Assessing Climate Change Vulnerability of Tribal Livelihoods in Madhya Pradesh, India: A Multi-Dimensional Approach

Ph.D. Thesis

By

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SCHOOL OF HUMANITIES AND SOCIAL SCIENCES

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Assessing Climate Change Vulnerability of Tribal Livelihoods in Madhya Pradesh, India: A Multi-Dimensional Approach

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Submitted in partial fulfillment of the requirements for the award of the degree
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Amit Kumar

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Dedicated To

My Family

INDIAN INSTITUTE OF TECHNOLOGY INDORE

I hereby certify that the work which is being presented in the thesis entitled **Assessing Climate Change Vulnerability of Tribal Livelihoods in Madhya Pradesh, India: A Multi-Dimensional Approach** 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 2022 to May 2025 under the supervision of Dr. Mohanasundari Thangavel, Assistant Professor, and School of Humanities and Social Sciences, 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.

Amit Kumar 26/05/2025

Signature of the student with date

Amit Kumar

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

T. MOS 26/05/2025

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Amit Kumar has successfully given his/her Ph.D. Oral Examination held on **26th May 2025**.

T. MOS 26/05/2025

Signature of Thesis Supervisor with date

Dr. Mohanasundari Thangavel

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NOMENCLATURE

CH_4	Methane
CO_2	Carbon dioxide
N_2O	Nitrous oxide
°C	Degree Celsius
β	Coefficient
μ	Mean
σ	Standard deviation
CO_2	Carbon Dioxide

ACRONYMS

CC	Climate Change
IPCC	Intergovernmental Panel on Climate Change
GHG	Greenhouse gases
U.S.	United States
DFID	Department of International Development
LVI	Livelihood Vulnerability Index
ST	Scheduled Tribes
PVTG	Particularly Vulnerable Tribal Group
ENSO	El Niño-Southern Oscillation
VAF	Vulnerability assessment frameworks
CBA	Community-based adaptation
LVI-IPCC	Livelihood Vulnerability Index - Intergovernmental Panel on Climate Change framework
T_{mean}	Mean temperatures
T_{max}	Maximum temperatures
T_{min}	Minimum temperatures
IMD	India Meteorological Department
MK	Mann-Kendall test
SS	Sen's slope estimator
IDW	Inverse Distance Weighted
GIS	Geographic Information System
CV	Coefficient of Variance
mm	Millimeter
EVI	Environmental Vulnerability Index
SVI	Socioeconomic Vulnerability Index
UNDP	United Nations Development Programme
HDI	Human Development Index
SC	Schedule caste
ST	Schedule tribe
CVI	Composite Vulnerability Index
ITA	Innovative Trend Analysis

SPI	Standardized Precipitation Index
BLR	Binary Logistic Regression
MLR	Multiple Linear Regression
NTFP	Non-timber forest product
OR	Odds Ratio
std. errs.	Standard error
VI	Vulnerability index
MGNREGA	Mahatma Gandhi National Rural Employment Guarantee Act
PDS	Public Distribution System
SDG	Sustainable Development Goal

Abstract

Climate change poses significant challenges to marginalised communities, particularly in regions with highly vulnerable populations like rural and tribal communities. These communities, highly dependent on natural resources, are disproportionately affected due to their reliance on agriculture, water resources, and traditional practices. Climate change exacerbates existing problems, such as poverty, illiteracy, poor facilities essential services, with marginalised groups facing the burden of its consequences globally. People with limited resources and adaptive capacity are the most vulnerable to climate risks, especially in developing nations like sub-Saharan Africa, Southeast Asia, and South Asia. The adverse effects of climate change have become more apparent in India. Shifts in monsoon patterns, increasing temperatures, and more frequent extreme weather events such as floods and droughts severely impact agriculture, which remains the primary livelihood for the rural population. Tribal communities in India, which constitute 8.6% of the total population, are among the most vulnerable to these changes. Their livelihoods are directly connected to climate-sensitive resources, including water, forests, and agriculture. Madhya Pradesh, located in central India, where the country's 21.1 % tribal population reside, is witnessing significant climate shifts, including rising temperatures, erratic rainfall, and increased frequency of extreme events. These changes intensified the sustainability of agriculture and access to water, which is essential for the tribal livelihood in this region.

Despite the significant impacts of climate change on tribal communities, there is a notable gap in multidisciplinary analyses that integrate tribal people's perceptions with scientific approaches. Previous studies on climate change mostly concentrate on smallholder farmers and marginalised populations, with less emphasis on the vulnerability of tribal communities, especially in Madhya Pradesh. Furthermore, most research overlooks the integration of indigenous knowledge in assessing and addressing climate change vulnerability, and limited research has explored these communities' socioeconomic and climatic impacts in this region, majorly with ground data. Therefore, it is necessary to understand the complex relationship between climate change and the vulnerability of tribal livelihood at the ground level. This study examines the climate dynamics, climate change vulnerability at the regional scale, perception on climate change impacts, and tribal livelihood vulnerability to climate variability in Madhya Pradesh from their perspectives through secondary and primary information. The primary objectives are (a) exploring the Spatiotemporal Climatic Dynamics of Madhya Pradesh using Long-Term Gridded Data (1951-2021), focusing on temperature and precipitation patterns, (b) assessing district-level climate vulnerability in Madhya Pradesh, central India, integrating environmental and socioeconomic approach, (c) understanding the perceptions of climate change and its impacts among tribal communities in Chhindwara and Dhar, and analyse how these perceptions influence their livelihood strategies, and (d) evaluating the livelihood vulnerability to climatic variability among tribal communities in Chhindwara and Dhar, and identify the major socioeconomic and environmental determinants of their vulnerability.

This study employs a mixed-methods approach, combining both quantitative and qualitative data. Gridded data from the India Meteorological Department (IMD) is used to analyse climate patterns (temperature and rainfall) from 1951 to 2021. The Mann-Kendall test, Sen's slope estimator, and Pettitt's test were applied to detect trends and identify change points in the climatic data. Inverse distance weighting methods allow for examining spatial changes, revealing the geographical distribution of certain climatic variables. The environmental (8 indicators) and socioeconomic (5 indicators) data were collected from various secondary sources for the district-level vulnerability assessment. The data is analysed using an indicator-based approach, normalisation, weighting, and developing vulnerability indices. This section is structured in three parts: Environmental Vulnerability Index (EVI), Socioeconomic Vulnerability Index (SVI), and Composite Vulnerability Index (CVI). Furthermore, Innovative Trend Analysis (ITA), Standardised Precipitation Index-3 (SPI-3), household surveys, binary logistic regression, and multiple linear regression were used to correlate perceived changes in rainfall and temperature with climatic trends and the socioeconomic determinants influencing these perceptions in Dhar and Chhindwara districts. Primary data collection involved a multistage sampling procedure where a household survey was conducted across both districts, yielding a sample size of 535 households from 53 villages (27 villages from Dhar and 26 villages from Chhindwara). A Livelihood Vulnerability Index-Intergovernmental Panel on Climate Change (LVI-IPCC) framework was applied using survey data to assess livelihood vulnerability and, once again, the Multiple Linear Regression model to determine the determinants of livelihood vulnerability.

Long-term climatic data analysis reveals significant temperature and precipitation trends in Madhya Pradesh, worsening agricultural challenges, water scarcity, and health risks. The rainfall showed declines in annual ($Z = -1.023$), monsoon ($Z = -0.933$), winter ($Z = -0.764$), and post-monsoon seasons ($Z = -0.735$), while pre-monsoon rainfall exhibited an increasing trend ($Z = 0.288$). The analysis illustrated a consistent increase in T_{mean}, T_{max}, and T_{min} across all seasons, with significant differences in different areas. The change point analysis identified shifts in rainfall patterns in 1998 (monsoon, annual), 1955 (pre-monsoon), 1987 (post-monsoon), and 1986 (winter). The annual temperature, with T_{mean} rising from 25.45 °C in 1951-2004 to 25.77 °C in 2005-2021 (+0.32 °C), T_{max} shifting from 45.77 °C in 1951-2010 to 46.24 °C in 2011-2021 (+0.47 °C), and T_{min} increasing from 2.65 °C in 1951-1999 to 3.19 °C in 2000-2021 (+0.46 °C). Spatiotemporal distribution maps depicted irregular rainfall, with some areas experiencing

drastic declines in rainfall after 1998. Maximum average annual rainfall reduced from 1769 mm to 1401 mm after 1998, affecting water availability.

The district-level climate vulnerability analysis presented that districts with a lower CVI (0.321 - 0.378), such as Gwalior, Jabalpur, and Bhopal, exhibited decreased vulnerability because of a lower level of climatic extremes affected areas, reduced percentage of socially deprived population and a higher value of HDI. Districts with medium CVI (0.381 - 0.407), such as Damoh, Indore, and Shahdol, exhibited moderate resilience. On the other hand, districts with high (0.409 - 0.402) and very high CVI (0.448 - 0.540), such as Narsimhapur, Betul, Balaghat, Chhindwara, Alirajpur, and Barwani, faced higher vulnerability because of factors such as dependence on agriculture, a higher proportion of socially deprived population, occurrences of droughts and floods. Hierarchical cluster analysis validated vulnerability classifications, enhancing the credibility of assessments.

The tribal communities are highly vulnerable to climate change, primarily due to their dependence on rainfed agriculture, limited access to water resources, and socioeconomic constraints. Tribal communities' perceptions reflected observed climate changes, with over 90% of respondents observing erratic rainfall and summer days becoming hotter in the Dhar and Chhindwara districts. The binary logistic regression results revealed that education, occupation, and access to infrastructure appeared as essential determinants of climate change perception, with disparities between the districts (Pseudo R^2 = 0.2584 & 0.3286). Moreover, the multiple linear regression model demonstrated that socio-demographic factors, such as income and occupation, significantly influenced perceptions of climate change impacts on agricultural productivity, water availability, and health risks.

The LVI-IPCC results showed moderate vulnerability among surveyed households, with Dhar exhibiting higher vulnerability than Chhindwara. Furthermore, LVI-IPCC results were validated using other vulnerability

assessment approaches. Multiple linear regression analysis highlights the significant influence of key determinants, such as primary income source, extreme weather events, access to safe drinking water, and livelihood strategies, on vulnerability, emphasising the importance of addressing socioeconomic disparities and enhancing adaptive capacity.

The findings highlight the urgent need for targeted policies to address the livelihood vulnerabilities of tribal communities in Madhya Pradesh. Policymakers must prioritise including tribal communities in climate change adaptation efforts to ensure policies are tailored to improve their livelihoods. This study offers a comprehensive assessment of livelihood vulnerability to climate change among tribal communities in Madhya Pradesh. Combining scientific climate data with tribal people's perceptions and livelihood assessments provides valuable insights into these communities' challenges. It ~~also~~ calls for collective efforts between academicians, policymakers, and tribal communities to develop sustainable climate-resilient frameworks that protect the livelihoods of those most at risk from climate change.

Keywords: Climate change, Spatiotemporal analysis, Tribal communities, Tribal perception, Cluster analysis, Environmental Vulnerability Index, Socioeconomic Vulnerability Index, Livelihood vulnerability, Tribal vulnerability, Vulnerability assessment, Madhya Pradesh, Central India

Chapter 1

Introduction and Literature Review

1.1 Prologue

Climate change has emerged as a universal challenge of the 21st century that threatens ecosystems, economies, and societies (Abbass et al., 2022; Birkmann et al., 2022; Kuniyal et al., 2021). It has a severe impact on marginalised communities, especially in developing nations like India, Bangladesh, Nepal, Brazil, and African countries, since these regions are more exposed to climatic disasters and cannot adapt (Ahmad et al., 2018), because of higher dependency on natural resources for their livelihoods (Patel et al., 2020; Abbass et al., 2022; Rawat et al., 2024). Tribal communities, primarily residing in ecologically sensitive areas, are among the most vulnerable groups due to their reliance on climate-sensitive activities such as agriculture and forestry, limited resource access, and socioeconomic marginalisation (Kahane et al., 2013; Raj et al., 2022). Agriculture, the primary livelihood source for these communities, is highly vulnerable to climate variability, with an increased risk of crop failure, reduced yields, and degradation of land resources (Saleem et al., 2024). Moreover, the lower capital to spend on climate-resilient agricultural practices, such as crop diversification, irrigation, and soil conservation, further increases these communities' climate-related challenges (Mishra et al., 2019; Singh & Chudasama, 2021). So, understanding the vulnerability of these communities to climate change and variability is essential for developing effective adaptation and resilience strategies.

As per the Global Climate Risk Index 2019, released at the Climate Summit (COP 24) in Katowice, Poland, India is ranked 14th among the world's most vulnerable nations to climate change (Joshi & Rawat, 2021). In India, where tribal communities constitute 8.6% of the total population (Balkrishna et al., 2024), Madhya Pradesh is home to 21.1% of the tribal population to the country's total tribal population whose livelihoods are linked to the natural environment (Yadava & Sinha, 2020). The region has experienced significant climatic shifts, including uneven rainfall and rising temperatures, negatively affecting its tribal populations (George et al., 2023). This study investigates the livelihood vulnerability of tribal communities in Madhya Pradesh. It adopts a multidimensional framework to assess vulnerability, integrating environmental, socioeconomic, and institutional factors, using both primary as well as secondary data.

This study focuses on the districts of Dhar and Chhindwara, tribal-dominated districts, where tribal communities are deeply connected to agriculture and natural resources for their daily livelihoods. These regions are more vulnerable to climate-induced risks due to their dependence on rainfed agriculture, limited adaptive capacities, and socioeconomic limitations. The research addresses major gaps in existing studies by exploring the physical impacts of climate variability and the socioeconomic determinants of vulnerability. By combining empirical data with a robust analytical framework, this study provides valuable insights into the challenges faced by tribal communities and identifies pathways for enhancing their adaptive capacity. The findings inform policy interventions prioritising sustainable development and climate resilience for marginalised populations. This thesis serves as a step toward understanding and addressing the livelihood vulnerabilities of tribal communities to climate change, calling the urgent need for inclusive and targeted strategies to ensure their sustainable livelihoods in these changing climatic scenarios.

1.2 Thesis Organisation

This thesis has been written to present detailed information on the background, objectives, methodology, findings, policy suggestions, limitations of the research carried out, and the scope for future research based on the experience gained while conducting the research. In the present study, emphasis has been placed on tribal livelihood vulnerability to climate change and variability in Madhya Pradesh. This thesis has been organised into six chapters. Ongoing **Chapter 1** presents a brief discussion about the impact of climate change, the concept of vulnerability, and the association of tribal livelihoods. It also provides vulnerability indicators, assessment models and tools, case studies with applications, adaptation and resilience strategies, and challenges previous researchers faced. Based on the lacunae in the literature, the research questions, objectives and methodology of the current study are explained in this chapter. The Spatiotemporal Climatic Dynamics of Madhya Pradesh using Long-Term Gridded Data (1951-2021), focusing on rainfall and temperature patterns, is described in **Chapter 2**. **Chapter 3** assesses district-level climate vulnerability in Madhya Pradesh, central India, integrating environmental and socioeconomic approaches. **Chapter 4** focuses on the perceptions on climate change and its impacts among tribal communities in Chhindwara and Dhar and analyses how these perceptions influence their livelihood strategies. The livelihood vulnerability to climatic variability of tribal communities identifying their vulnerability's major socioeconomic and environmental determinants is presented in **Chapter 5**. **Chapter 6** summarises this study's major findings, limitations, scope for future research and policy suggestions.

1.3 General Aspects

Climate change (CC) describes long-term shifts in temperature, precipitation patterns, and other atmospheric variables on Earth (Kuniyal et al., 2021; Singh et al., 2024). This occurrence has been mainly caused by human activity, specifically releasing of greenhouse gases (GHGs) such as methane (CH_4), carbon dioxide (CO_2), and nitrous oxide (N_2O) (Li et al., 2024). The Intergovernmental Panel on Climate Change (IPCC) has projected that the global temperature will increase by 1.5 °C by the end of the 21st century, which will have profound consequences for natural and human systems (Phuong et al., 2023). These extensive changes are affecting environments and communities globally.

1.3.1 Concepts

Climate change: "Climate Change is a change in the climate's state that persists for decades or longer" (IPCC, 2021). CC agrees with the warming trend, variability proposes complexity and unpredictability in weather events (Scafetta, 2024).

Climate variability: Climate variability discusses short-term variations in climate constraints around the long-term mean, including phenomena like El Niño and La Niña, which cause significant fluctuations in weather patterns over seasons and years (Lee et al., 2022; Singh et al., 2023).

Vulnerability: The IPCC's 4th assessment report specifies vulnerability as "the degree to which a system is susceptible to and unable to cope with adverse effects of climate change, including climate variability and extremes. Vulnerability is also a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity" (IPCC, 2007; Kasthala et al., 2024). In the 6th assessment report, vulnerability is described 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" (Kasthala et al., 2024).

Livelihood: Livelihood is defined as activities essential to everyday life that are conducted over one's life (Khan et al., 2020). Such activities include securing food, water, shelter, clothing, fodder, and medicine. It reflects a way of life shaped by individual or household capabilities, assets, and productive endeavours (Ahmad et al., 2023).

Adaptation: Adaptation is the process of modifying or adjusting to fit one's environment. It can also be described as the condition of having successfully adapted (Berkhout, 2012).

Mitigation: Mitigation is "the action of reducing the severity, seriousness, or painfulness of something" (Zwahlen, 2022). The United Nations Office for Disaster Risk Reduction defined mitigation as “the lessening or minimising of the adverse impacts of a hazardous event”.

Resilience: As per the United Nations Office for Disaster Risk Reduction, resilience is defined as “the ability of a system, community or society exposed to hazards to resist, absorb, accommodate, adapt to, transform and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions through risk management”.

1.3.2 Impact of Climate Change

CC and variability have significantly affected livelihoods across different geographical areas over various time scales. The United States (U.S.) has faced more frequent extreme hot temperatures and precipitation events, with a fall in extreme cold events, especially in northern regions (Monier & Gao, 2015). Rural communities are more vulnerable than urban areas due to the demographics, literacy, occupations, incomes, prevalence of poverty, and reliance on government funding (Demissie & Kasie, 2017). However, CC effects may vary with region and economic sector, with some rural areas benefiting while others suffer. Climatic conditions in the Northeast U.S. might be advantageous for agricultural and forestry activities, whereas the Southwest and Southeast could face heightened water stress and energy costs, respectively (Lal et al., 2011). It is projected that Latin America, and the Caribbean will experience a mean temperature increase of up to 4.5 °C by the end of the 21st century, compared to pre-industrial (Reyer et al., 2017) due to changed rainfall patterns, heat extremes, drought, and rising sea levels. These changes will influence agriculture, livestock, fisheries, and water resources, although some opportunities, like increased rice yields and fish catch capacity, may rise in specific regions. CC is expected to increase global temperatures past +1.5 °C in the coming decades, potentially boosting summer tourism and reducing electricity demand in Western Europe (Jacob et al., 2018). However, the frequency and intensity of extreme events increased due to CC, directly impacting human health through injuries and fatalities and indirectly through effects on water, food, air quality, mental well-being, productivity, and harm to residential and health services in Australia (Lansbury Hall & Crosby, 2022). Sub-Saharan Africa suffered undernutrition, disease outbreaks, and agricultural vulnerabilities, leading to urban migration and increased food prices due to CC (Serdeczny et al., 2017). Similarly, South Asia faced a lack of freshwater supply, glaciers melting, reduced agriculture productivity, loss of biodiversity, poor human health, extreme weather events, and resource strain due to climate-induced immigration from neighbouring countries (Verma, 2021). Furthermore, increasing mean annual temperatures decrease land productivity for most crops, jeopardising the food safety of India's small and marginal farming households (Praveen & Sharma, 2020).

1.3.3 Impact of Climate Change on Tribal Livelihood

CC is a significant global issue that disproportionately impacts vulnerable communities, especially those reliant on natural resources for livelihood (Sahoo et al., 2023). Tribal communities, often living in environmentally sensitive and marginal regions, are most affected (Kumar et al., 2023). These communities play an essential role in preserving cultural diversity and environmental sustainability (Priyadarshini & Abhilash, 2019). Spread across 90 countries, they constitute over 476 million people worldwide but account for 15% of the world's extreme poor (Malhotra, 2024a; Stewart-Withers & Hapeta, 2023). These communities heavily depend on agriculture, hunting, fishing, gathering, forestry, and other natural resource-based activities, making them highly vulnerable to the detrimental impacts of CC and variability. CC events have been reported to substantially impact the ecosystems crucial for tribal livelihoods (Pratap & Pratap, 2021). As a result, tribal communities face threats to food security, water availability, health, and socioeconomic stability due to CC and retain traditional knowledge and practices for resilience construction (Mallick et al., 2024;

Rahmah & Sulistyono, 2024). Despite their importance, mainstream climate adaptation strategies often overlook these practices.

