Pradesh

Socioeconomic characteristics	Total state population	SC	ST	Non SC/ST
Percentage of social group in total population	100	15.6	21.1	63.3
Percentage of social group residing in rural area	72.4	72.9	93.2	65.3
Sex Ratio	931	920	984	917
Literacy rate	69.3	66.2	50.6	76
Gender gap in Literacy rate	19.5	22	18.1	18.9
Work Participation Rate	43.5	43.6	49.9	41.3
Gender gap in work participation rate	10.8	18.4	6.7	26.5
Percentage of marginal workers among total workers	28.1	31	36.3	24
Percentage of workers depending on agriculture sector	69.8	67.2	87.6	63.3
Access to electricity	67.1	65.2	54	72.1
Access to safe drinking water	72.2	75.5	68.3	72.6
Access to latrine within premises	28.8	20	8.5	38.2

Source: GoI, 2011

Table A.3 Agriculture sector dependence among different social groups of Madhya Pradesh

Name	Percentage of population depending on agriculture sector			
	District Population	SC	ST	Non SC/ST
Sheopur	69.8	80.4	89.2	75.9
Morena	80.0	63.2	74.9	68.0
Bhind	67.0	75.1	44.0	74.9
Gwalior	74.8	38.0	66.8	34.5
Datia	36.6	77.7	66.1	76.8
Shivpuri	76.8	81.0	85.3	77.9
Tikamgarh	79.5	78.7	81.9	81.5
Chhatarpur	80.8	69.5	77.7	72.3
Panna	71.9	77.7	80.3	76.4
Sagar	77.4	46.5	80.4	58.1
Damoh	57.9	55.5	77.4	62.9
Satna	63.5	63.2	78.2	63.3
Rewa	65.8	75.0	84.0	69.7
Umaria	72.8	65.9	79.2	66.4
Neemuch	72.9	73.5	87.0	73.1
Mandsaur	74.5	88.1	87.4	78.5
Ratlam	80.6	80.3	93.3	64.9
Ujjain	75.9	73.7	73.1	62.4
Shajapur	65.9	88.3	88.1	80.1
Dewas	82.3	78.6	92.8	71.6
Dhar	76.9	73.6	92.2	60.7
Indore	80.1	29.4	59.8	22.4
Khargone	26.5	82.2	93.9	72.2
Barwani	82.0	77.4	94.4	55.0
Rajgarh	84.9	84.7	87.6	81.9
Vidisha	82.6	75.7	80.3	70.5
Bhopal	72.1	27.1	23.1	19.2
Sehore	20.6	78.8	87.0	68.8
Raisen	73.1	71.4	85.3	66.8
Betul	70.8	65.4	89.0	68.6
Harda	77.7	70.6	90.3	63.3
Hoshangabad	73.3	59.9	79.5	58.2
Katni	62.4	58.0	74.0	57.3
Jabalpur	61.9	36.2	72.5	30.2
Narsimhapur	38.8	79.2	89.5	74.7
Dindori	77.8	81.7	91.6	78.8
Mandla	87.5	67.3	91.6	71.4
Chhindwara	83.6	61.1	86.3	66.0

Seoni	73.7	72.6	89.7	74.2
Balaghat	80.4	60.0	87.6	80.0
Guna	80.4	73.3	90.9	72.4
Ashoknagar	75.7	78.7	87.2	73.1
Shahdol	75.9	69.2	82.8	59.2
Anuppur	72.0	62.3	82.9	54.9
Sidhi	71.0	70.5	86.5	76.7
Singrauli	79.0	71.4	87.4	68.2
Jhabua	75.3	43.0	92.2	41.1
Alirajpur	86.4	74.9	94.5	24.7
Khandwa	90.0	75.1	93.3	69.8
Burhanpur	79.3	67.7	95.1	51.3
Madhya Pradesh	**69.8**	**67.2**	**87.6**	**63.3**

Source: GoI, 2011

Table A.4 Distribution of operational holdings of different social groups by group size

Social Group	Year	Marginal	Small	Semi medium	Medium	Large
SC	2000-01	48.6	28.5	16.2	6.2	0.5
	2005-06	52.1	28.4	14.3	4.8	0.3
	2010-11	55.6	27.8	12.6	3.8	0.2
	2015-16	59.0	26.9	11.2	2.9	0.1
ST	2000-01	36.1	27.4	22.3	12.3	1.7
	2005-06	38.5	28.2	21.2	10.8	1.3
	2010-11	42.0	28.7	19.6	8.7	0.9
	2015-16	47.0	27.8	17.7	6.9	0.6
Non SC/ST	2000-01	37.5	25.9	20.3	13.6	2.7
	2005-06	38.7	26.6	20.5	12.3	1.9
	2010-11	42.3	27.2	19.5	9.9	1.2
	2015-16	46.9	27.1	17.4	7.8	0.7

Source: Computed from Agricultural Census database

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