1.3.4 Vulnerability to Climate Change

CC studies consistently explore the concept of vulnerability as a fundamental and evolving concept. Vulnerability to CC-induced natural disasters is divided into social, physical, economic, and environmental categories (Kasthala et al., 2024). Fig. 1.1 shows the key dimensions influencing the vulnerability of tribal communities to CC. Tribal communities face increased exposure to climate variability due to geographical isolation and inadequate infrastructure, significant sensitivity due to high dependence on climate-sensitive resources, and inadequate adaptive capacity due to socioeconomic constraints, highlighting their exposure to climate impacts.

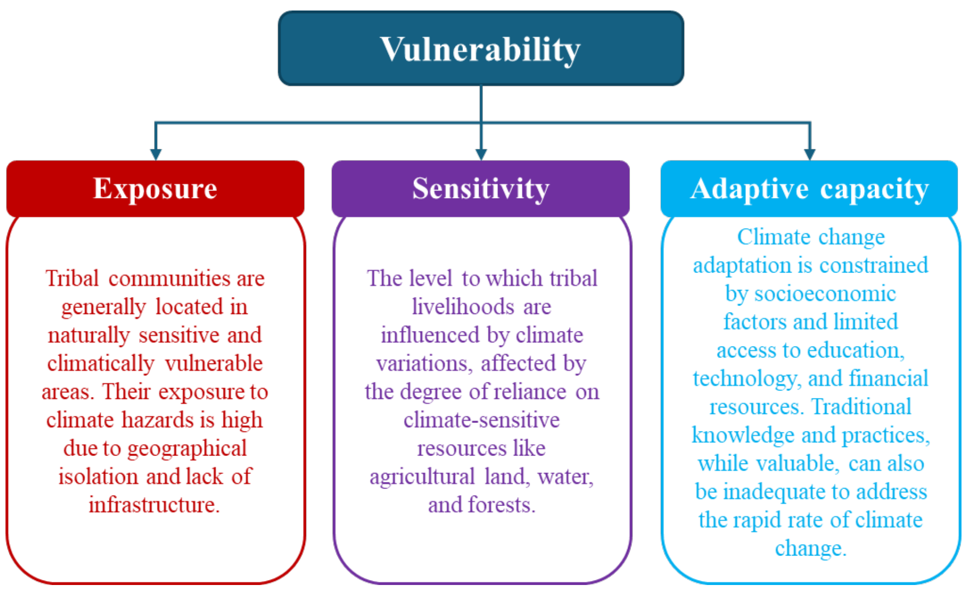


Fig. 1.1: Contributing factors of livelihood vulnerability

The literature on CC vulnerability, while extensive, lacks a focus on tribal livelihood vulnerability assessment in the context of changing climatic conditions (Berrang-Ford et al., 2015; Crane et al., 2017; Kasthala et al., 2024; Kumari et al., 2023; Räsänen et al., 2016; Singh et al., 2017). However, many researchers/scholars still use the Department of

International Development's (DFID) livelihood framework. Expanding on this model, Hahn et al. (2009) developed the Livelihood Vulnerability Index (LVI), a promising indicator-based technique for assessing livelihood vulnerability, incorporating elements from DFID and IPCC frameworks. Furthermore, Reed et al. (2013) incorporated theoretical understanding from analyses of sustainable livelihoods and analytical frameworks to investigate the livelihood vulnerability to CC. Researchers have also explored various methodologies to evaluate livelihood vulnerability; however, the literature lacks a universal framework for all ecosystems and geographies (Kasthala et al., 2024; Kumari et al., 2023). With this research gap, it is necessary to understand and develop a comprehensive framework that can correctly evaluate the vulnerability of tribal livelihoods across various ecosystems and geographies. This framework should combine climatic, socioeconomic, and ecological variables and be acceptable to local contexts. Understanding these nuanced vulnerabilities is essential for designing effective adaptation strategies and policies to mitigate CC's adverse impacts on tribal communities. Therefore, this study investigates the livelihood vulnerability of tribal communities in the context of CC, providing a critical tool for policymakers and practitioners to enhance resilience among these vulnerable populations.

1.4 Tribal Communities: An Overview

1.4.1 Global Perspective

Tribal communities, also known as indigenous peoples, constitute about 5% of the world's population (Das & Basu, 2022) (Fig. 1.2). According to Oxford Advanced Learner's Dictionary, "Tribe is a group of people of the same race, and with the same custom, language, religion, etc. living in a particular area and often led by a chief". Globally, major tribal groups include the Maasai of East Africa, known for their pastoral traditions (Hezron et al., 2024); the Inuit of the Arctic, adapted to extreme cold conditions (Malik & Ford, 2025); the Māori of New Zealand, celebrated for their sustainable practices (Lawrence et al., 2024); and Aboriginal Australians, among the oldest continuous cultures (Baulch, 2024). In the Americas, tribes such as the Navajo, Cherokee, and Quechua hold a wealth of traditional knowledge (Urrieta, 2016).

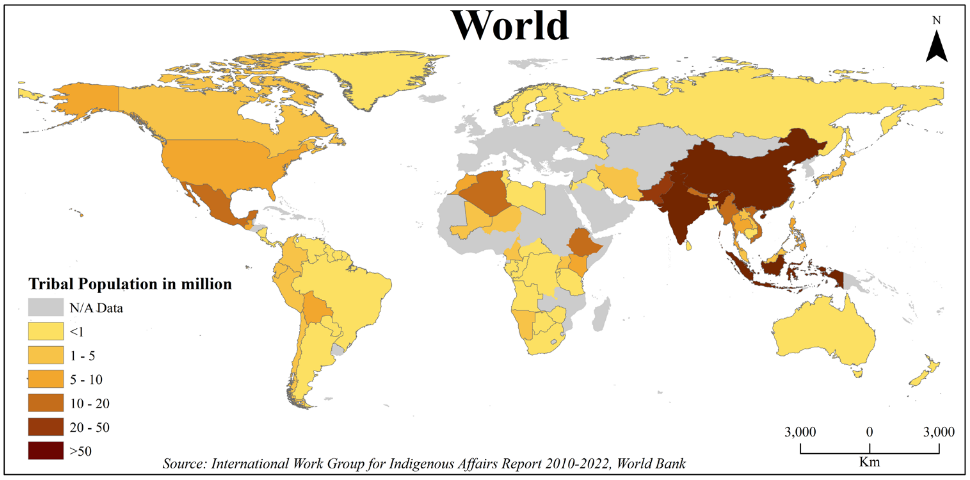


Fig. 1.2: Worldwide distribution of the indigenous population

1.4.2 India

India, home to the world's largest tribal population, has 705 Scheduled Tribes (STs) comprising 8.6% of India's population (Census, 2011) (Fig. 1.3). These communities reside in diverse ecological zones, from the Himalayan highlands to the coastal plains. Major tribal groups include the Bhil, the largest tribe in India, predominantly found in Madhya Pradesh, Rajasthan, and Gujarat (Khan & Thakur, 2023); the Gond, known for their folklore and traditional agricultural practices (Rana, 2024); and the Santhal, concentrated in Jharkhand, Odisha, and West Bengal, with a rich agrarian heritage (Kadariya, 2024). The Naga tribes of the northeastern states, the Baiga of central India, the Toda and Irula of Tamil Nadu, and the Warli of Maharashtra each exhibit unique cultural identities and traditions (Malhotra, 2024b). Tribal people in India experience socioeconomic difficulties, such as reduced literacy rates, poor health care, and relocation because of infrastructure development, even though there are constitutional protections (Kuttiatt et al., 2025). Tribal cultural heritage preservation along with equitable development, are the primary objectives of policies like the Forest Rights Act (2006) and Tribal Sub-Plan.

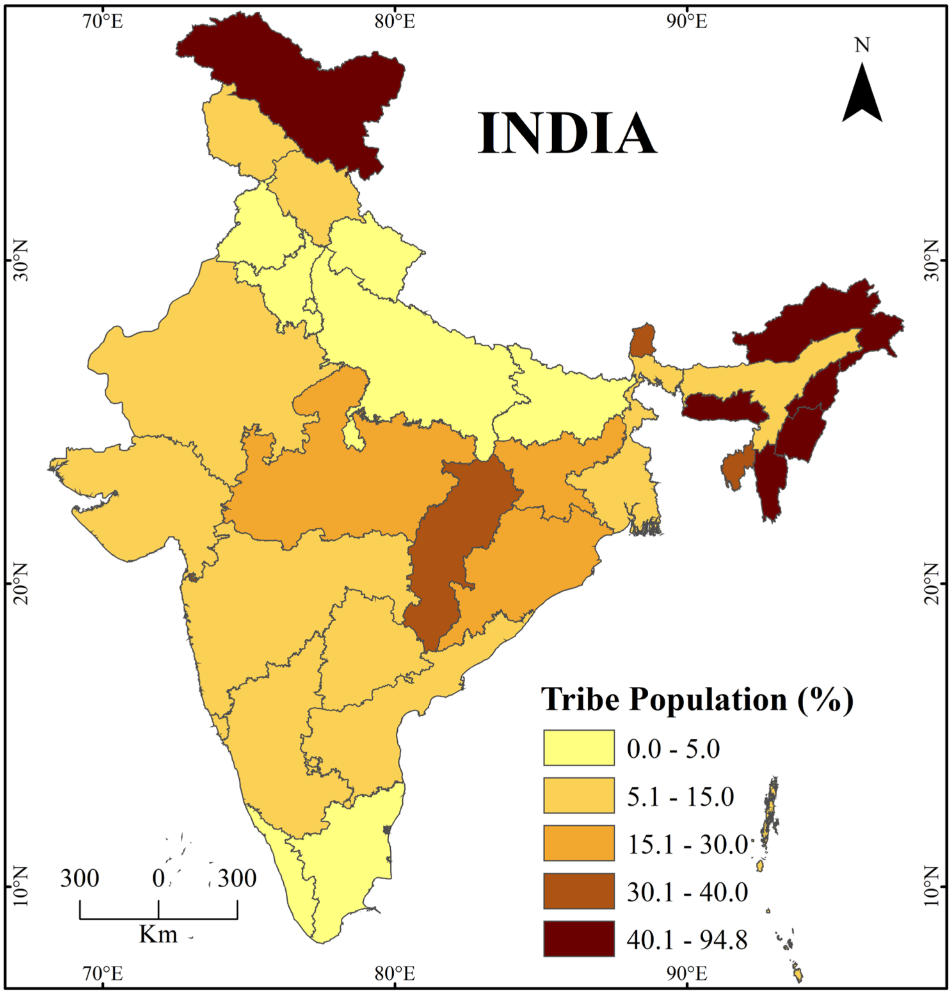


Fig. 1.3: Distribution of tribal population in India

1.4.3 Madhya Pradesh

Madhya Pradesh, also known as the "tribal heartland" of India, has the largest number of tribal populations in the nation, comprising over 21% of the state's population (Census, 2011) (Fig. 1.4). The state is home to various tribal communities, including the Bhil and Bhilala, who mostly live in the Dhar, Jhabua, and Alirajpur districts and rely on agricultural and forest resources (Hariwal et al., 2024). The Gond, who live in Mandla, Chhindwara, and Betul, are recognised for their art and culture (Malhotra, 2024b). Similarly, the Baiga, a Particularly Vulnerable Tribal Group

(PVTG), practised traditional agricultural practices (Patidar et al., 2020) in Mandla and Dindori districts. Other tribal groups include the Korku, living in the Satpura hills and recognised for their sustainable farming practices (Kala, 2022); the Sahariya of Gwalior and Chambal regions, dependent on forest produce and seasonal labour (Swarnkar, 2023); and the Kol, concentrated in Rewa and Satna, who primarily work as agricultural labourers (Kumar, 2013).

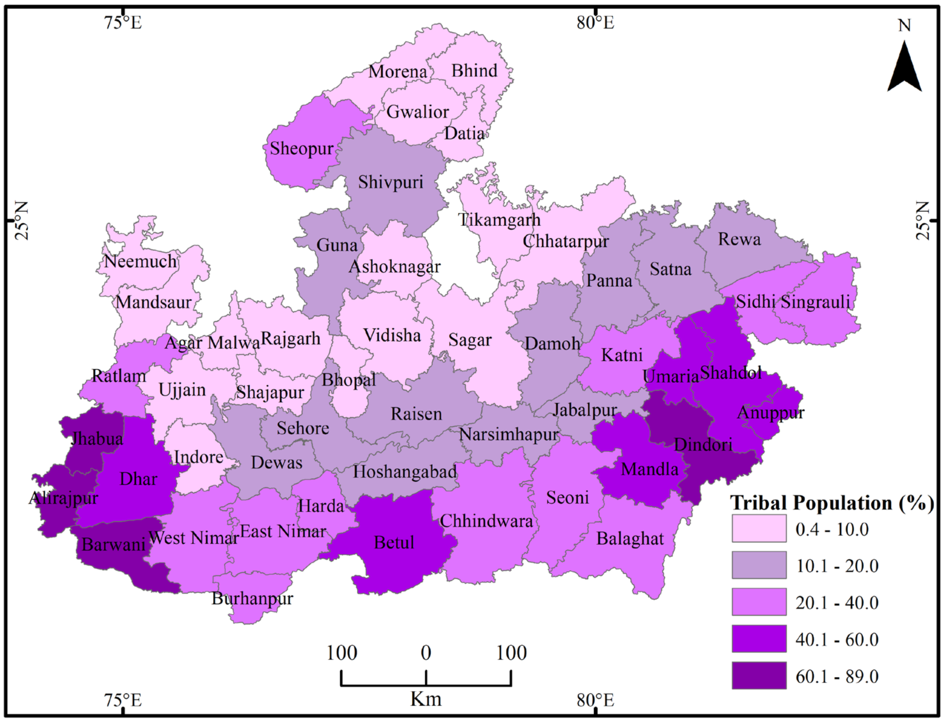


Fig. 1.4: Distribution of tribal population in Madhya Pradesh

1.4.4 Characteristics of Tribal Communities

The basic characteristics of tribal communities are shown in Fig. 1.5. However, these communities face several challenges that hamper their development and well-being. Geographic isolation confines their access to essential services such as education, healthcare facilities, and markets, leaving them disadvantaged compared to others (Ramya & Chaudhuri, 2024). Several environmental challenges, such as deforestation, land degradation, and biodiversity loss, faced by tribal communities (Kumar et al., 2022) have been intensified by colonial and post-colonial policies that often marginalised them and limited their access to traditional lands and resources (Chiweshe, 2023). The CC impacts add another layer of difficulty, threatening the sustainability of their traditional livelihoods (Parrotta & Agnoletti, 2012). The depletion of natural resources and shifting climatic patterns have disrupted their traditional livelihoods, forcing them to migrate for alternative employment (Singh, 2023).

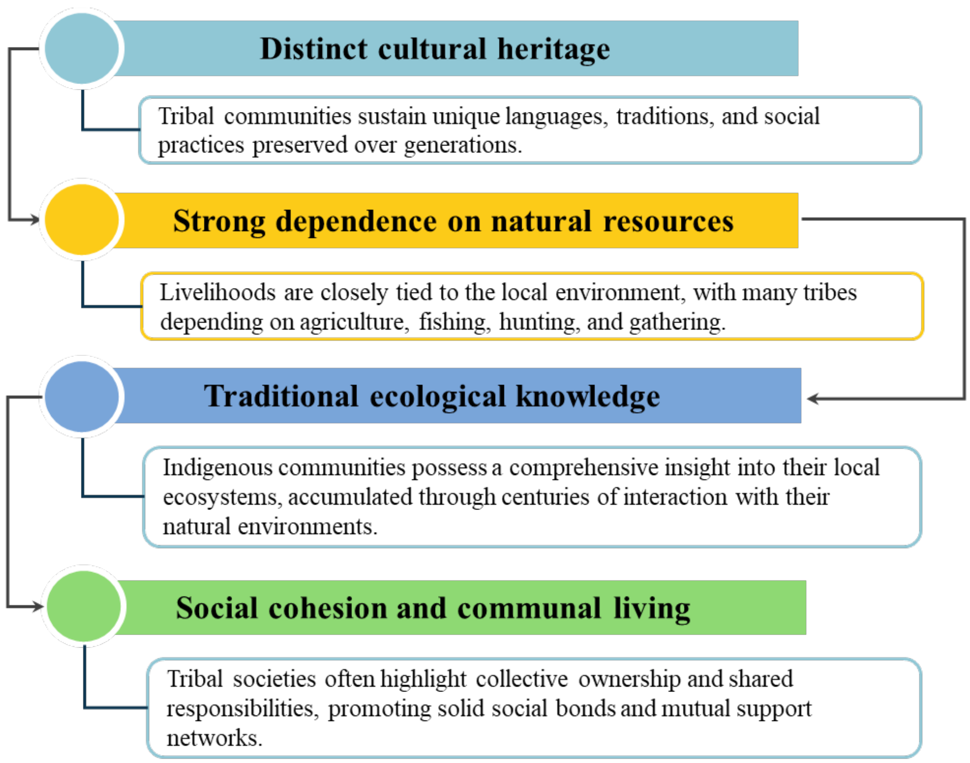


Fig. 1.5: Common characteristics of tribal communities

Furthermore, the lack of adequate representation in decision-making processes excludes their demands and goals in development planning (Bansal et al., 2024). There is great ethnic diversity that appears in the broad range of economic opportunities among tribal groups in India. In many developing countries such as India, Indonesia, Nepal, Brazil, and Africa, tribal peoples depend primarily on forest products such as food, fuel wood, fodder, lumber, and medicinal plants (Kumar & Saikia, 2020). These resources are not only for generating financial income but also for meeting their subsistence needs. Tribal communities, despite their rich cultural heritage, frequently face socioeconomic marginalisation, limited access to education and healthcare, and political exclusion (Panda et al., 2022), which increase their susceptibility to CC.

1.5 Relationship between Climate Change Impacts and Tribal Livelihoods

The relationship between CC impacts and the livelihoods of tribal communities is complex and dynamic (Mallick et al., 2024). Tribal communities are among the most vulnerable to CC due to their heavy dependence on natural resources, marginal socioeconomic status, and often limited adaptive capacity (Hazarika et al., 2024). The complex impacts of CC on tribal livelihoods include agricultural practices, water resources, forest and biodiversity dependence, health and well-being, and socioeconomic implications, as discussed below.

1.5.1 Agricultural Practices

Agriculture is the backbone of tribal economies, ensuring food security and livelihoods for millions (Nautiyal & Goswami, 2022). Tribal communities are involved in cultivating crops and raising livestock to meet their basic needs (Ramakrishnan et al., 2024). However, changing climatic patterns have disturbed traditional agricultural practices, reducing crop yields (Aich et al., 2022). Several studies have reported the loss of traditional crops, decreased crop yields, and increased pest and disease pressures in many tribal regions (Aich et al., 2022; Atta et al., 2023; Grigorieva et al., 2023; Hussain et al., 2020; Kar et al., 2024; Lin et al., 2008; Praveena & Malaisamy, 2024). Tropical Asia suffered crop losses and decreased rice and wheat productivity in tropical Asia due to changing monsoon patterns, which influenced the timing and distribution of rainfall (Huggi et al., 2024). The reduced rainfall in American monsoon regions, including southern Chile, southwestern Argentina, southern Peru, and west-central America, has negatively impacted the productivity of major crops like wheat, soybean, and maize. In addition, maize productivity has declined from 0.01 to 0.05 tonnes yearly in the U.S., primarily attributed to internal variability in the El Niño-Southern Oscillation (ENSO). The Sahel region of Africa experienced a significant decrease in groundnut productivity from 850 kg/ha in 1966-67 to 440 kg/ha in 1981, mainly because of variations in rainfall distribution during growing seasons (Huggi et al., 2024). Studies also reported that grasslands in Africa are at risk due to monsoon variability, reducing fodder availability for livestock, and rising temperatures accelerating pest and disease spread, causing further crop failures (Grigorieva et al., 2023). Extreme weather events like floods and droughts can lead to soil erosion and nutrient depletion, reducing agricultural productivity (Kulkarni, 2021).

1.5.2 Water Resources

Tribal communities reliant on rivers, lakes, and groundwater are at a higher threat due to CC, which disrupts hydrological cycles and limits access to clean water sources (Soomro et al., 2024). Reduced water availability during dry seasons (like droughts) and increased frequency of extreme weather events (for example, floods) poses significant sustainability challenges (Shiva Shankar et al., 2021). Despite significant developments in infrastructure, modified water management strategies, and technological innovations that enhance water use efficiency, water scarcity remains an important global issue (Tzanakakis et al., 2020). More than 2 billion people have inadequate access to safe drinking water and reside in locations with severe water stress. Approximately 3.4 million die annually from contaminated water, and 50% of hospital beds are filled with affected individuals (Tzanakakis et al., 2020). Population growth, improved lifestyles, and rising temperatures have increased household water usage, causing water quality issues for drinking, agriculture, and other purposes (Cozzetto et al., 2013).

1.5.3 Forest and Biodiversity Dependence

Many tribal communities depend on forests and biodiversity for their livelihoods, including food, fuel, medicine, and cultural practices, but CC threaten their resilience, impacting forest dynamics, species, and ecosystem services (Azhar et al., 2022; Voggesser et al., 2013). Forests provide resources such as fruits, tubers, honey, and medicinal plants, which are essential to the subsistence and health of tribal populations (Min et al., 2024). Non-timber forest products (NTFPs) like bamboo, resin, and lac form the backbone of tribal economies, contributing to their income and employment (Sharma et al., 2024). CC has affected the timing of flowering, fruiting, and seed dispersal, disrupting ecological connections and traditional harvesting customs (Hamilton et al., 2024). Moreover, amplified frequency and intensity of deforestation, forest fires, pests, and diseases have further destroyed forest ecosystems, reduced resource availability and threatened tribal livelihoods that depend on forest resources (Kumar et al., 2022). The loss of biodiversity also limits the availability of culturally important plants and animals, affecting traditional knowledge systems and practices (Bhatt et al., 2024). Tribal populations find their capacity to effectively manage forest resources severely hampered by the changing climate and policy restrictions. Globally, forests act as carbon sinks and absorb around 2 billion metric tonnes of carbon dioxide yearly (Nzabarinda et al., 2025). Approximately 20-25% of global greenhouse gas emissions are attributable to deforestation, with one million species in danger of extinction (Pal, 2022). For tribal communities, this environmental deterioration is not only an ecological problem but a direct danger to their food security, water availability, and cultural identity. Climate-induced changes in forestry composition and productivity also influence wildlife populations, affecting the hunting and gathering practices essential for tribal livelihoods (Das, 2024).

1.5.4 Health and Well-being

CC leads to extreme weather events, increasing vector-borne diseases, waterborne illnesses, malnutrition, and mental health issues among tribal populations (Chandra & Mukherjee, 2022; Donatuto et al., 2020). Rising temperatures raise the risk of heatstroke and dehydration, particularly for vulnerable populations like older adults and children (Ndlovu & Chungag, 2024). Moreover, the dependence of tribal communities on unclean water sources makes them highly vulnerable to waterborne infections during floods and cyclones (Rahman et al., 2024). Prolonged droughts can lead to water scarcity and food insecurity, strengthening the risk of malnutrition and related health issues (Jones, 2019; Ngcamu & Chari, 2020). Limited access to healthcare facilities in isolated tribal locations increases these issues, delaying treatment and worsening risks to health (Kumari, 2024). Climate-induced crises also influence the mental health of tribal communities. Loss of livelihoods due to agricultural failure, relocation from ancestral lands, and the degradation of natural resources create psychological stress, anxiety, and depression (White et al., 2023). Similarly, floods and cyclones can result in water contamination, displacement, and injuries, aggravating health vulnerabilities among tribal communities (Suar et al., 2024).

1.5.5 Socioeconomic Implications

CC impacts tribal livelihoods, affecting household incomes, employment opportunities, social cohesion, agricultural productivity, natural resource-based livelihoods, and traditional knowledge systems, causing financial instability and resilience (Bora & Mahanta, 2024; Rautela & Karki, 2015). These changes also influence livestock health and production because increased heat stress, decreasing water availability, and degraded grazing pastures harm animal husbandry, an important aspect of tribal subsistence (Goswami & Rajput, 2024). Overgrazing and reducing pastures, worsened by climatic unpredictability, push communities to adopt unsustainable grazing approaches (Rajput, 2024), further harming the environment. The dependency of tribal communities on natural resources for fuelwood, fodder, and medicinal plants makes them more vulnerable to resource degradation caused by deforestation, soil erosion, and irregular weather patterns (Mallick et al., 2024). These shifts result in decreased family incomes and reduced job opportunities, forcing several households into financial instability. Furthermore, climate-induced displacement and migration can drain social networks and augment conflicts over resources and land (Warner & Wiegel, 2021). Tribal communities' vulnerability to CC is aggravated by limited access to markets, financial resources, and social services (George et al., 2023). Traditional practices are at risk of cultural loss as younger generations may abandon them due to their unsustainable nature (Abdullah & Khan, 2023).

1.6 Vulnerability Assessment Frameworks

Vulnerability assessment frameworks (VAFs) are essential to understanding the relationships between CC impacts and tribal livelihoods. Frameworks assess the vulnerability of tribal communities to climate-induced disasters, providing insights into contributing factors and recommending targeted adaptation and resilience strategies. Therefore, it is necessary to discuss the key components of VAFs, commonly used indicators, assessment models/tools, and present case studies illustrating their application in worldwide tribal communities.

1.6.1 Vulnerability Indicators

Indicators play a significant role in assessing vulnerability (Yadava & Sinha, 2020), incorporating multiple dimensions, such as socioeconomic, environmental, and institutional factors collectively affecting communities' adaptive capacity. Socioeconomic indicators are income levels, education, access to healthcare, and social networks, especially the available community resources for coping with CC impacts (Hahn et al., 2009).

Table 1.1: Indicators of livelihood vulnerability in tribal communities

Sl. No.	Category	Indicators	Explanation	References
1.	Socio-economic Indicators	Income	• Low-income levels frequently suggest limited resources for adaptation and recovery.	Yadava & Sinha (2020)
		Education	• Higher levels of education increase adaptive capacity through improved awareness and access to information.	Das & Basu (2022); Phuong et al. (2023)
		Access to Services	• The availability of healthcare, infrastructure, and social services influences resilience.	Ghosh & Ghosal (2021); Rehman et al. (2022)
		Employment Patterns	• Reliance on climate-sensitive areas such as agriculture or forestry can increase vulnerability.	Das & Basu (2022)
2.	Environmental Indicators	Dependence on Natural Resources	• Dependency on agriculture, forests, water bodies, and biodiversity for livelihoods	Pandey et al. (2017)
		Climate Sensitivity	• Exposure to climate extremes like floods, droughts, or cyclones	Mehzabin & Mondal (2021)
		Geographic Location	• Proximity to disaster-prone areas such as coastal regions, forests, or arid lands	Mehzabin & Mondal (2021)
3.	Cultural and Institutional Indicators	Cultural Identity	• Conservation of traditional knowledge and practices for adaptation.	Makondo & Thomas (2018)
		Social Cohesion	• Strength of community networks and support systems.	Townshend et al. (2015)
		Access to Decision-making Practices	• Inclusion in local governance and policy formulation	Brugnach et al. (2017)
		Legal Rights	• Identification of land tenure and resource ownership rights	Whyte (2013)
4.	Health and Well-being Indicators	Health Infrastructure	• Accessibility of healthcare facilities and services.	Das & Basu (2022); Hahn et al. (2009); Venus et al. (2022)

		Prevalence of Diseases	• Vulnerability to climate-related health risks like water and vector-borne diseases or malnutrition	Rai et al. (2022)
		Food Security	• Accessibility and availability of nutritious food sources	Phuong et al. (2023)
5.	Adaptive Capacity Indicators	Infrastructure Development	• Access to technologies for climate-resilient agriculture, water management, etc.	Srivastav et al. (2021)
		Capacity Building	• Participating in training, knowledge exchange, and skill development programs can increase adaptation.	Phuong et al. (2023); Venus et al. (2022)
		Financial Resources	• Access to loans, insurance, and social safety nets for recovery post-disaster.	Rai et al. (2022); Venus et al. (2022)
6.	Governance and Policy Indicators	Policy Support	• Adaptive policies and programs exist at local, national, and international levels.	Reed et al. (2006)
		Institutional Capacity	• Acceptability of institutions for disaster management, climate adaptation, and disaster risk reduction	Birkmann & von Teichman (2010)
		Participation and Inclusivity	• Participation of tribal communities in decision-making practices and policy implementation	Menon & Hartz-Karp (2019)

Environmental factors focus on natural resource dependence, land tenure systems, and ecological resilience, emphasising the vulnerability of tribal livelihoods to changes in climatic conditions (Bora & Mahanta, 2024; Long & Steel, 2020; Mallick et al., 2024; Ramakrishnan et al., 2024). Institutional factors are the effectiveness of governance policies, structures, and institutional support systems in facilitating adaptation and resilience-building attempts within tribal communities (Mehta, 2024). Table 1.1 presents vulnerability indicators in tribal communities, providing a comprehensive understanding of CC and variability and aiding in developing targeted interventions and adaptation strategies.

1.6.2 Assessment Models and Tools

Various assessment models and tools have been developed to measure vulnerability and guide decision-making activities in tribal areas, as presented in Table **1.2**. These models range from qualitative to quantitative approaches. Qualitative methods such as participatory vulnerability assessments and community-based risk mapping prioritise community engagement and local knowledge, allowing tribal communities to identify and select vulnerability factors based on their lived experiences and observations (Smit & Wandel, 2006). Quantitative models, such as vulnerability index construction, situation-based modelling, and indicator-based models, use statistical procedures and geographic information system (GIS) mapping to analyse vulnerability hotspots, quantify risk levels, and prioritise intrusion areas (Panda, 2017). Integrating quantitative and qualitative methods in indicator-based models, utilising data from censuses, surveys, and climatic records, provides a comprehensive understanding of vulnerability dynamics (Hahn et al., 2009; Phuong et al., 2023).

Table 1.2: Assessment tools and models for evaluating vulnerability

Sl. No.	Assessment Framework/Model	Description	Key Features	References
1.	IPCC Vulnerability Assessment Framework	Developed by the Intergovernmental Panel on Climate Change (IPCC), this framework provides a systematic approach to assess vulnerability to climate change.	Considers exposure, sensitivity, and adaptive capacity	IPCC (2014)
2.	Livelihood Vulnerability Index	A composite index is used to measure livelihoods' vulnerability to climate change.	Incorporates socioeconomic, environmental, and institutional factors	Ahmad et al. (2023); Hahn et al. (2009); Joshi & Rawat (2021); Venus et al. (2022)
3.	Community-Based Vulnerability Assessment	Focuses on participatory approaches involving local communities in assessing their vulnerability to climate change impacts	Emphasises local knowledge and perceptions	Andrachuk & Smit (2012)
4.	Composite Social Vulnerability Index	Measures socioeconomic vulnerability to climate change by integrating social, economic, and demographic variables.	Calculating Infrastructural, Social, and Climate Vulnerability Index	George et al. (2023); George & Sharma (2022)
5.	Socio-ecological vulnerability	Socio-ecological vulnerability assessment of climate change by integrating socioeconomic, agriculture, water, and forest	Quantifies exposure, sensitivity, and adaptive capacity	Jha & Negi (2021)
6.	Composite Vulnerability Index	Assessed the local dimensions of vulnerability using a composite vulnerability index based on environmental and socioeconomic factors	Evaluate and map the environmental, socioeconomic, and composite vulnerability index.	Sarun et al. (2018)
7.	Household Vulnerability Index	Evaluate household-level vulnerability to climate change	Includes income loss, crop loss, housing loss, and overall livelihood loss	Ghosh & Ghosal (2020)
8.	Climate Change Vulnerability Index	Examine climate change vulnerability among the agriculture-dependent and forest resource-dependent villages.	Quantifies exposure, sensitivity, adaptive capacity, and climate change vulnerability index	Ghosh & Ghosal (2021)

Vulnerability Index Tools are often used to quantify vulnerability by aggregating multiple indicators into a single index score. Tools like the Socioeconomic Vulnerability Index (George et al., 2023; George & Sharma, 2022) or the Climate Vulnerability Index are commonly used (Ghosh & Ghosal, 2021). Participatory assessment methods involve directly engaging communities to recognise their perceptions of vulnerability, adaptive capacities, and specific challenges (Andrachuk & Smit, 2012). Participatory assessment tools such as community mapping, seasonal calendars, and vulnerability and capacity assessments are samples of such attempts (Ghosh & Ghosal, 2020; Jha & Negi, 2021). GIS are extensively applied to map vulnerability spatially by overlaying climate, environmental, and socioeconomic data (Sarun et al., 2018). GIS tools can assist in finding areas most vulnerable to CC impacts and select intrusions accordingly. Livelihood assessment tools aim to understand the diverse livelihood strategies employed by communities and the impact of CC on these strategies (Ahmad et al., 2023; Hahn et al., 2009; Joshi & Rawat, 2021; Venus et al., 2022). Livelihood frameworks assess community vulnerability by examining assets, capabilities, and strategies, while adaptation planning tools identify intervention areas based on vulnerability assessments (Tuler et al., 2020). Cost-benefit analysis and scenario planning are frequently employed to estimate the effectiveness of various adaptation alternatives (Kwakkel, 2020).

1.7 Review of Past Studies

CC impacts on Indigenous peoples and local communities are diverse, widespread, and visible, emphasising the need for context-specific adaptation strategies and recognising their experiences in addressing loss and damage across different climate zones globally (Reyes-García et al., 2024). Case studies can highlight specific regions, as shown in Table 1.3. Tribal communities in the coastal areas of the U.S. use effective strategies rooted in cultural practices and values to address climate-induced

Table 1.3: Past studies on tribal livelihood vulnerability and adaptation

Sl. No.	Location	Spatial granularity	Objective	Main Findings	References	Literature Synthesis Insights
1.	Worldwide (48 sites across all climate zones)	Global level	Identify climate change indicators and impacts experienced locally by Indigenous Peoples and local communities.	• Ongoing, tangible, and widespread impacts • Affected multiple elements of social-ecological systems across different climate zones and livelihood activities • Identifying economic and non-economic loss and damage due to climate change through local reports.	Reyes-García et al. (2024)	• Climate change impacts vary according to climate zone and livelihood activity, demonstrating the need for localised adaptation strategies.
2.	United States	National and regional level	Examine the impact of climate change-induced displacement on tribal communities and explore their adaptation strategies.	• Using innovative strategies to mitigate the impacts of forced relocation due to sea level rise, land erosion, and permafrost thaw. • A significant risk of cultural and economic loss, health impacts, and exacerbated poverty and injustice	Maldonado et al. (2013)	• Inadequate governance mechanisms and budgets are major barriers. • Community-led efforts that align with cultural practices are more effective.
3.	United States	National level	Investigate the impacts of climate change on tribal traditional foods and the cultural, economic, and health implications.	• Significantly affecting native fungi, plant, and animal species is essential for tribal traditional foods. • Legal and regulatory relationships with the federal government influence access to these resources.	Lynn et al. (2013)	• Tribal traditional foods are vital to culture and economy • Adaptation strategies involving tribal participation can enhance resilience and inform

						broader governmental strategies
4.	Alberta, Canada	Local level	Assess the tribal vulnerabilities and adaptive capacity related to climate change.	• Reduces water supplies, impacting Pyramid Lake and the endangered cui-ui fish, vital for cultural and economic sustenance. • Limited economic opportunities and reduced federal support constrain adaptive capacity.	Gautam et al. (2013)	• The tribe shows sustainability-based values, strong technical capacity in natural resource management, proactive invasive species control, robust scientific networks, and high awareness of climate change.
5.	Louisiana, United States	Regional level	Evaluate the impact of environmental changes, forced displacement, and inadequate governance mechanisms on tribal communities.	• Forcibly displacing tribal communities due to Environmental changes, leading to severe social, cultural, health, and economic consequences. • Inadequate governance mechanisms exacerbate these issues. • Communities face a dilemma between staying in place and relocating.	Maldonado (2014)	• Adaptive governance structures are critical for supporting in-situ adaptation or community-led relocation efforts. • Multiple forms of knowledge need to be integrated into the adaptation process.
6.	Latin America	Local level	Analyse the impact of climate-induced relocation on Indigenous Peoples and assess the effectiveness of managed retreat as an adaptation strategy.	• Rising sea levels and increasing climate threats make climate-induced relocation necessary. • Poses significant risks, including the loss of cultural identity, community cohesion, and traditional knowledge	Felipe Pérez & Tomaselli (2021)	• Relocation processes indicate adverse impacts such as loss of community cohesion, cultural identity, and traditional knowledge among Indigenous Peoples. • Managed retreat faces resistance due to the potential loss of cultural

						heritage and social networks.
7.	Chile	Local level	Examine climate change impacts and vulnerability trends among Mapuche communities from 1990 to 2015	• Trends in water scarcity, reduced agricultural production, vegetation colonisation, and population migration to higher altitudes due to climate change. • Increased pressure on Andean ecosystems and loss of traditional Mapuche knowledge	Parraguez-Vergara et al. (2016)	• Limited local capacity for adaptation • Governmental initiatives not fully meeting community needs • Critical need for local resilience-building efforts.
8.	Norway, Finland, Sweden, Russia	Regional level	Develop a framework for understanding the holistic effects of climate change on the Saami people.	• Significantly impacting Saami reindeer culture and traditional practices • The health of Saami is slightly better than other populations in the region, but mental health risks related to changing environments are emerging concerns.	Jaakkola et al. (2018)	• Identified the interconnectedness of climate change impacts on cultural and health aspects among the Saami
9.	Bukavu, DR Congo	Local level	Explore vulnerability and adaptation strategies to climate change in local communities.	• The perception of climate change depends on observable impacts. • Climate-related risks compound existing vulnerabilities, worsening poverty. • Various adaptation measures are practised or planned, including local knowledge integration. • Implementation of adaptation faces significant barriers, such as financial constraints and lack of institutional support.	Bele et al. (2014)	• Participatory action research provided insights into local perceptions and realities of climate impacts, emphasising the need for context-specific adaptation strategies.

10.	South Africa	Local level	Investigate climate vulnerability and risks to an Indigenous Nama community.	• Climate hazards identified include drought, hot temperatures, and strong winds. • Lack of access to critical natural resources in the adjacent national park increases vulnerability.	Samuels et al. (2022)	• A remarkable disparity in access to natural resources impacts vulnerability levels. • The community reveals moderate vulnerability due to mixed adaptive capacity and sensitivity levels.
11.	Taiwan	Local level	Understand the role of culture in the recovery process of relocating Indigenous communities through tourism livelihood.	• Appeal to culture, rather than land, as the foundation for community resilience and conflict reduction post-disaster. • Indigenous culture-based tourism can sustain livelihoods and support long-term development.	Lin & Lin (2020)	• The existing literature focuses primarily on rebuilding and renovating physical infrastructure. • There is a gap regarding the social aspects of recovery, particularly in indigenous perspectives.
12.	Taiwan	Local level	Develop a livelihood vulnerability analytical framework and apply it to Indigenous communities regularly exposed to typhoons and geological hazards.	• Least vulnerable communities with abundant livelihood capitals • Intermediate vulnerability due to exposure to market and typhoon-related stresses • Most vulnerable communities are trapped in poverty and vulnerability cycles • A spatially explicit livelihood vulnerability index was developed to diagnose vulnerability dimensions and distribution.	Lin & Polsky (2016)	• Historical development strongly influences current vulnerability patterns. • Need for continuous longitudinal tracking of vulnerability dynamics for future research.

13.	Doi Mae Salong, Thailand	Mountainous landscape	Explore farmers' perceptions of climate change's impact on farming and adaptation measures.	• Changes in climate patterns affect farming negatively. • Adapt alternate farming practices using traditional techniques. • Higher vulnerability was observed at higher elevations compared to lower elevations.	Shrestha et al. (2017)	• Significant autonomous adaptation efforts are evident, yet challenges remain due to limited knowledge and financial resources.
14.	Vietnam	National level	Study the livelihood vulnerability under climate change in rural areas.	• Higher LVI-IPCC value due to increased exposure to disasters like floods, sea storms, and tropical depressions, significantly impacting livelihoods.	Vo & Tran (2022)	• Emphasise the critical role of geographic location and exposure to climate-related hazards in determining vulnerability. • Highlight the importance of comprehensive datasets like VARHS in understanding multidimensional aspects of rural livelihood vulnerability.
15.	Sherpur and Mymensingh, Bangladesh	District level	Examine the impact of agricultural modernisation on sustainable livelihoods among tribal and non-tribal farmers.	• Tribal farmers generally had lower education levels than non-tribal farmers, affecting their adoption of modern agricultural practices. • Expressed the need for training in new technologies • Usage of modern agricultural practices was limited • Education, irrigation facilities, and community memberships positively influenced livelihood diversification.	Jannat et al. (2021)	• Limited educational opportunities among tribal farmers hindered the adoption of modern agricultural practices.

16.	Nepal	District level	Analyse the micro-level vulnerability of the rural Chepang community	• Highlighting local-level differences in exposure and adaptive capacity. • Poor households with low adaptive capacity are consistently vulnerable regardless of location.	Piya et al. (2012)	• Importance of local-level vulnerability assessment for targeted policy measures
17.	Himachal Pradesh, India	Subdivision level	Develop a Tribal Household Livelihood Vulnerability Index focusing on Lahaul, Udaipur, and Spiti subdivisions in the western Himalayas cold deserts.	• The vulnerability of tribal households varies significantly across different socioeconomic and ecological conditions due to differences in adaptability, sensitivity, and exposure to climate change.	Kumar et al. (2023)	• The literature review showed significant variations in vulnerability metrics across Lahaul, Udaipur, and Spiti, influenced by socioeconomic and ecological factors unique to each subdivision.
18.	Uttarakhand, India	Regional Level	Assess the trend of climatic variations, impacts, and adaptation strategies by the community.	• Periodic climatic fluctuations, including a downward annual and seasonal rainfall trend • Community perception notes reduced monsoon intensity, decreased winter snowfall, and erratic precipitation patterns. • Reduced crop yields and horticultural production due to climate change impacts	Pratap & Pratap (2021)	• Community adaptation strategies include varying crops, changing planting schedules, and enhancing water management practices.
19.	Gujarat, India	State level	Examine the livelihood conditions of tribal communities in Gujarat amidst rapid	• Significant poverty and deprivation among tribal communities despite economic growth	Shah & O.G. (2009)	• Recognition of the Important role of forest resources in tribal livelihoods and the degradation challenges

			economic growth and widening disparities. Also, explore policy options for mitigating poverty among these communities, focusing on forest-based livelihoods and climate change adaptation.	• Dependence on forest resources for livelihoods, exacerbated by degradation and inadequate entitlements • Policy emphasis on forest regeneration, conservation, and sustainable management is crucial for poverty alleviation and climate resilience.		• Identification of policy gaps and the need for stronger entitlements and conservation incentives
20.	Madhya Pradesh, India	Local level	Evaluate climate change vulnerability and identify key drivers for effective adaptation strategies.	• Economic conditions, education level, and livelihood strategy significantly influence vulnerability more than social class. • Government programs must be inclusive and focus on the welfare of all social classes.	Yadava & Sinha (2020)	• The vulnerability index revealed critical insights into vulnerability drivers. • Household economic status and livelihood choices emerged as pivotal factors.
21.	Madhya Pradesh, India	Local level	Assess the impact of MGNREGA on vulnerability to climate change among tribal communities.	• MGNREGA has significantly reduced vulnerability related to climate variability, agriculture, water, and household economic conditions. • Increased water availability, diversified agriculture, improved crop yields and employment opportunities, and enhanced the economic status of tribal peoples.	Jha et al. (2017)	• The MGNREGA program effectively integrates natural and human systems, enhancing resilience to climate impacts.

22.	West Bengal, India	Local level	Measure and compare livelihood vulnerability among Santal, Munda, Bhumij, and Lodha tribal communities in response to climate change.	• Tribal households exhibit greater sensitivity to climate change and have less capacity for adaptation. • The absence of alternative employment opportunities and planned activities exacerbates the impact of climatic variability on livelihoods, particularly agriculture-based ones.	Das & Basu (2022)	• It highlights the significance of beta regression modelling in determining vulnerability factors.
23.	West Bengal, India	Local level	Determine livelihood vulnerability among tribal farmers in the face of water scarcity.	• Income level, irrigation facilities, credit patterns, and social group participation strongly influence the higher LVI. • Monocrop cultivation and limited livelihood options augment vulnerability.	Mukherjee et al. (2022)	• A composite Livelihood Vulnerability Index model and IPCC-LVI technique were employed.
24.	North-East India	Local level	Characterise Indigenous community-based climate vulnerability and capacity assessment in the Garo hills	• The Garo indigenous communities are highly vulnerable to climate change due to factors such as high poverty levels, dependence on natural resources, and frequent climatic hazards like cyclonic storms and droughts. • Climate change disrupts agriculture, water availability, and livelihoods.	Yadav & Sarma (2013)	• The study highlights strategic and short-term adaptation strategies rather than long-term planning.
25.	Nagaland, India	Local level	Explore the community-level vulnerability due to climate extremes and variability	• Minor exposure, sensitivity, or adaptive capacity changes could make the communities vulnerable. • Reducing sensitivity through safe housing infrastructure, food security, and sanitation development	Kuotsu et al. (2017)	• The Ao communities show somewhat higher vulnerability than the Angami tribes, but both are statistically vulnerable at similar levels.

26.	Tripura, India	District level	Assess the extent of climate vulnerability using the LVI-IPCC technique among tribal and non-tribal populations in Tripura.	• Significantly impacts agricultural-based livelihoods. • Tribal households are more exposed to climate change impacts, leading to higher vulnerability than non-tribal households. • Exhibit greater sensitivity and lower adaptation capacity.	Roy et al. (2023)	• The LVI-IPCC method provides a structured approach to assessing vulnerability across demographic groups.
27.	Jharkhand, India	Village level	Estimate household vulnerability indices among tribal rural households	• Need for urgent income enhancement and livelihood improvement interventions. • Declining rainfall exacerbated vulnerability. • Efforts to improve irrigation and farm incomes showed limited impact.	Vatta et al. (2017)	• Declining rainfall exacerbated vulnerability, shifting additional households into more vulnerable categories. • Efforts to increase irrigation and farm incomes showed localised improvements but were insufficient, given the scale of vulnerability.
28.	Jharkhand, India	Village level	Investigating the impact of climate change on NTFPs	• Increased maximum temperature has led to a significant decrease in NTFP yield. • Degraded the quality of NTFPs • Lack of incorporating Indigenous knowledge of climate change into institutional processes	Magry et al. (2023)	• Integrating Indigenous knowledge into adaptation strategies, addressing infrastructure development impacts, and enhancing institutional support for NTFP-based livelihoods
29.	Jharkhand, India	State level	Assess the impact of climate change on tribal economy and livelihoods	• Increased incidence of drought, affecting rain-fed agriculture and natural resource availability for tribal communities	Barla (2016)	• Evidence shows a visible increase in drought frequency and intensity in Jharkhand, impacting tribal

				• Result in livelihood insecurity, decreased crop production, and increased vulnerability to diseases among crops and livestock		communities heavily dependent on natural resources and rain-fed agriculture.
30.	Jharkhand and Odisha, India	Village-level	Examine the perception of the Sauria Paharia community regarding climate change impacts on agroforestry and dietary diversity and assess adaptation strategies.	• Local climatic variability reduces crop productivity and food availability from forests and water bodies. • Declining agroforestry produce and diversity reduces household income, food insecurity, and migratory wage labour. • Use of climate-resilient Indigenous crop varieties, seed conservation, and reliance on Indigenous Forest foods during lean periods	Ghosh-Jerath et al. (2021)	• Limited resources and coping mechanisms of the Sauria Paharia community underline severe vulnerability to climate impacts. • Importance of promoting sustainable adaptation strategies to enhance resilience, income, and food security
31.	Jharkhand, India	District level	Assess livelihood vulnerability among 15 tribes, including 8 Particularly Vulnerable Tribal Groups (PVTGs)	• Landless families are highly vulnerable. • Forest dwellers face challenges in education and healthcare access. • Minor forest produces and social welfare measures serve as crucial safety nets. • Improved access to banking, housing, and sanitation facilities • Need to enhance livelihood opportunities for forest-dwelling communities.	Behera et al. (2022)	• The study indicates the effectiveness of participatory approaches in assessing vulnerability. • Challenges in education and healthcare and the importance of safety nets are critical areas for policy intervention.

displacement, highlighting the importance of community-led and government-supported relocation programs (Maldonado et al., 2013). CC presents severe threats to the accessibility and quality of traditional foods that are essential to the survival of American Indian and Alaska Native tribes, influencing their cultural, economic, and social welfare, with varied consequences observed in different ecosystems. (Lynn et al., 2013). In coastal Louisiana, tribal communities facing forced displacement due to environmental changes such as rising sea levels, historical discriminatory processes, and industrial growth need adaptive governance structures that support both in-situ adaptation and community-led relocation, integrating diverse knowledge systems (Maldonado, 2014). The Pyramid Lake Paiute Tribe in Nevada illustrates the impact of CC on cultural and economic prosperity by reducing crucial water inflows for the survival of endangered cui-ui fish. The tribe's adaptation to changes is influenced by their commitment to sustainability, resource management, control over invasive species, collaboration with scientists, and awareness of CC (Gautam et al., 2013).

The Saami, who are the only tribal community in the European Union, exhibit similar or even better health conditions in comparison to the neighbouring communities. Still, the impact of CC is already evident in their reindeer culture and mental health, making them vulnerable to the changing conditions around them, particularly in the Sápmi region (Jaakkola et al., 2018). However, Climate-induced planned relocations in Latin America and the Caribbean, experienced by the Guna people in Panama and tribal communities in Chiapas, often worsen cultural and socioeconomic problems due to inadequate planning and execution rather than effectively dealing with the challenges of CC (Felipe Pérez & Tomaselli, 2021). Mapuche communities in the Araucanía region of Chile are more vulnerable to CC due to factors such as water scarcity, decreased agricultural productivity, ecological pressure, and the loss of traditional knowledge, imposing local resilience and tailored adaptation measures (Parraguez-Vergara et al., 2016). CC increases existing vulnerabilities, requiring integrated adaptation strategies focusing on essential sectors and decentralised governance structures to improve resilience and reduce the effect on economic growth and poverty reduction initiatives in the Democratic Republic of Congo, Africa (Bele et al., 2014). The Nama community in South Africa is moderately vulnerable to CC, mainly because of drought, high temperatures, and strong winds. It might increase as the harsh weather patterns become more severe. Therefore, it is important to use the existing co-management models with the South African National Park to mitigate the risks related to CC (Samuels et al., 2022).

In Asia, the communities least vulnerable to hostile effects are in the most isolated areas and have sufficient resources to reduce their vulnerability. The communities with moderate vulnerability face a dual risk from the market and natural hazards. On the other hand, the most vulnerable communities are trapped in a loop of poverty along with vulnerability (Lin & Polsky, 2016). The Tsou Indigenous community in Taiwan experienced a resilient recovery after being relocated because of Typhoon Morakot due to their culturally based tourism livelihoods. It illustrates the importance of using indigenous culture, rather than land, as the foundation for community growth, as it promotes social resilience and decreases internal conflicts in the impact of a disaster (Lin & Lin, 2020). The Doi Mae Salong region in Northern Thailand reveals farmers' awareness of CC's impact on agriculture and their strategies for coping, highlighting the economically poor population's vulnerability (Shrestha et al., 2017). The regions of North Central and South-Central Coasts in Vietnam are most vulnerable due to the increased frequency of floods, sea storms, and tropical depressions, which underlines the urgency for targeted interventions in these regions to protect rural livelihoods against climatic risks (Vo & Tran, 2022). The study reveals tribal farmers in the Sherpur and Mymensingh districts of Bangladesh have lower education levels but are keen on technology training, indicating the potential for improved living standards (Jannat et al., 2021). The study in Nepal's rural Chepang community highlights the importance of targeted interventions in improving households' adaptive capacity, particularly among the poorest families, to mitigate climate variability (Piya et al., 2012).

The study highlights the need for sustainable livelihood policies in Himalayan tribal communities in India due to the varying vulnerabilities they face across socioeconomic and ecological conditions (Kumar et al., 2023). The Jaunsar-Bawar tribal region in the Central Himalayas has been facing a decline in rainfall since the late 1980s, necessitating institutional support for adaptation (Pratap & Pratap, 2021). Rapid economic growth in Gujarat has worsened tribal community disparities, emphasising the importance of sustainable resource management and forest-based livelihoods (Shah & O.G., 2009). The study highlights the significance of socioeconomic factors like education, economic status, and livelihood type in assessing households' vulnerability to CC impacts in forest peripheral villages in Madhya Pradesh (Yadava & Sinha, 2020). The Mahatma Gandhi National Rural Employment Guarantee Act 2005 (MGNREGA) programmes significantly decrease vulnerability to CC and poverty among tribal communities, enhancing income, employment opportunities, agricultural diversification, crop yield, and water availability (Jha et al., 2017). Policy interventions in West Bengal are suggested to address the vulnerability of tribal livelihoods to CC, considering factors such as agriculture income, family size, poverty, and water availability (Das & Basu, 2022; Mukherjee et al., 2022). The Garo tribal communities in Meghalaya are at heightened risk due to high poverty, reliance on natural resources, and frequent disruptions to their livelihoods due to cyclonic storms and droughts (Yadav & Sarma, 2013). Even minor exposure, sensitivity, or adaptive capacity changes could make communities vulnerable, demanding the enhancement of housing, food security, and sanitation (Kuotsu et al., 2017). Tribal households, closely dependent on agricultural activities, have greater sensitivity and lower adaptive capacity than non-tribal households, thus increasing their vulnerability to climate impacts (Roy et al., 2023). CC has significantly decreased the productivity and quality of non-timber forest products (NTFPs), showing the challenge faced by the lack of integrating Indigenous knowledge into institutional processes (Magry et al., 2023). The increasing incidence of drought and decline in forest cover in Jharkhand due to CC disproportionately affects the tribal communities, threatening their livelihoods and economy (Barla, 2016). The Sauria Paharia tribal community is vulnerable to CC, reducing crop productivity, agroforestry diversity, and household food insecurity (Ghosh-Jerath et al., 2021). Therefore, executing sustainable adaptation strategies is crucial to improving resilience and ensuring food security for the community. Landless forest dwellers, including vulnerable tribal groups, in Jharkhand and Odisha face vulnerability due to inadequate access to education, healthcare, and social welfare measures (Behera et al., 2022). The necessity of focused development initiatives is highlighted by the need for comprehensive interventions to enhance income and livelihoods for tribal rural communities, with CC exacerbating levels of vulnerability (Vatta et al., 2017) These empirical analyses can identify best practices, lessons learned, and opportunities for scaling up adaptation efforts to enhance the resilience of tribal communities in the face of CC.

1.8 Adaptation and Resilience Strategies

Climate change poses significant tasks to tribal communities, affecting their traditional livelihoods, cultural practices, and overall well-being. Tribal communities worldwide are employing various adaptation and resilience strategies to cope with these changes and build sustainable futures (Fig. 1.6). The diverse range of adaptation and resilience strategies used by tribal communities, focusing on indigenous knowledge and practices, community-based approaches, and policy interventions, is discussed here.

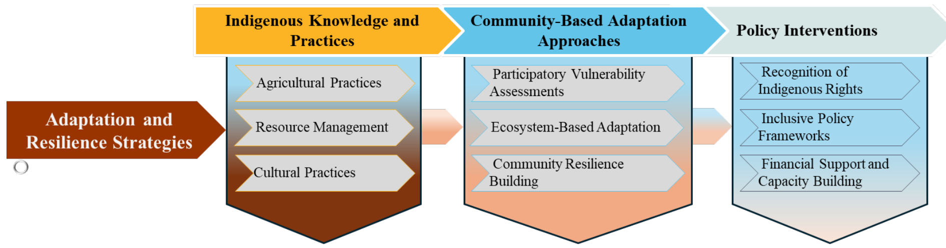


Fig. 1.6: Adaptation and resilience strategies to cope with climate changes

1.8.1 Indigenous Knowledge and Practices

In response to CC, tribal communities worldwide employ various adaptation and resilience strategies to cope with these changes and build sustainable futures. Various adaptation and resilience strategies are employed by tribal communities, focusing on indigenous knowledge, community-based approaches, and policy interventions. Indigenous people deeply understand their local environments and develop through generations of coexisting peacefully with nature (Carrin, 2024). This conventional ecological knowledge forms the basis of many adaptation strategies that tribal communities utilise (Mallick et al., 2024; Parrotta & Agnoletti, 2012). From agricultural practices to resource management techniques, indigenous knowledge systems offer constructive insights into sustainable living in changing climatic scenarios. Tribal communities mainly depend on agriculture and use traditional farming methods tailored to the local environment in response to CC. In arid regions, Indigenous communities are implementing water-saving methods such as rainwater harvesting, contour ploughing, and crop diversification to mitigate the effects of droughts and erratic rainfall patterns (Haddis, 2018). Apart from agricultural practices, tribal communities have complex techniques for managing natural resources sustainably (Kala, 2022). Many tribes have traditional forest management practices, including rotational grazing, selective logging, and forest fire management techniques (Charnley et al., 2007). These practices help maintain biodiversity, prevent soil erosion, and enhance ecosystem resilience in climate-related challenges (Lin & Lin, 2020). Traditional knowledge holders pass down ancestral knowledge and rituals that raise social cohesion, spiritual well-being, and collective action (Xu et al., 2005). These cultural practices provide emotional support during harsh conditions and advance environmental stewardship and adaptive capacity within tribal communities.

1.8.2 Community-Based Adaptation Approaches

Tribal communities use community-based adaptation (CBA) approaches to address CC impacts collaboratively (Fischer, 2021). CBA highlight local participation, empowerment, and decision-making, enabling communities to recognise their vulnerabilities and develop context-specific adaptation strategies (McNamara & Buggy, 2017). Tribal communities perform participatory assessments to recognise key climate risks and vulnerabilities (Long & Steel, 2020; Mehta, 2024). These assessments engage community members, local leaders, researchers, and non-governmental organisations (NGOs) to collect data, analyse findings, and prioritise adaptation actions (Salvador Costa et al., 2022; Samaddar et al., 2021). Integrating local and scientific knowledge in these assessments ensures that adaptation strategies are rooted in the realities of tribal livelihoods and environments.

Furthermore, many tribal communities are adopting ecosystem-based adaptation methods that harness the resilience of natural ecosystems to boost human well-being (Chaudhary et al., 2021; Panmei & Selvan, 2024; Saikia et al., 2020). Ecosystem-based adaptation strategies include restoring degraded habitats, conserving biodiversity hotspots, and creating green infrastructure to buffer against climate impacts such as floods, storms, and heat waves (Inácio et al., 2020). By protecting and restoring natural ecosystems, tribal communities adapt to CC and contribute to global mitigation efforts (Chong, 2014). However, CBA methods emphasise building social capital and encouraging community resilience through capacity building, knowledge exchange, and collective action (Carmen et al., 2022). Workshops, training programs, and community events were organised to raise awareness about CC, build adaptive skills, and strengthen social networks among tribal communities (Mallick et al., 2024; Mehta, 2024; Nursey-Bray et al., 2022). CBA empowers community members to take charge of their adaptation processes, promoting self-reliance and long-term resilience (Mehta, 2024; Samaddar et al., 2021).

1.8.3 Policy Interventions

Tribal communities, despite their cultural heritage and ecological knowledge, frequently face challenges in adaptation due to limited resource access, land tenure insecurity, and insufficient government funding. Effective policy interventions are needed to address these challenges and build an assisting environment for tribal adaptation and resilience, as presented in Table 1.4. Indigenous rights to land, resources, and self-determination are crucial for tribal adaptation efforts, and governments must respect traditional governance systems and involve tribal communities in decision-making processes (Brugnach et al., 2017). In addition, policymakers should develop inclusive and participatory policy frameworks that incorporate indigenous knowledge systems, cultural values, and community priorities into national and regional adaptation plans (Wheeler & Root-Bernstein, 2020). Governments, international organisations, and development agencies should support tribal communities in implementing adaptation projects and initiatives by mainstreaming Indigenous perceptions into climate policies (Mehta, 2024). There should be provision to include funding for climate-resilient infrastructure, livelihood diversification programs, disaster preparedness training, and climate information packages tailored to the needs of tribal communities.

Table 1.4: Policy interventions for enhancing tribal resilience

Sl. No.	Policy Intervention	Description	Advantages	References
1.	Integration of Indigenous Knowledge Systems	Incorporation of traditional knowledge into climate change adaptation and resilience strategies	• Enhances cultural significance and acceptance of adaptation strategies • Influences time-tested, locally adapted practices • Strengthens community engagement and ownership	Mehta (2024).
2.	Community-Based Natural Resource Management	Policies advancing community ownership and management of natural resources	• Promote sustainable use of resources • Empowers communities • Improves resource conservation and resilience against climate impacts	Mishra et al. (2021)
3.	Capacity Building Initiatives	Training programs and workshops are needed to improve the capacity of tribal communities to adapt.	• Builds local skills and knowledge • Increases community resilience • Enhances ability to implement and maintain adaptation measures	Nursey-Bray et al. (2022)
4.	Access to Climate Information and Early Warning Systems	Establishment of systems for spreading climate information and early warning systems	• Provides timely information to prevent and mitigate climate impacts • Reduces loss of life and property • Enhances preparedness and response capabilities	Panda et al. (2023)
5.	Sustainable Livelihood Diversification	Policies encouraging diversification of livelihoods to decrease dependency on climate-sensitive sectors	• Reduces risk of income loss from climate events • Enhances economic stability • Promotes resilience by spreading risk across multiple sectors.	Mehta (2024)
6.	Land Tenure Security	Measures to secure land rights for tribal communities, preventing land catching and displacement	• Ensures long-term access to land and resources • Reduces conflicts over land • Provides a stable source for livelihood activities and investment	Naik & Madhanagopal (2022)

7.	Disaster Risk Reduction Strategies	Implementation of strategies to decrease vulnerability to climate-induced disasters	• Reduce damage and loss from disasters • Enhance community safety • Reduces economic costs associated with disaster recovery	Kumar et al. (2023)
8.	Financial Support Systems	Provision of financial support, grants, and subsidies for climate adaptation programs.	• Facilitate implementation of adaptation strategies • Reduces financial burden on communities • Encourages innovation and practical adaptation	Craig, (2022)
9.	Institutional Support for Indigenous Governance Structures	Recognition and cooperation for Indigenous governance systems in decision-making processes	• Strengthens governance and representation • Ensures culturally applicable solutions • Enhances authenticity and compliance with adaptation measures	Lefthand-Begay et al. (2024)
10.	Research and Data Collection	Funding and support for research initiatives to collect data on climate change impacts on tribal livelihoods	• Inform evidence-based policymaking • Identifies specific vulnerabilities and needs • Supports targeted and effective adaptation strategies	Mishra et al. (2019)

1.9 Challenges

Understanding the challenges and interpreting the vulnerability of tribal communities to CC is necessary for developing effective adaptation and mitigation strategies. The challenges faced by the government, policymakers, and NGOs in implementing CC adaptation and mitigation strategies for tribal communities are detailed in Fig. 1.7.

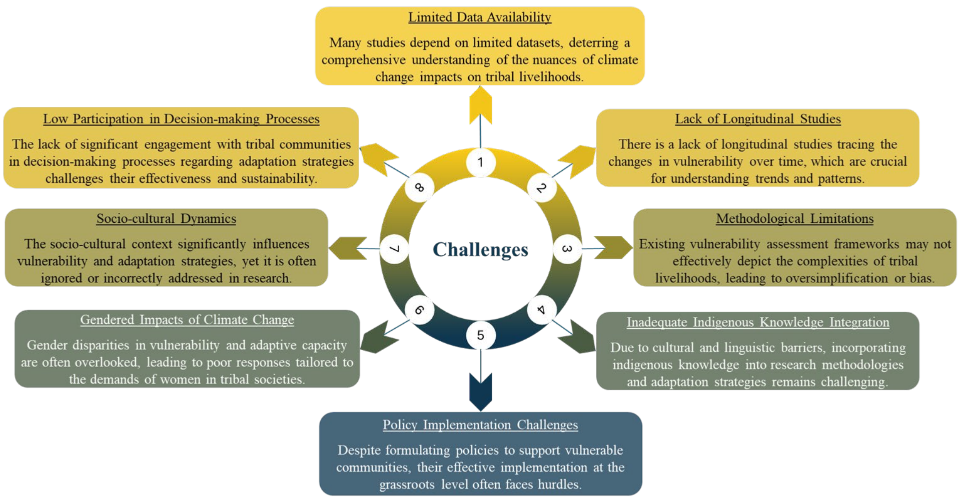


Fig. 1.7: Summary of challenges

1.9.1 Data and Research Limitations

The limited availability and accessibility of reliable data are one of the primary challenges in evaluating the vulnerability of tribal communities to CC. Many tribal regions lack robust monitoring methods and data collection infrastructure, indicating gaps in understanding CC's specific impacts on these communities. Furthermore, there is a need for more interdisciplinary research that incorporates traditional ecological knowledge with scientific approaches. CC impacts vary spatially and temporally, posing challenges in correctly capturing and predicting these dynamics at the regional level (Nissan et al., 2019). Most existing studies focus on broader regional or national scales, neglecting the nuanced vulnerabilities of specific tribal groups residing in diverse ecological sites. Several authors faced various challenges regarding data availability such as difficulty in data collection due to the remoteness, tribal-dominated areas, including language barriers and limited village access (Magry et al., 2023); reliance on peer-reviewed journal articles, excluding other relevant literature related to tribal communities (Fan et al., 2022); unavailability of data at a consistent scale for all required variables; inconsistencies in data availability, with some variables being spatially continuous and others only available at administrative levels (Kasthala et al., 2024); lack of significant quantifiable literature on indigenous agricultural practices in India; and absence of direct studies assessing CC risk (Aich et al., 2022).

1.9.2 Policy and Implementation Barriers

Tribal communities often encounter marginalisation in decision-making practices and policy formulation related to CC adaptation and mitigation (Ahmed et al., 2022; Fischer, 2021; Mallick et al., 2024). The lack of indigenous representation leads to policies that may inadequately direct the exceptional needs and priorities of tribal communities. Moreover, limited financial resources for CC adaptation and mitigation strategies in tribal regions augment vulnerabilities (Hazarika et al., 2024; Mallick et al., 2024; Mehta, 2024; Mishra et al., 2019). Insufficient funding limits the performance of adaptation strategies, such as infrastructure development, capacity building, and community-based initiatives (Fischer, 2021). However, many CC adaptation policies and programs follow top-down methods that do not consider the knowledge, preferences, and priorities of local tribal communities. Various studies highlighted policy and implementation barriers in CC adaptation, emphasising the need for culturally sensitive, context-specific approaches, effective stakeholder engagement, tangible benefits, capacity-building, and integration of Indigenous knowledge to confirm the resilience and empowerment of rural and Indigenous communities (Datta & Kairy, 2024; Nkoana et al., 2018; Salvador Costa et al., 2022; Samaddar et al., 2021).

1.9.3 Socio-cultural Challenges

Rapid modernisation and globalisation augment cultural erosion, leading to a loss of identity and social cohesion among tribal communities (Ozer & Obaidi, 2022). Additionally, gender disparities within tribal communities' composite vulnerability to CC effects. Women often show the impact of environmental degradation and resource scarcity. However, in decision-making processes about adaptation and attempts to create resilience, their views are typically marginalised (Matsa, 2021) Several studies have demonstrated significant socio-cultural challenges in their research on tribal communities, including struggles with cultural identity, traditional sickness perceptions affecting healthcare access, the integration of indigenous knowledge in sustainability efforts, and barriers to education and economic development (Mallick et al., 2024; Maske et al., 2015; Mishra, 2023; Yoganandham, 2023).

Overcoming data limitations, advancing inclusive policy frameworks, and promoting socio-cultural resilience are critical steps towards confirming the well-being and sustainability of tribal communities in a changing climate. Addressing the challenges mentioned above is crucial for effectively developing the resilience of tribal communities to CC.

1.10 Conclusions

This study has shed light on the relationship between CC and the vulnerability of tribal communities' livelihoods. A review of available literature showed the impacts of CC on several dimensions of tribal livelihoods, including agriculture, water resources, forests, health, and socioeconomics. It also revealed the different adaptation and resilience strategies used by tribal communities, leveraging indigenous knowledge, community-based approaches, and policy interventions. However, it is evident that challenges continue, including data limitations, policy gaps, and socio-cultural barriers. There is an urgent need for collaborative efforts among researchers, policymakers, and tribal communities to address these challenges and improve the adaptive capacity of tribal livelihoods in the face of CC. It is advised that governments and development organisations give tribal communities' rights top priority and safeguard them while also incorporating indigenous knowledge systems into CC adaptation planning and implementation. CC can contribute to developing more resilient and sustainable futures for tribal communities.

1.11 Research Gap

Climate change directly or indirectly impacts tribal communities due to higher dependency on agriculture and natural resources for their livelihoods. Despite the growing recognition of these challenges, several gaps persist, especially in the Indian context, which focuses on Madhya Pradesh. Some of the major gaps are discussed below:

- ❖ Lacking long-term climatic trends at the regional level.
- ❖ Existing studies frequently depend on short-term datasets, which fail to capture long-term climatic trends.
- ❖ District-level climate vulnerability assessment was scarce.
- ❖ Limited research exists on how tribal populations across India perceive and respond to climatic changes. The diverse tribal communities in Dhar and Chhindwara, with distinctive socio-cultural settings, are lessened in perception-based studies.
- ❖ Tribal communities remain understudied in vulnerability assessments due to their reliance on climate-sensitive resources. Research especially focusing on the diverse tribal communities in Madhya Pradesh, including Dhar and Chhindwara, is scarce.
- ❖ Frameworks like LVI and IPCC-AR6 are widely used, but their application to tribal communities is limited. Few studies integrate environmental, socioeconomic, and perception-based indicators into a vulnerability assessment. Additionally, index validation is often neglected.

- ❖ There is limited research on how exposure, sensitivity, and adaptive capacity shape livelihood vulnerability for tribal communities. Existing studies fail to assess how climatic and socioeconomic factors affect livelihoods precisely.
- ❖ While climate vulnerability is widely studied, the determinants of vulnerability for tribal livelihood remain inadequately explored. Advanced statistical methods, such as multiple linear regression, are not often used to quantify the factors contributing to climate vulnerability.

This study combines scientific climate data, district-level vulnerability assessments, household perceptions, and multidimensional vulnerability frameworks to evaluate the livelihood vulnerability of tribal communities in Madhya Pradesh, addressing the above lacunae. It aims to comprehensively understand their challenges while emphasising the importance of integrating indigenous knowledge. It also provides evidence-based suggestions to enhance resilience and inform policy interventions for tribal populations.

1.12 Research Questions

After identifying the lacunae, this study tries to answer the following questions:

- ❖ What are the spatiotemporal climatic dynamics (rainfall and temperature patterns) in Madhya Pradesh?
- ❖ How do environmental and socioeconomic factors contribute to district-level climate vulnerability in Madhya Pradesh, and what are the regional variations in vulnerability across different districts?
- ❖ What are tribal communities' perceptions on climate change and its impacts in the Chhindwara and Dhar districts, and how do these perceptions influence their livelihood strategies?

- ❖ What are the key socioeconomic and environmental determinants of livelihood vulnerability to climatic variability among tribal communities in these districts?
- ❖ How do the perceptions of climate change among tribal communities correlate with observed climatic trends, and what are the key socio-demographic factors influencing these perceptions?

1.13 Objectives of the Study

The primary objectives of this study are (a) exploring the spatiotemporal climatic dynamics of Madhya Pradesh using long-term gridded data (1951-2021), focusing on rainfall and temperature patterns, (b) assessing district-level climate vulnerability in Madhya Pradesh, central India, integrating environmental and socioeconomic approach, (c) understanding the perceptions on climate change and its impacts among tribal communities in Chhindwara and Dhar, and analyse how these perceptions influence their livelihood strategies, and (d) evaluating the livelihood vulnerability to climatic variability among tribal communities in Chhindwara and Dhar, and identify the major socioeconomic and environmental determinants of their vulnerability. The above objectives are further expanded.

- ❖ The spatiotemporal climatic dynamics have been explored by framing objectives as to (a) examine the spatiotemporal variability in rainfall and temperature across Madhya Pradesh from 1951 to 2021, (b) detect significant shifts or transition points in rainfall and temperature patterns, (c) assess regional differences in climatic trends within Madhya Pradesh, and (d) evaluate the potential consequences of rainfall and temperature variability on critical sectors such as agriculture and water resources which will directly affect livelihood.
- ❖ The district-level climate change vulnerability has been assessed with objectives to (a) evaluating the CC vulnerability of districts in Madhya Pradesh by integrating environmental and socioeconomic

dimensions, (b) classifying districts based on their vulnerability levels and identifying the most and least vulnerable regions, and (c) employing hierarchical cluster analysis for validating the categorization of vulnerability levels and identifying patterns across districts.

- The perceptions of tribal communities on climate change and its impacts on their livelihoods have been analysed, which aims to (a) analyse tribal perceptions of CC and its impacts on their livelihoods in Dhar and Chhindwara, (b) assess observed regional climatic variations using rainfall and temperature data and link them to local perceptions, and (c) identify sociodemographic factors influencing climate awareness and its impacts.
- The livelihood vulnerability to climate variability among tribal communities has been evaluated with the focus to (a) assess the livelihood vulnerability of tribal households in Chhindwara and Dhar districts using the LVI-IPCC framework, (b) validate the LVI-IPCC results, (c) determine the important factors affecting the vulnerability of tribal households in the study areas using multiple linear regression model, (d) compare the vulnerability levels between the two districts to understand regional differences and (e) provide policy recommendations to enhance adaptive capacity and resilience among tribal communities.

This research aims to assess the livelihood vulnerability of tribal communities in Madhya Pradesh to climate change by integrating scientific data, indigenous knowledge, and household perceptions. It also identifies climatic trends, evaluates district-level vulnerability, and determines key factors influencing tribal resilience, providing insights for targeted policies and adaptive strategies.

1.14 Research Methods

This study follows a mixed-method approach to assess livelihood vulnerability to climate change and variability among tribal communities in Madhya Pradesh. The theoretical framework for vulnerability assessment is based on the IPCC conceptualization, which defines vulnerability as a function of three interrelated components: exposure to climatic hazards, the sensitivity of systems to these hazards, and adaptive capacity to cope and adapt (IPCC, 2007, 2014; Kasthala et al., 2024). This framework guides the selection of environmental and socioeconomic indicators and highlights the composite index approach used to quantify vulnerability in the study area.

Secondary data were collected from various sources, including daily gridded rainfall and temperature data (1951-2021) from the India Meteorological Department (https://www.imdpune.gov.in/), MODIS land use data (https://earthexplorer.usgs.gov/), floods and droughts from the State Disaster Management Plan – Madhya Pradesh (http://www.mpsdma.mp.gov.in/uploads/media/MP-SDMP-2307141.pdf) and socioeconomic indicators from the Census of India (2011) (http://www.censusmp.gov.in) and other government reports. Primary data were collected through scheduled interviews with 535 tribal households in Chhindwara and Dhar districts, selected using a multistage purposive random sampling method. All these data were analysed using various statistical techniques: the Mann-Kendall test and Sen's slope estimator for trend analysis, Pettitt's test for change point detection, and the Inverse Distance Weighted (IDW) method for spatial distribution. District-level climate vulnerability was assessed using a composite index approach, combining Environmental Vulnerability Index (EVI) and Socioeconomic Vulnerability Index (SVI) with hierarchical cluster analysis for validation. Perception data were analysed using descriptive statistics, binary logistic regression, Livelihood Vulnerability Index - Intergovernmental Panel on Climate Change (LVI-IPCC) framework and multiple linear regression (MLR) was employed to identify key determinants of climate change impacts and vulnerability (Fig. 1.8). All analyses were conducted using MS Excel, MATLAB, R-Studio, STATA, Origin 2024, and ArcGIS.

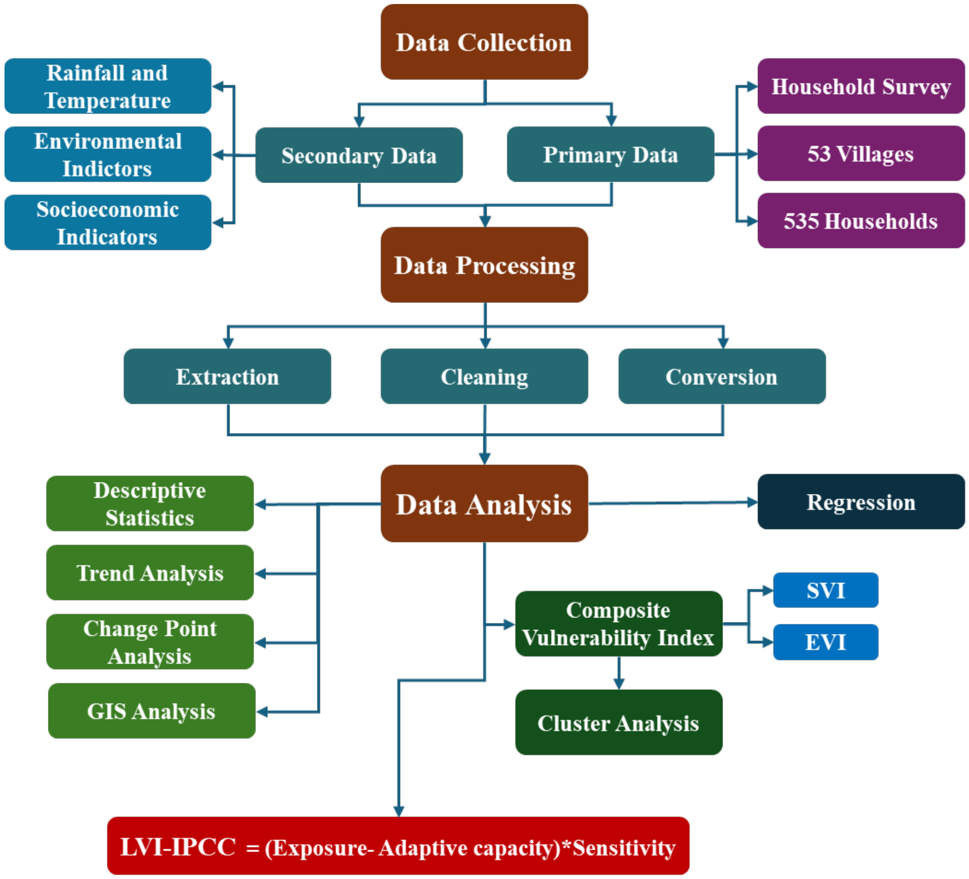


Fig. 1.8: Overall methodology flowchart

Chapter 2

Exploring the Spatiotemporal Climatic Dynamics of Madhya Pradesh using Long-Term Gridded Data (1951-2021)

This chapter explores the spatiotemporal dynamics of rainfall and temperature in Madhya Pradesh using long-term gridded data (1951–2021) from the India Meteorological Department (IMD). It aims to capture regional and temporal variations in climatic variables and their implications for climate change. This analysis identifies transition points and trends in the main climatic variables namely, rainfall and temperature, offering valuable insights for understanding climate change impacts on agriculture, water resources, and livelihoods particularly in Madhya Pradesh.

2.1 Introduction

The increased atmospheric CO_2 and associated climate warming have presented serious worldwide concerns, triggering disruptions in regular climatic patterns (Daniel Tang, 2022; IPCC-AR5, 2014; Nadeau et al., 2022). The changes in Earth's climate are visible via several indicators, including variations in global rainfall patterns and the frequency of high temperatures (Berg et al., 2009; Diffenbaugh, 2020; Tabari, 2020). Daramola & Xu (2022) revealed that drylands have suffered from heat and reduced precipitation in recent decades. Global temperatures have risen by 0.032 °C during the last 40 years, while precipitation has decreased by 0.074 mm per month. These variations in temperature and rainfall are essential climatic characteristics, severely influencing Earth's ecosystems, agriculture, food security, and economic stability (Malhi et al., 2021).

In India, climate change (CC) has mainly damaged agricultural areas, tremendously affecting natural resources and the lives of millions (Thakur et al., 2020). Despite profits from industrialization, India's economy mainly depends on the agricultural sector for its 16% GDP and 46% employment contribution. The dependency on monsoon rainfall for crop cultivation affects agricultural productivity, water resource management, and the broader economy (Birthal & Hazrana, 2019; Jongaramrungruang et al., 2017). Various research has explored rainfall and temperature patterns at local and regional levels to understand these implications better. Machiwal et al. (2017) and Kumar et al. (2010) have investigated long-term rainfall variations locally and reported regional and temporal heterogeneity in rainfall trends. Katzenberger et al. (2021) found a decline in annual rainfall across India in recent decades, with increased severe rainfall events in the northeastern and southern regions. Shah et al. (2021) observed a significant decrease in the proportion of rainy days and monsoon rainfall in Gujarat. Banerjee et al. (2020) reported that rainfall declined by an average of 15.75 mm per decade from 1983 to 2008 in Uttarakhand. Considering the significant impacts of climatic variables, several studies have analysed the temperature variables apart from the rainfall. India had an average temperature increase of 0.7 °C between 1901 and 2018, predicted to reach 4.4 °C by 2100 (Negi et al., 2022). Over the past few years, certain regions of northwest India, specifically Rajasthan and Gujrat, have experienced extremely high temperatures, reaching 50 °C (Dubey et al., 2021). Thakur et al. (2020) noted an increase in mean (T_{mean}), maximum (T_{max}), and minimum (T_{min}) temperatures of 0.37, 0.5, and 0.25 °C, respectively, between 1951 and 2013. Ray et al. (2019) presented positive trends in seasonal temperatures throughout India, except T_{min}. Mall et al. (2021) showed an increasing trend in T_{max} of 0.078 °C each decade from 1951 to 2016.

Madhya Pradesh, situated in central India, has a declining trend in rainfall and an increasing trend in temperature (Kundu et al., 2017). Yadav & Singh (2023) explored rainfall trends in East and West Madhya Pradesh from 1871 to 2016. They found that in West Madhya Pradesh, there was a significant decreasing trend in rainfall in June but a significant increase in August, with no significant seasonal or annual trends. There is a significant decreasing trend in annual and seasonal monsoon rainfall in East Madhya Pradesh. Changes in T_{mean} also affect the hydrological system, covering adjustments in precipitation patterns (Madhukar et al., 2021). The above studies also highlight the importance of analysing rainfall and temperature at local and regional scales. It is essential for developing policies to reduce implications of CC, especially for vulnerable groups like tribal communities in Madhya Pradesh.

This chapter focuses on the changing dynamics of rainfall and temperature in Madhya Pradesh. The primary objectives of this chapter are (a) examining the spatiotemporal variability in rainfall and temperature across Madhya Pradesh from 1951 to 2021, (b) detecting significant shifts or transition points in rainfall and temperature patterns, (c) assessing regional differences in climatic trends within Madhya Pradesh, and (d) evaluating the potential consequences of rainfall and temperature variability on critical sectors such as agriculture and water resources which will directly affect livelihood of the study population. Using long-term gridded data (1951-2021) from the India Meteorological Department (IMD), this study examines the variations in rainfall and temperature over Madhya Pradesh. It also includes identifying transition points in rainfall and temperature throughout the area, indicating major shifts in climatic conditions. The findings of this research will give important insights into how Madhya Pradesh adapts to the effects of CC. Assessing long-term spatiotemporal changes in rainfall and temperature will help researchers and policymakers better understand the region's CC dynamics. This research will help to analyse the possible impacts of varied rainfall and temperature patterns on critical sectors like agriculture and water supply, which are essential for tribal livelihoods. Practical methods and efforts can prevent the negative consequences of CC in Madhya Pradesh, providing sustainable development and resilience for tribal people.

2.2 Methodology

2.2.1 Study Area

The study area comprises the entire state of Madhya Pradesh in central India, covering a total geographical area of 308,252 km² (Fig. 2.1). Madhya Pradesh constitutes 9.38% of India's total geographical area, located between 21°03' to 26°52' N latitude and 78°02' to 82°48' E longitude. The state can be classified into four geographical zones: the low-lying areas in the north and northwest of Gwalior, the Satpura Range, the Vindhyan Range, and the Malwa Plateau. The Satpura Range is known for its dense forests and high hills. This region has three main seasons: summer, monsoon, and winter. The study area experiences a subtropical climate depicted by cold winters and scorching, dry summers. The average annual rainfall is 1194 mm. Most rainfall occurs from June to September, showing that the southwest monsoons start mid-June and bring typical monsoon conditions to Madhya Pradesh. The northwest areas usually get less rainfall, but the south and southeast regions experience heavy rain. Districts such as Mandla, Jabalpur, Balaghat, Sidhi, and other eastern areas experience rainfall above 1,500 mm. The western parts of the state get less than 800 mm annual rainfall. However, this average rainfall covers significant geographical diversity, resulting in issues in water supplies for drinking, agriculture, and ecological sustainability.

Rainfall is the primary water source for the state's major rivers, including the Narmada, Ken, Son, Betwa, Chambal, and Shipra. These rivers are essential for water resources and agricultural activities in Madhya Pradesh. During the summer, the state experiences an average T_{max} of 34.6 °C. In winter, average T_{min} varies from 10 to 25 °C, presenting a mild and pleasant climate and some places dropping to 1 °C or lower, resulting in cold weather. However, summer temperatures reach 48 °C or higher, creating hot and arid conditions. The relationship between temperature and rainfall significantly impacts micro-climate, affecting various aspects of the state's environment and livelihood.

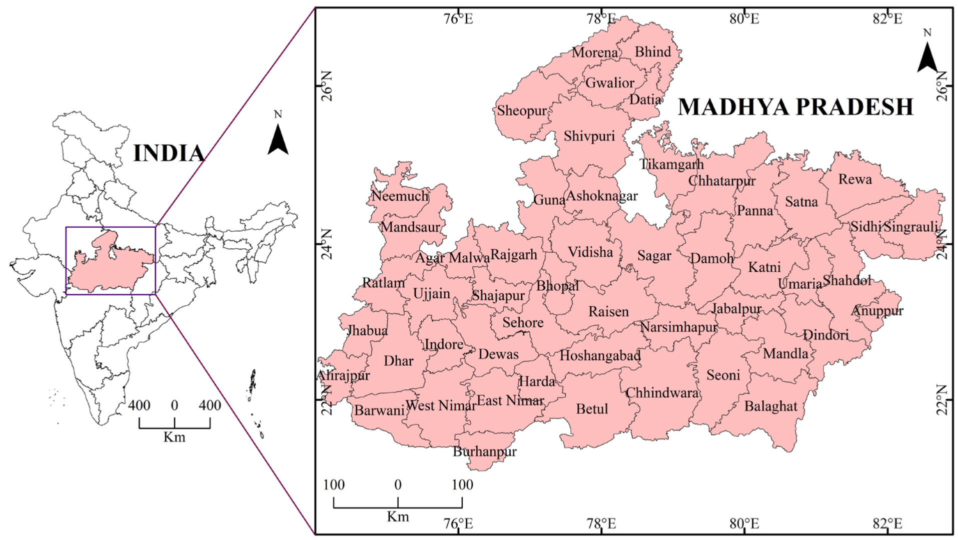


Fig. 2.1: Study area map

2.2.2 Rationale of the study area

Madhya Pradesh was selected as the study area due to its diverse geographical features, major agricultural contribution, highest forest cover in India, and vulnerability to CC. The varied topography, from low-lying plains to the Satpura and Vindhyan Ranges, makes it ideal for exploring rainfall and temperature dynamics. Understanding these changes is essential because the region relies on monsoon rainfall for agriculture, its extensive forest cover, and its susceptibility to extreme weather events. The state's location and diverse climate zones offer a comprehensive understanding of how different geographical regions are impacted by CC. Madhya Pradesh plays a significant role in India's agriculture sector, and its higher proportion of marginalized populations emphasizes the importance of this study, as millions depend on its water resources for agricultural activities and forest resources for livelihood. The availability of climatic data and technological resources further helps this assessment, aiming to offer valuable insights for developing policies, urban planning, and farming strategies to improve resilience against CC.

2.2.3 Data Collection

For this study, daily rainfall and temperature gridded data were collected from the India Meteorological Department (IMD) (https://www.imdpune.gov.in/) for past 71 years (1951 to 2021). IMD utilized 6955 rain gauges across India to create high-resolution gauge-based gridded daily rainfall and temperature data with a spatial resolution of 0.25° × 0.25° and 1° × 1°, respectively (Bharti et al. 2016), and it is responsible for providing weather and climate-related forecasts and warnings in India. The gridded dataset was created by integrating data from gauge station records and weather satellites (INSAT series), ensuring a systematic representation of the region's climate (Roshani et al., 2023). Various research has utilized the IMD gridded dataset as an observed/reference dataset, and multiple hydro-climatological investigations have assessed the accuracy and reliability of this gridded dataset (Gupta et al., 2020). Collecting this data is crucial due to a shortage of weather stations, restrictions on observation, unequal distribution, and lack of data. This study used daily T_{max} and T_{min} from 26 grid points, while rainfall data from 439 grid points covered the entire state. Additionally, the year is segregated into four seasons: pre-monsoon (March-May), monsoon (June-September), post-monsoon (October-November), and winter (December-February) (Shree & Kumar 2018). The monsoon season has heavy rainfall, the post-monsoon season experiences a decrease in rainfall, the pre-monsoon season is hot with occasional thunderstorms, and winter is cool and dry. The timing and length of each season can vary depending on the location and climate.

2.2.4 Data Analysis

The daily rainfall, T_{max} and T_{min} time series data of all grid points were summed up to observe the descriptive statistics (mean, standard deviation, and coefficient of variance), trend, abrupt change point, and spatio-temporal distribution of the seasonal rainfall, T_{mean}, T_{max}, and T_{min} of Madhya Pradesh. The T_{mean} was calculated using T_{max} and T_{min}. The daily rainfall and temperature in Madhya Pradesh were calculated by taking the mean value from all grids point data to examine the trend and conduct a change point analysis. The spatiotemporal distribution was assessed by calculating the average value of each grid point for seasonal data.

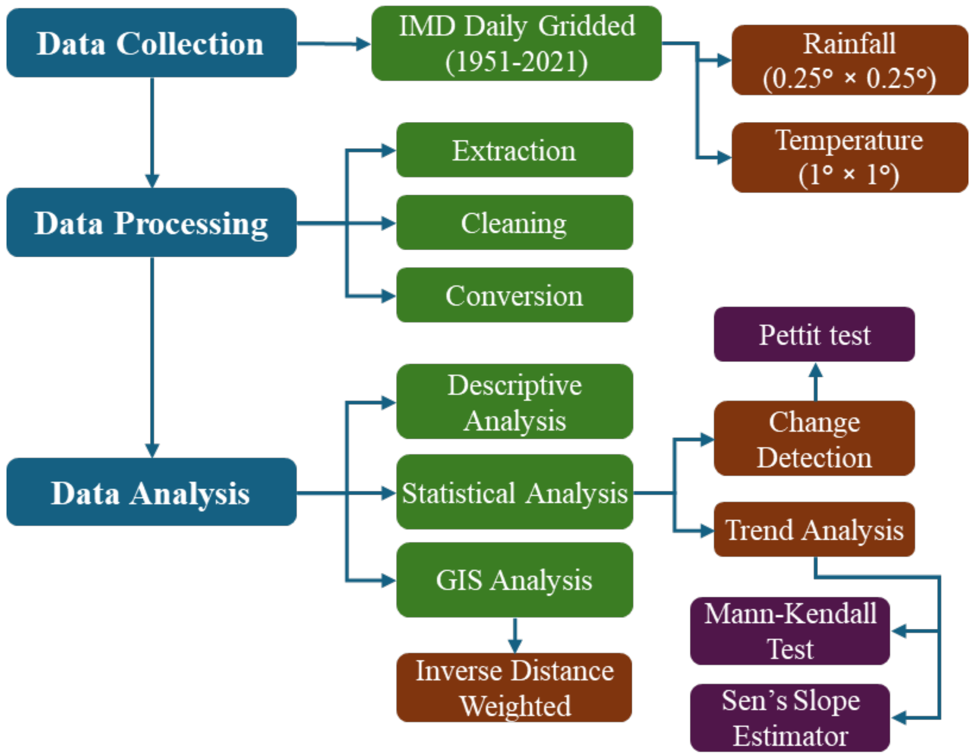


Fig.2.2: A comprehensive methodology framework

Analysing trends in datasets requires non-parametric and parametric techniques, which provide a comprehensive and robust analysis (Punia et al., 2015; Shree & Kumar, 2018). The magnitude and trends of the rainfall, T_{mean}, T_{max}, and T_{min} were examined in this research using the Mann-Kendall test (MK) and Sen's slope estimator (SS). By analysing the fluctuations from 1951–2021, Pettitt's test was employed to identify change points within the rainfall and temperature time series data. Using Inverse Distance Weighted (IDW), the spatial distribution of rainfall and temperature patterns in Madhya Pradesh is demonstrated. The comprehensive methodological framework is shown in Fig.2.2[1]. MS Excel was used for cleaning and converting data and descriptive statistical analysis, MATLAB R2023a for extracting data and trend and change point analysis, and ArcGIS 10.8 was employed for GIS analysis. Following is a brief explanation of each technique that was used.

2.2.4.1. Coefficient of Variance (CV)

This study utilized the CV to examine the variation of every data point from the mean for temperature variability, where a more significant value indicates greater variability (Sarkar et al., 2021). This study used the statistical dataset's CV for rainfall, T_{mean}, T_{max}, and T_{min} variability. It was computed by dividing the data's standard deviation by the mean and expressing the result as a percentage, as shown in Equation 3.1.

$$CV = \frac{\sigma}{\mu} \times 100 \qquad (2.1)$$

where σ = standard deviation and,

μ = mean precipitation.

A *CV* categorized the degree of variability of meteorological variables as low (*CV* < 20%), moderate (20% > *CV* <30%), and high (*CV* > 30%) (Bharath et al., 2023; Getahun et al., 2021).

2.2.4.2. Mann Kendall test (MK)

The MK, a non-parametric statistical test, determines whether hydrological and climatic variables exhibit a monotonic trend (Kendall 1975; Mann 1945). This test is often utilized to investigate time series data trends, including rainfall (Sahu & Khare, 2015). This test does not require data to be regularly distributed (Libiseller & Grimvall, 2002). The Mann-Kendall test, on the other hand, employs the plus or minus signs (+ or -) to minimize

[1] It is noted that at stage 3 (data analysis), different stationarity tests have been conducted (ADF, KPSS, etc.) and the annual series of different rainfall seasons found to be stationary at level, i.e., I (0).

the influence of trends (Birsan et al. 2005). The *p*-value determines how statistically significant the trend is, with a lower *p*-value suggesting a greater level of significance for the observed difference (Roshani et al., 2023). It should be noted that these tests need an independent data pattern. The 5% level of significance was used to analyse these patterns. Equation 2.2 defines the Mann-Kendall statistics (S).

$$S = \sum_{b=1}^{n-1} \sum_{c=b+1}^{n} sign(x_c - x_b) \qquad (2.2)$$

where x_b and x_c = annual values in years *b* and *c*.

The later observations in the time series tend to be greater than the earlier observations if *S*>0, and the opposite is true if *S*<0. Equation 2.3 is used to compute the variance of *S*.

$$var\ (S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{q} f_p\left(f_p - 1\right)\left(2f_p + 5\right)\right] \qquad (2.3)$$

where n = number of data points

q = number of tied groups

f_p = The number of data values in the qth group

Equation 2.4 is used to determine the test statistics *Z* using the values of *S* and var (*S*).

$$Z = \begin{cases} (S-1)/sr, if\ S > 0 \\ 0, if\ S = 0 \\ (S+1)/sr\ , if\ S < 0 \end{cases} \qquad (2.4)$$

where *sr* = square root of *var* (*S*)

2.2.4.3. Sen's Slope Estimator (SS)

The trend slope of a sample of N data pairs can be estimated using the Theil-Sen estimator, a non-parametric technique (Sen, 1968; Theil, 1950). This method uses simple linear regression to estimate the median slope of two dependent and independent variables. The slope (T) can be calculated using Equation 2.5.

$$T_i = \frac{x_{ab} - x_{ac}}{j - k} \quad \text{for a = 1,2,3, 4….N} \qquad (2.5)$$

where x_{ab} and x_{ac} =data value, b and c ($b > c$)

Sen's slope estimator (Q) is computed using Equation 2.6.

$$Q = \begin{cases} T_{\left[\frac{(N+1)}{2}\right]}, & if\ N\ is\ odd \\ \dfrac{T_{\left[\frac{N}{2}\right]} + T_{\left[\frac{(N+2)}{2}\right]}}{2}, & if\ N\ is\ even \end{cases} \qquad (2.6)$$

2.2.4.4. Pettitt's test

The Pettitt test (Pettitt, 1979), a non-parametric statistical test, helps identify abrupt changes in climatic records. This test is preferred due to its high accuracy for detecting breaks in the central portion of a time series data (Wijngaard et al., 2003). Dhorde & Zarenistanak (2013) and other researchers have already explained the statistical computation used in the Pettitt test. The first step involves computing the V_k statistics using Equation 2.7.

$$V_k = 2\sum_{i=0}^{n} m_i - k(n+1) \qquad (2.7)$$

where m_i = rank of the i^{th} observation

k = values from 1, 2, ..., n.

$$K_n = max|V_k| \qquad (2.8)$$

A transition point occurs when V_k reaches a series' maximum value of K (Equation 2.8). The statistical change point (SCP) test is then defined by solving Equation 2.9.

$$K_\alpha = \{-1n\,\alpha(n^3 + n^2/6)\}^{1/2} \tag{3.9}$$

where n = number of observations and,

α = level of significance

2.2.4.5. Inverse Distance Weighted (IDW)

The IDW is often used for tasks like spatial interpolation of rainfall, temperature, air quality, or any other continuous variable observed at multiple places in various disciplines, including geography, environmental science, and geo-statistics. It is a popular method in spatial interpolation, a technique for estimating values at unknown places based on values observed at known locations (Kumar et al., 2023). IDW provides weights to neighbouring known data points in the context of spatial data depending on their distances from the target location. These weights are then used to compute a weighted average, which estimates the value at the targeted location. The underlying premise of IDW is that data points closer to the target location have a higher impact on the estimated value than those further away (Karami et al., 2023). The IDW is calculated using Equation 2.10.

$$W(x, y) = \sum_{i=1}^{N} \lambda_i w_i \tag{2.10}$$

$$\lambda_i = \frac{(1/d_i)^P}{\sum_{K=1}^{N}(1/d_i)^P}$$

where W denotes the estimated value at location (x, y), N represents the number of known locations nearby (x, y), λ_i indicates the weight assigned to the known values w_i in (x_i, y_i), d_i stands for the Euclidean distance between each point in locations (x, y) and (x_i, y_i), and p describes the power that is impacted by weight w_i on w.

2.3 Results and Discussion

Analysing climatic variability, detecting trends, and assessing regional distribution is essential for gaining deep insights into the implications of CC and enhancing resource and infrastructure planning. Meteorological data is an essential source of knowledge for comprehending these alterations. In climate research, non-parametric tests are often used because they enable the identification of patterns in time series data without making presumptions about the distributions of components. These tests are beneficial for assessing several meteorological variables, including precipitation, temperature, wind speed, and humidity, across different magnitudes. Examining spatial distribution is essential to understanding local alterations in climatic variables and their historical changes (Ampofo et al., 2023).

2.3.1 Descriptive Analysis

The descriptive statistics of climate variability in Madhya Pradesh (1951-2021) revealed significant fluctuations in rainfall and temperature, characterized by different seasonal variations (Table 2.1). Mean annual rainfall (1041.36 mm) indicates the highest yearly variations (σ = 179.18). The monsoon season provides the most annual rainfall but demonstrates high variation (σ = 166.19) with a low level of CV (17.51). Pre-monsoon, post-monsoon, and winter seasons show even more significant variability, with coefficients of variation exceeding 79%, exposing their erratic nature. Temperature shows relatively lower variability compared to rainfall. The annual T_{mean} is 25.52 °C with a low CV of 1.42%, indicating lower variations (σ = 0.36) in temperature over the years. However, seasonal T_{mean} shows more variability during the post-monsoon (CV = 3.47) and winter (CV = 3.23) seasons. T_{max} also has a lower level of variability, but T_{min} exposes significant seasonal variations. T_{min} shows a high CV value in the annual (CV = 39.64) and winter seasons (CV = 39.20), indicating higher cold season variability. The findings of a recent study on rainfall variability align with other studies, such as Chandniha et al. (2017), Shree & Kumar (2018) and Warwade et al. (2018). Specifically, the study found high pre-monsoon, post-monsoon, and winter rainfall variability. According to earlier research, the region is vulnerable to floods and droughts (Pandey & Ramasastri, 2001). High variability in rainfall affects agricultural productivity and water availability, which is essential for subsistence farming practiced by many tribal communities. Unpredictable pre-monsoon and post-monsoon rainfall exacerbates agricultural problems, increasing vulnerability to crop failures and food insecurity. The CV values provide helpful information about the temperature variability in Madhya Pradesh.

Table 2.1: Descriptive statistics of climate variability in Madhya Pradesh (1951-2021)

Variables	Categories	Mean (μ)	Standard deviation (σ)	CV (%)	Max (mm/°C)	Min (mm/°C)
Rainfall	Annual	1041.36	179.18	17.21	1530.20	645.72
	Monsoon	949.02	166.19	17.51	1367.22	597.97
	Pre-monsoon	20.57	17.07	82.99	84.05	2.43
	Post-monsoon	42.71	36.32	85.04	150.17	0.63
	Winter	29.05	23.19	79.82	97.89	0.39
T_{mean}	Annual	25.52	0.36	1.42	26.48	24.48
	Monsoon	28.28	0.49	1.73	29.44	26.97
	Pre-monsoon	29.75	0.68	2.29	31.86	28.17
	Post-monsoon	23.76	0.83	3.47	25.54	21.83
	Winter	18.80	0.61	3.23	20.62	17.62
T_{max}	Annual	45.85	1.10	2.39	47.70	42.70
	Monsoon	44.99	1.58	3.50	47.60	40.60
	Pre-monsoon	45.42	1.07	2.37	47.50	42.70
	Post-monsoon	36.66	1.24	3.38	38.90	33.70
	Winter	35.40	1.33	3.77	38.50	32.20
T_{min}	Annual	2.80	1.11	39.64	5.80	0.40
	Monsoon	19.48	1.15	5.88	21.50	13.80
	Pre-monsoon	10.13	1.77	17.49	13.90	5.80
	Post-monsoon	8.11	1.65	20.38	13.20	4.00
	Winter	2.86	1.06	37.20	5.80	0.40

The low CV values for T_{mean} and T_{max} indicate stability and consistency. However, the high CV value for T_{min} indicates significant variability that should be considered when analysing the region's temperature patterns. It can broadly impact various sectors like agriculture, health, energy, and overall ecosystem stability, which are crucial for sustaining tribal livelihoods. For example, sudden temperature drops could lead to frost and damage to crops, reducing the yield or altering the time of yield among non-timber forest products (NTFPs) and could also lead to health problems like hypothermia. The findings of this study on temperature variability align with other studies, such as Pal & Al-Tabbaa (2010), Punia et al. (2015), Radhakrishnan et al. (2017), and Roshani et al. (2023). The high variability in both rainfall and temperature need adaptive strategies to mitigate adverse impacts on agriculture and water resources. Improving water management practices, promoting climate-resilient crops, and enhancing infrastructure can help against climatic shocks. Policymakers and stakeholders must consider building climate resilience among tribal communities to ensure sustainable livelihoods amidst changing climatic conditions.

2.3.2 Temporal Trend Analysis

Table 2.2 presents the trend analysis results of seasonal rainfall and temperature (T_{mean}, T_{max}, T_{min}) in Madhya Pradesh from 1951 to 2021, evaluated using the MK test and SS estimator at a 5% significance level. The analysis indicates a non-significant decreasing trend in annual rainfall (Z = -1.023) and monsoon rainfall (Z = -0.933) (Fig. 2.3(a)) at 0.05% significance level with a yearly magnitude of -0.990 mm and -0.977 mm, respectively. The negative trend in annual rainfall suggests that the region is experiencing a decline in rainfall patterns, which could adversely affect agricultural production and other water-dependent activities. Decreasing monsoon rainfall could result in water shortages during the monsoon season, reducing water supply. Similarly, the post-monsoon (Z= -0.764) and winter (Z= -0.735) seasons have shown a non-significant decreasing trend (Fig. 2.3a) with an annual magnitude of -0.116 mm and -0.067 mm, respectively. This trend is particularly concerning since these periods are essential for recharging groundwater and maintaining water levels in rivers and reservoirs. However, the pre-monsoon (Z= 0.288) season shows a non-significant increasing trend (Fig. 2.3(a)) with an annual magnitude of 0.018 mm. The positive trend in pre-monsoon rainfall suggests that this season receives more rainfall and that changes in rainfall patterns will positively impact water availability for agricultural production at the right time and duration in addition to other sectors. These results are consistent with several studies on Central and Central West India.

Table 2.2: Trend analysis results of annual and seasonal rainfall

Variables	Categories	Z-Stat.	Q-Stat.	*P*-value	Trend
Rainfall	Annual	-1.023	-0.990	0.307	Decreasing
	Monsoon	-0.933	-0.977	0.351	Decreasing
	Pre-Monsoon	0.288	0.018	0.773	Increasing
	Post Monsoon	-0.764	-0.116	0.445	Decreasing
	Winter	-0.735	-0.067	0.463	Decreasing
T_{mean}	Annual	2.898	0.006	0.004	Increasing
	Monsoon	1.092	0.003	0.275	Increasing
	Pre-Monsoon	1.052	0.005	0.293	Increasing
	Post Monsoon	3.594	0.018	3.26e-04	Increasing
	Winter	0.149	0.050	0.882	Increasing
T_{max}	Annual	1.772	0.011	0.076	Increasing
	Monsoon	1.449	0.011	0.148	Increasing
	Pre-Monsoon	1.241	0.009	0.215	Increasing
	Post Monsoon	0.834	0.007	0.404	Increasing
	Winter	0.074	0	0.941	Increasing
T_{min}	Annual	2.452	0.017	0.0142	Increasing
	Monsoon	0.551	0.002	0.582	Increasing
	Pre-Monsoon	2.422	0.026	0.015	Increasing
	Post Monsoon	3.891	0.033	9.96e-05	Increasing
	Winter	2.750	0.018	0.006	Increasing

For example, Kundu et al. (2017) reported a negative trend in monsoon, post-monsoon, winter, and annual rainfall over the past 111 years (1901-2011), while pre-monsoon reported an increasing trend. Jain et al. (2023) found a non-significant decline in annual and monsoonal rainfall in Madhya Pradesh during the last 146 years (1871-2016). Moreover, Kumar et al. (2010) identified a declining trend of annual and monsoonal rainfall and a positive trend of pre-monsoonal rainfall over the past 135 years (1871-2005). Pal & Al-Tabbaa (2011) also reported a negative annual and monsoonal rainfall trend in central India from 1951 to 2003. Rai et al. (2014) and Devi et al. (2020) observed similar trends in decreasing rainfall across Madhya Pradesh.

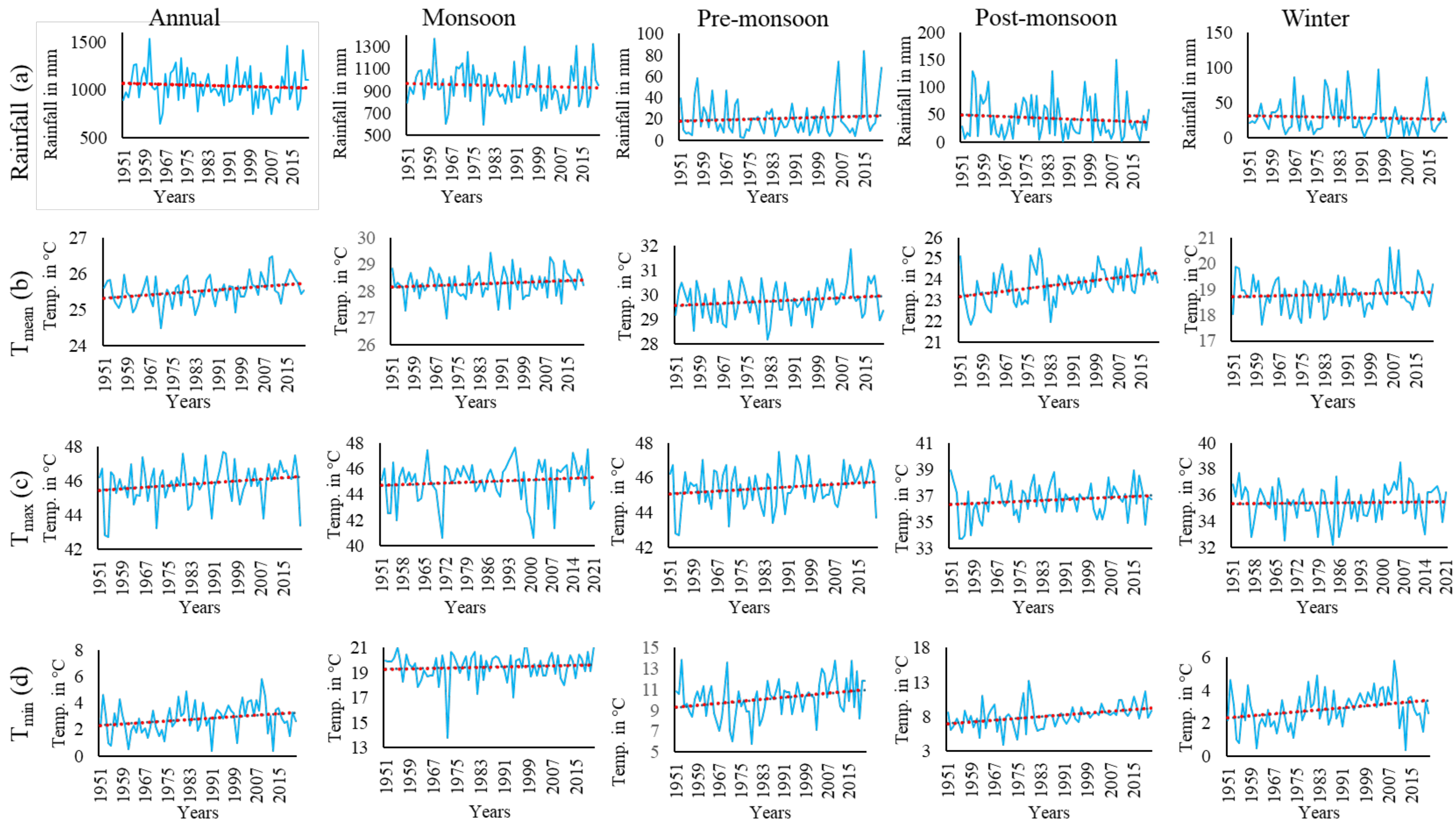


Fig. 2.3: Trends in seasonal rainfall (a), T_{mean} (b), T_{max} (c), T_{min} (d) of Madhya Pradesh

Contrary to rainfall, temperature variables significantly increase across all categories. The annual T_{mean} shows a statistically significant increasing trend (Z = 2.898), indicating a change of 0.006 °C per year. Seasonal analyses further provide evidence of this trend, with the monsoon (Z = 1.092), pre-monsoon (Z = 1.052), post-monsoon (Z = 3.594), and winter temperatures (Z = 0.149) all exhibiting rising patterns (Fig. 2.3(b)), indicating a change of 0.003 °C, 0.005 °C, 0.018 °C, 0.050 °C per year, respectively. T_{max} and T_{min} trends are similarly increasing annually and seasonally, demonstrating a broader warming pattern. The annual T_{max} illustrates an increasing trend (Z = 1.772) at 0.006 °C yearly. Similarly, the monsoon (Z = 1.449), pre-monsoon (Z = 1.241), post-monsoon (Z = 0.834), and winter temperatures (Z = 0.074) presented inclining patterns (Fig. 2.3(c)). It indicates a long-term warming trend with significant consequences for marginal people vulnerable to CC in Madhya Pradesh. However, the annual T_{min} also presents a statistically significant increasing trend (Z = 2.452), with a rate of 0.017 °C per year, highlighting a significantly increasing trend during this period. Correspondingly, the monsoon (Z = 0.551), pre-monsoon (Z = 2.422), post-monsoon (Z = 3.891), and winter temperatures (Z = 2.750) presented inclining patterns (Fig. 2.3(d)). Duhan et al. (2013) reported an increased temperature of 0.60 °C for the annual T_{mean}, T_{max}, and T_{min} over 102 years (1901-2002). Shukla et al. (2017) and Shukla & Khare (2013) identified a significant increasing trend in the T_{mean} of Madhya Pradesh over 105 years (1901-2005). Devi et al. (2020) observed a noteworthy increasing trend in T_{mean}, T_{max}, and T_{min} over 45 years (1971-2015) in Central India. Kundu et al. (2017), using 105 years (1901-2005) of T_{max} and T_{min} data from Madhya Pradesh, demonstrated an increasing trend in both variables, with the highest temperature rise occurring during the winters and post-monsoon seasons. Furthermore, Punia et al. (2015) and Singla et al. (2023) noted an upward trend in T_{max} and T_{min} in northwestern India after 1970. The results of this study align with previous studies conducted by Dubey et al. (2021), Pal &

Al-Tabbaa (2010), Radhakrishnan et al. (2017), and Srivastava et al. (2017), which also reported positive trends in T_{mean}, T_{max}, and T_{min} across various regions in India. However, Jhajharia et al. (2014) analysed trends in temperature over the Godavari River basin in Southern Peninsular India using 35 stations. They also reported that the specific number of stations presents an increasing trend in T_{mean}, T_{max}, and T_{min}.

These findings hold great significance for the region's ecology, agriculture, and economy, as well as for the tribal communities of Madhya Pradesh. Decreasing annual and monsoon rainfall jeopardizes the agricultural activities that these communities depend on, leading to potential decreases in crop yields, NTFP collection and food security. Reduced post-monsoon and winter rainfall strain water supplies essential to livelihood during the off-season agricultural months. The rising temperatures exacerbate these problems, leading to water shortages and ultimately impacting crop quality and productivity (Praveen & Sharma, 2020). Higher temperatures can raise evapotranspiration rates, decrease soil moisture, and require more water supply (Suliman et al., 2024), which isn't feasible for tribal farmers with limited resources. The climatic trends observed need urgent adaptive efforts to mitigate negative consequences on tribal livelihoods. These approaches can include developing drought-resilient crop types, making them adopt efficient water-management techniques through promotion of sprinkler irrigation, and improving community understanding and preparedness for climate resilience. Policymakers, stakeholders, and academicians must prioritize these strategies to ensure the sustainable development and adaptability of tribal communities due to CC.

2.3.2 Change Point Analysis

A change point is when there is a significant shift in the data with extended distribution. Abrupt changes in annual and seasonal trends in rainfall and temperature data for Madhya Pradesh were detected using Pettitt's test. It identifies trends and the year the movement starts (mutation point). Fig. 2.4

presents the results of Pettitt's test, detecting abrupt change points in the seasonal patterns of rainfall and temperature (T_{mean}, T_{max}, T_{min}) in Madhya Pradesh. The change points for the Monsoon, Pre-Monsoon, Post-Monsoon, Winter and Annual were 1998, 1955, 1987, 1986, and 1998, respectively, according to the results of Pettitt's test (Fig. 2.4(a)). The results indicated that the trend pattern abruptly changed after the 1980s, except for pre-monsoon rainfall. Similar studies were also done in different regions to detect sharp transition points in climatic variables. Zarenistanak et al. (2014) used time series data (1950-2007) of Iran and observed that the mutation point occurred in 1973. Kumar et al. (2023) used data from three stations, i.e., Mukteshwar, Hawalbagh, and Almora, from 1980 through 2019. They identified that annual rainfall trends abruptly changed in 2004, 1998, and 1991, respectively.

Similarly, for the T_{mean}, the change points for the monsoon, pre-monsoon, post-monsoon, winter and annual were 2007, 2000, 1998, 1959, and 2004, respectively (Fig. 2.4(b)). T_{max} exhibited significant changes across different periods, noticeable in 2010 for annual, 1990 for monsoon, 2008 for pre-monsoon, 1963 for post-monsoon, and 1966 for winter (Fig. 2.4(c)). T_{min} showed changes in 1999 for annual data and in 1960, 2003, 2008, and 1995 for the monsoon, pre-monsoon, post-monsoon, and winter seasons, respectively (Fig. 2.4(d)). These findings highlight significant changes in temperature dynamics within specific periods. Similar research has been conducted in other geographical locations to identify significant transition points in climate variables. For example, Shukla et al. (2017) identified 1963 as the change point for the T_{mean} time series spanning from 1901 to 2005 for the entirety of Madhya Pradesh. Chandole & Joshi (2023) observed a positive trend in T_{min}, which experienced a consistent change after 1986 in two districts of Gujarat. A study by Zarenistanak et al. (2014) focusing on Iran's annual and seasonal temperature data from 1950 to 2007 reveals mutation points between the 1980s and 1990s. However, Srilakshmi et al. (2022) applied Pettitt's test to the pan coefficient in the northeastern region

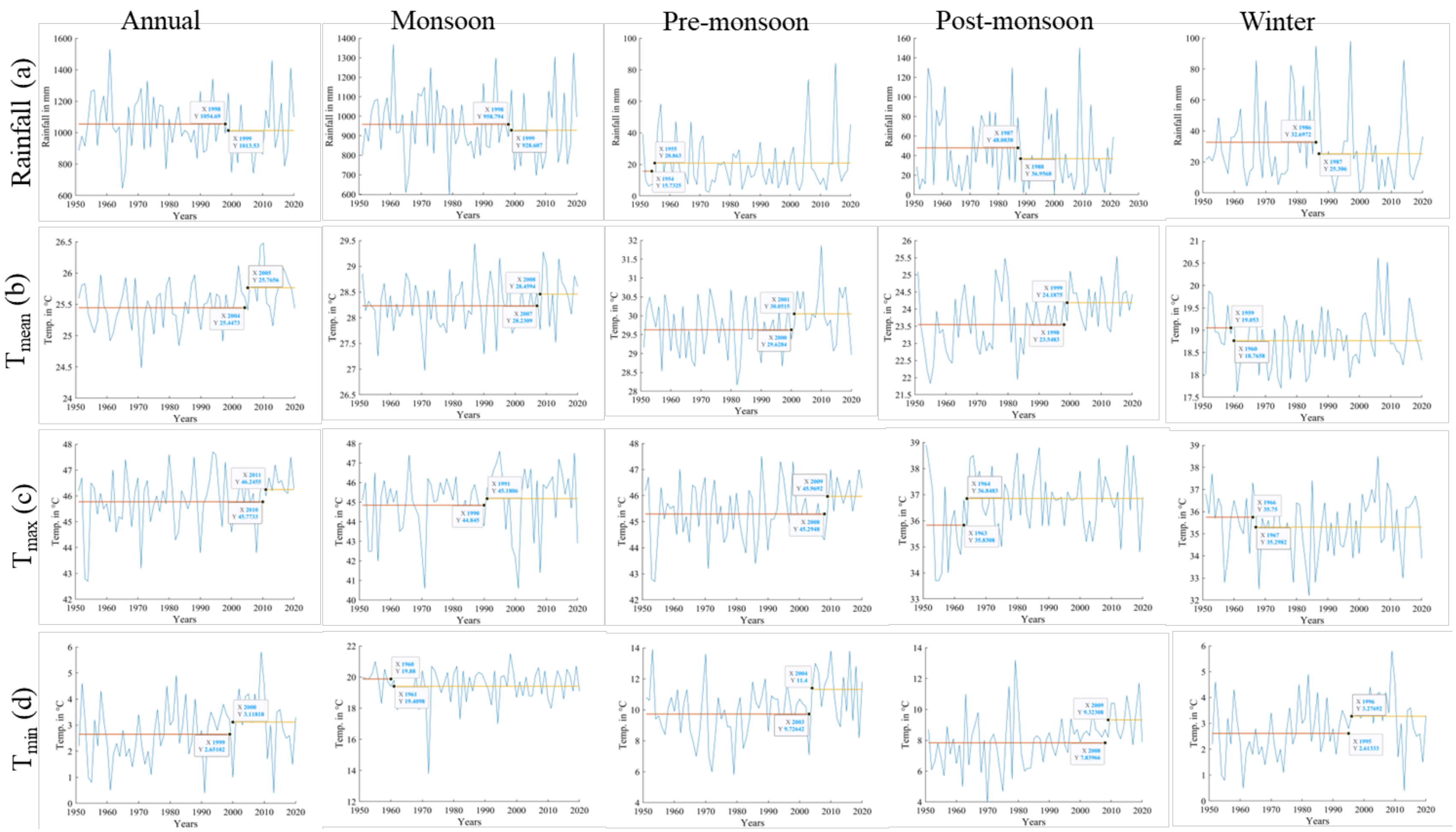


Fig. 2.4: Change point results of seasonal rainfall (a), T_{mean} (b), T_{max} (c), T_{min} (d)

of India and observed that abrupt change occurred after 1990 in four stations. Ahmadi et al. (2018) investigated the long-term temperature patterns in Iran by analysing data from 34 synoptic stations over 50 years (1961-2010) at both seasonal and annual time scales and observed change points from 1986 to 1994.

The identified change points in both rainfall and temperature are of critical significance to the tribal communities of Madhya Pradesh. These communities mostly rely on subsistence agriculture, which is strongly related to predictable climatic patterns. The sudden shifts in monsoon rainfall and changes in temperature patterns highlight an increased vulnerability to climate variability, posing threats to crop productivity and food availability. Abrupt changes in pre-monsoon and post-monsoon rainfall patterns can affect crop planting and crops and NTFP's harvesting timing, leading to potential mismatches in agricultural cycles and income derived from forest. Abrupt changes in winter rainfall and temperature are also essential as they affect water availability and soil moisture content, which is important for preparing fields for the main agricultural seasons. The detected change points can have hydrological impacts, affecting riverine flow and water availability, as the Madhya Pradesh Water Resources Department (MPWRD) reported in their State Water Resources Plan. These shifts in rainfall can also influence agricultural resilience, impacting crop yields and planting seasons (Raza et al., 2019). Additionally, the occurrence of sudden change in rainfall trends could have implications for ecosystem dynamics and wildlife habitat, highlighted in a report by the Madhya Pradesh Forest Department. Disaster preparedness and infrastructure planning could also benefit from the insights gained from these change points, as demonstrated in the Madhya Pradesh Disaster Management Plan. These changes influence the frequency and intensity of floods and droughts, directly impacting agriculture and human livelihood. So, some of the plans made by the government in the agriculture sector in

Madhya Pradesh State Action Plan on Climate Change, 2012, include the following:

- Promoting soil and water conservation technologies
- Planning cropping systems suitable for each agro-climatic zone
- Management of risks for sustainable productivity
- Enhancing dissemination of new and appropriate technologies developed by researchers and strengthening research
- Agriculture information management
- Additional impetus to mechanization and accessibility to markets
- Creation of rural business hubs
- Capacity building for sustainable agriculture

Furthermore, the warming trends replicated in the change points of T_{mean}, T_{max}, and T_{min} suggest an increased frequency of extreme weather events, such as heatwaves, which can adversely affect health and reduce agricultural productivity and water security. For tribal communities with limited access to modern agricultural technologies and financial resources, these climatic changes could exacerbate existing socioeconomic challenges, leading to increased food insecurity and reduced resilience to extreme weather events. Understanding these abrupt changes in climatic variables is essential for developing targeted adaptation measures to protect tribal livelihoods. Policymakers and stakeholders must consider these findings to design strategies that improve climate resilience, sustainable water management, and agricultural resource management, as well as provide alternative livelihood strategies to maintain the well-being of tribal populations in Madhya Pradesh amidst changing climate dynamics.

2.3.4 Spatial Change Analysis

The Inverse Distance Weighted method, a key interpolation component, was utilized in the spatial change analysis. The study considered the seasonal rainfall and temperature data of all the grid points to gain insights into the spatial change of rainfall and temperature patterns. The abrupt change point

(Pettitt's test results) of annual rainfall and temperature was used as the base year to compare seasonal rainfall and temperature changes. The long-term time series data was separated into two periods: 1951-1998 and 1999-2021 for rainfall, 1951-2004 and 2005-2021 for T_{mean}, 1951-2020 and 2011-2011 for T_{max}, and 1951-1999 and 2021 for T_{min}, to understand the spatiotemporal shifts in various parts of the state. The IDW maps in Fig. 2.5 to 2.8 show the comparative spatiotemporal distribution of seasonal rainfall, T_{mean}, T_{max}, and T_{min} in Madhya Pradesh.

Fig. 2.5 provides a comprehensive overview of the spatiotemporal distribution of seasonal rainfall patterns in Madhya Pradesh, and the results are both intriguing and concerning. During the pre-monsoon season, the area that receives less than 25 mm of rainfall increased after 1998, primarily in the northern and northwest parts of Madhya Pradesh. This study found that there has been a drastic decrease in the areas that receive rainfall above 1000 mm during the monsoon season after 1998. The important concern here is the maximum average monsoonal rainfall reduction, which decreased from 1623 mm to 1311 mm after 1998. The area receiving less than 25 mm of rainfall is increasing after 1998 during the post-monsoon season. Furthermore, the winter season has seen significant changes, with less than 25 mm rainfall receiving areas increasing and more than 50 mm rainfall areas are decreasing after 1998. After assessing all seasons of rainfall distribution, the average annual rainfall distribution was also changed after 1998. Only the Western and North parts of this region were getting less than 1000 mm of annual rainfall during 1951-1998, but the scenario changed after 1998, and this area (<1000 mm) increased. The 1000-1250 mm rainfall area was shifted, and more than 1250 mm rainfall area decreased. The maximum average annual rainfall was 1769 mm from 1951 to 1998, which changed to 1401 mm after 1998, with a more than 300 mm reduction. These findings suggest that Madhya Pradesh experienced a significant shift in its seasonal rainfall distribution after 1998, which requires further attention and investigation. The large-scale topography of the region, as well as the finer-scale features of the Western Ghats, have a significant impact on the spatial distribution of seasonal rainfall in central India (Singh et al., 2019).

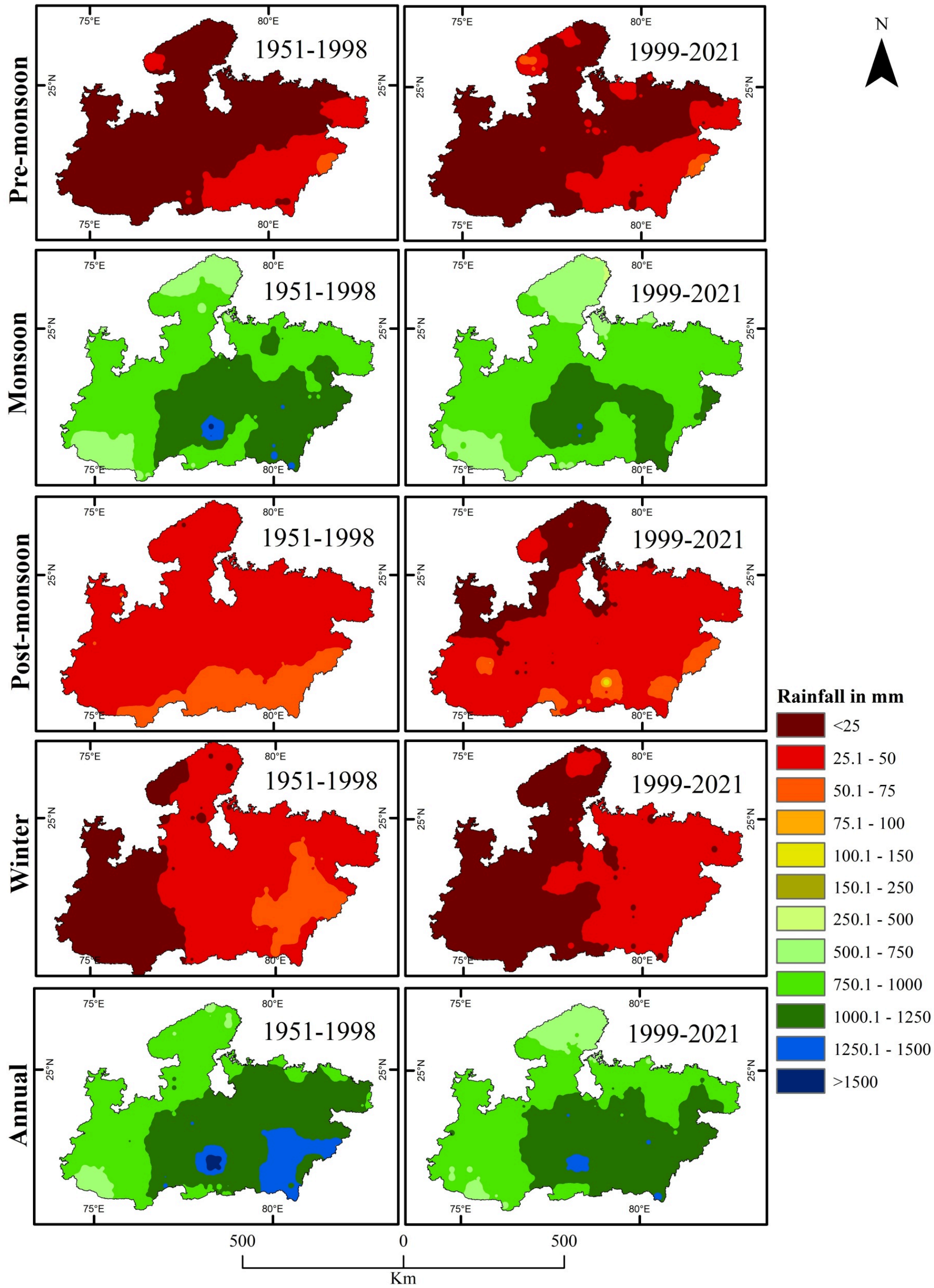


Fig. 2.5: Comparative spatial distribution of rainfall in Madhya Pradesh

The regional distribution of seasonal T_{mean} in Madhya Pradesh is shown in Fig. 2.6. Before 2004, the T_{mean} ranged from 29-30 °C, and it shifted to 30-31 °C throughout the monsoon and pre-monsoon seasons after 2004, with decreases in places below 28 °C and rises in areas which have above 28 °C. After the monsoon season, there were notable changes, with decreases in places with temperatures of 23-24 °C and increases in regions with temperatures of 24-26 °C. Winters saw changes, with reductions in places below 18 °C and increases in areas above 19 °C after 2004. Due to variations in seasonal T_{mean}, the annual T_{mean} pattern also shifted. Less than 25.5 °C area ultimately decreased, and higher than 25.5 °C area rapidly increased after 2004.

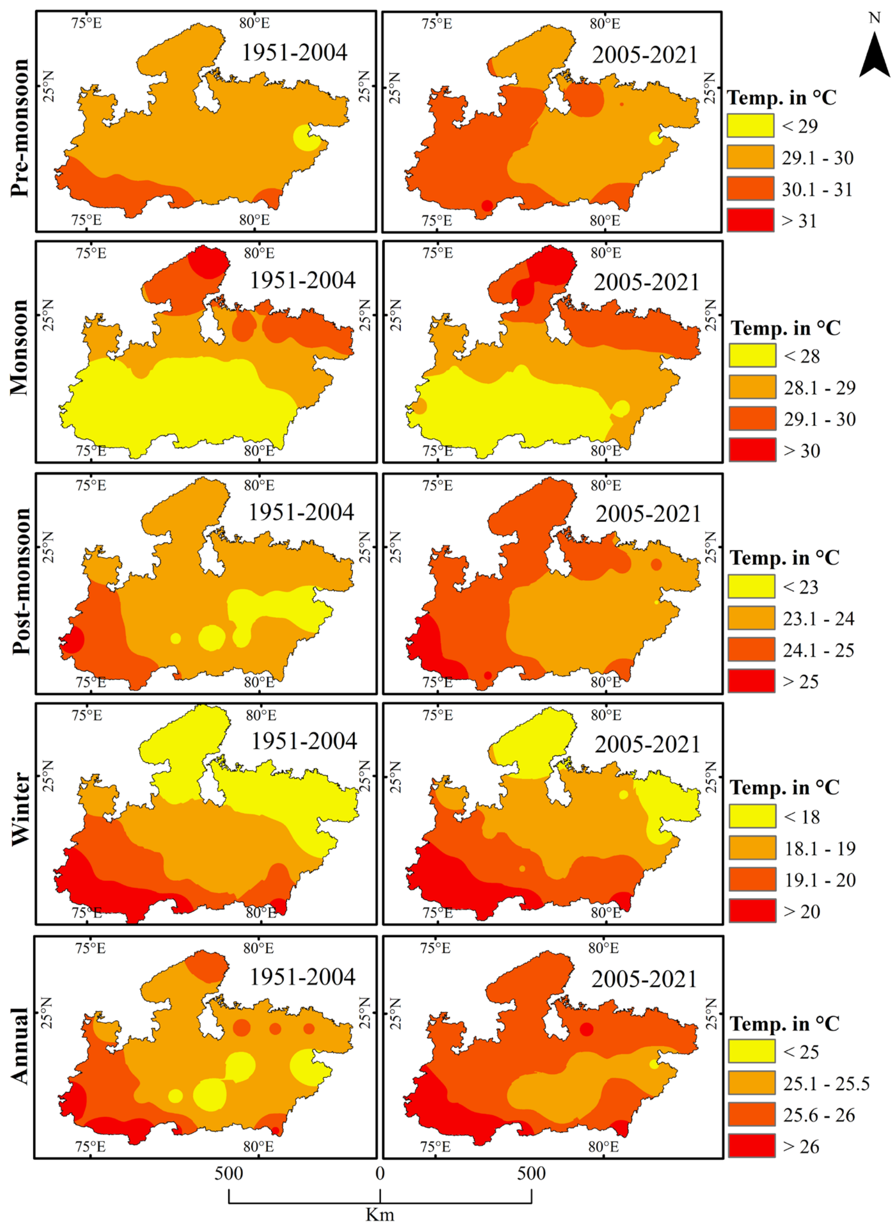


Fig. 2.6: Comparative spatial distribution of T_{mean} in Madhya Pradesh

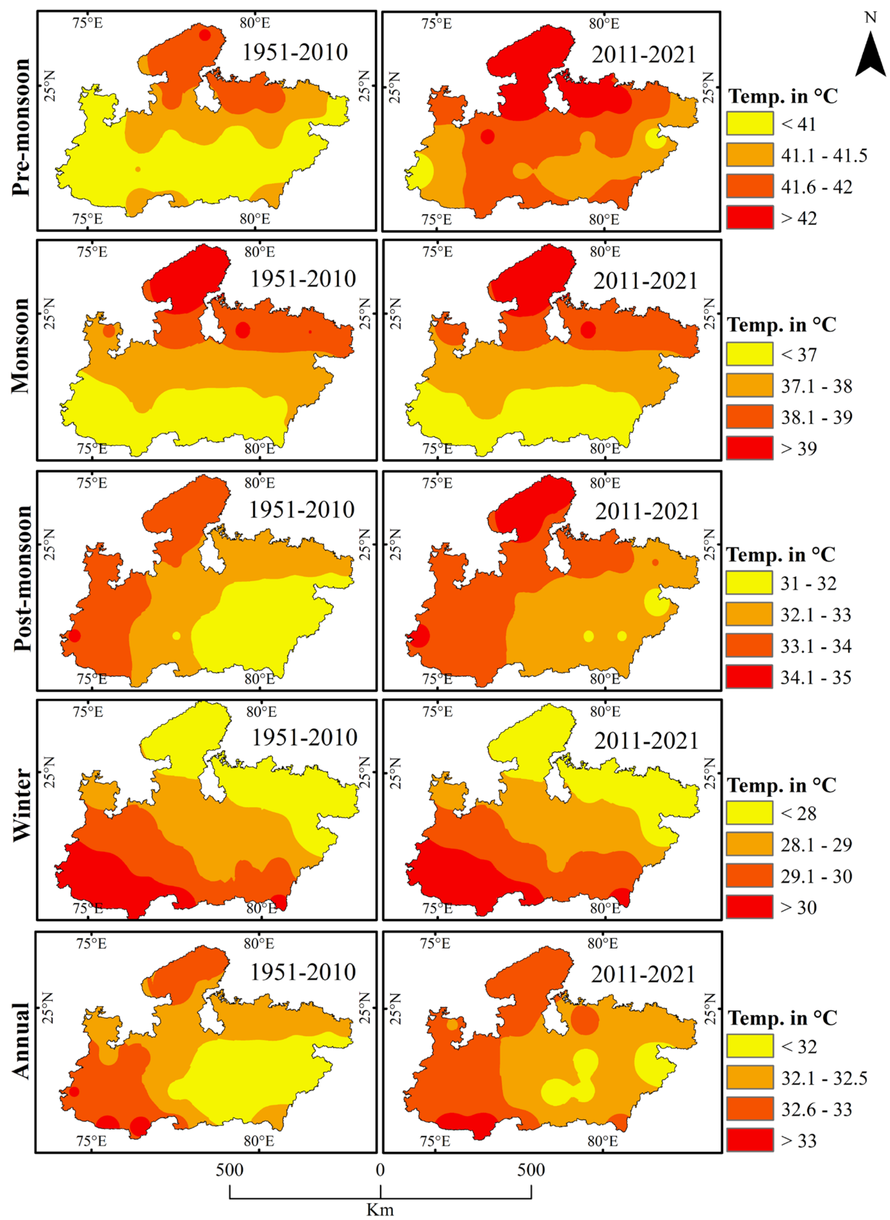


Fig. 2.7: Comparative spatial distribution of T_{max} in Madhya Pradesh

The geographical distribution of seasonal T_{max} in Madhya Pradesh is presented in Fig. 2.7. After 2010, significant changes have been seen, especially during the pre-monsoon and post-monsoon seasons. During the pre-monsoon season, the T_{max} rises in regions ranging from 41-43 °C. After the monsoon season, areas with temperatures over 34 °C increase, while regions below 32 °C disappear entirely. Minor changes appeared in the distribution of T_{max} in winter. The same shifting pattern is also visible in annual T_{max}. Less than 32 °C area decreased, and more than 32 °C area increased after 2010.

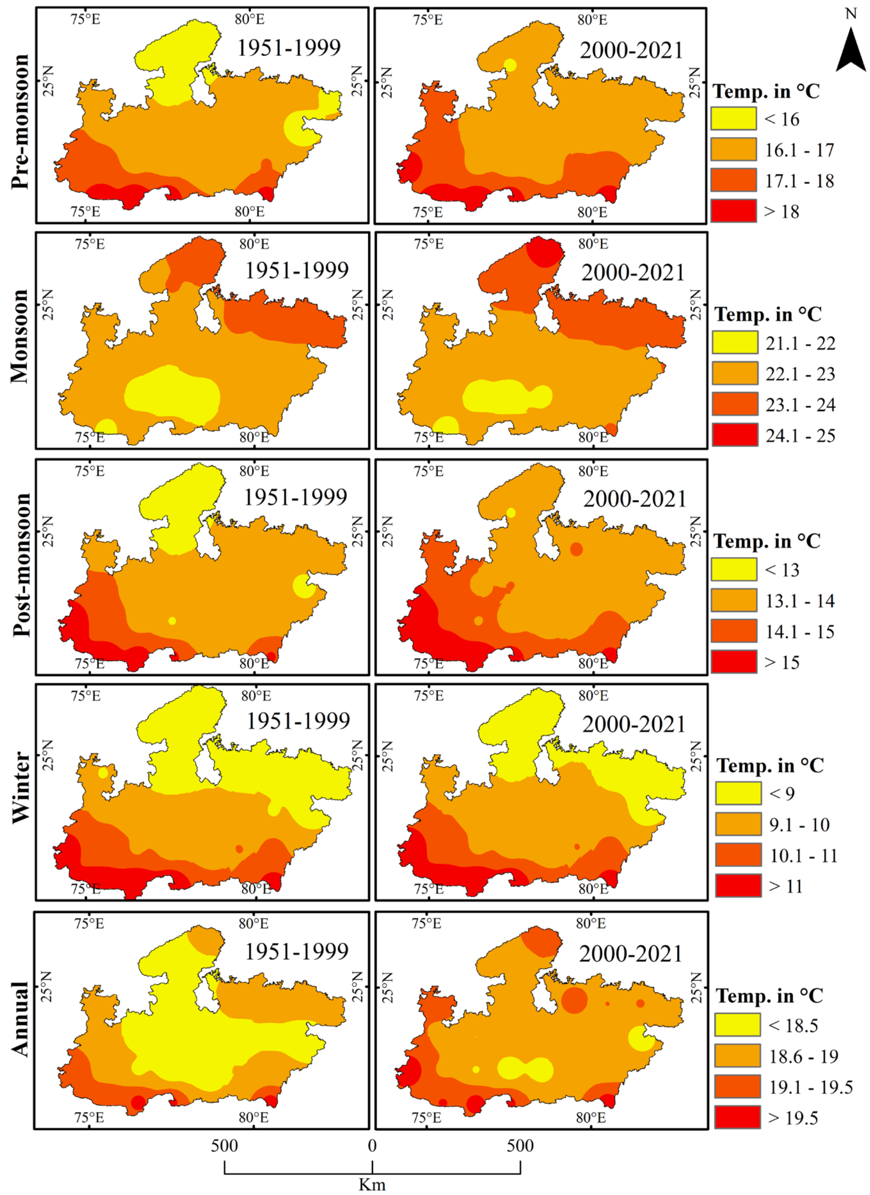


Fig. 2.8: Comparative spatial distribution of T_{min} in Madhya Pradesh

Fig. 2.8 illustrates the spatiotemporal distribution of seasonal T_{min} in Madhya Pradesh. The results show significant temperature fluctuations over different seasons and regions. Before the monsoon season, there was a decrease in temperatures below 16 °C and an increase in areas over 17 °C after 1999. Monsoon presents the appearance of regions with temperatures above 24 °C in the northern zones. After the monsoon season, temperatures have decreased in places below 13 °C and increased in areas over 14 °C. Winter temperatures have risen somewhat in locations where the temperature is above 9 °C, while they have decreased in regions where the temperature is below 9 °C since 1999. The annual T_{min} also presents a significant shift in temperature after 1999. Less than 18.5 °C area rapidly decreased, and 18.5 °C area increased and covered most of the state. Overall, the results of this study mention that the temperature range is increasing in most areas, which aligns with the global warming trend. Similar studies conducted by Yadav & Singh (2023) also reported that extreme rainfalls have decreased in the last few decades in this region. Duhan et al. (2013) focused on Madhya Pradesh, where they examined temperature data to analyse the spatial-temporal distribution of seasonal T_{mean}, T_{max}, and T_{min} over 102 years (1901-2002). Their findings highlighted increasing spatially diverse temperature trends. Sengupta & Thangavel (2023) also utilized meteorological data to examine temperature, rainfall, and drought severity (Standardized Precipitation Index-SPI) patterns across the research period (1990-2015). Based on multiple linear regression analyses, their findings indicated that Maharashtra's shifting precipitation patterns were the primary driver behind intensifying drought conditions, posing a risk to cotton crop yields. Furthermore, Nabi et al. (2023) reported changes in temperature patterns across different locations, with higher elevation zones consistently experiencing lower temperatures, while lower elevation zones exhibited higher temperature profiles.

CC and variability significantly challenge human livelihoods, particularly for tribal communities. The findings of this study reveal a distinct change in rainfall and temperature patterns. This change in rainfall and temperature trends emphasizes the dynamic nature of CC and its potential impact on several facets of human life, including tribal livelihoods. The consequences for tribal communities are acute, as they often depend heavily on natural resources and traditional agricultural practices, which are particularly vulnerable to climatic shifts. It emphasizes the critical need to understand

and adapt to these changes, promoting sustainable and resilient practices while mitigating adverse effects. This research is an important step towards a more nuanced understanding of the climate patterns in Madhya Pradesh, which will be helpful for future planning and decision-making, particularly in developing strategies to support and sustain tribal livelihoods due to CC.

2.4 Conclusions

The study presents a comprehensive analysis of climate change in Madhya Pradesh from 1951 to 2021, highlighting the need for adaptive measures in response to significant changes in rainfall and temperature patterns. Descriptive statistics show substantial variations in rainfall, particularly during pre-monsoon, post-monsoon, and winter seasons, emphasizing their irregular nature. T_{mean} and T_{max} appear to lower variability, while T_{min} exhibits significant seasonal variations, posing risks to agriculture and health. Temporal trend analysis utilizing the MK test implies a non-significant decrease in annual and monsoon rainfall, while pre-monsoon rainfall shows a minute increase. Temperature variables (T_{mean}, T_{max}, T_{min}) exhibit a statistically significant increasing trend, underlining a broader warming pattern. Change point analysis using Pettitt's test identifies abrupt changes in rainfall and temperature patterns, predominantly occurring after the 1980s. These findings align with regional studies and broader global warming trends, and a decrease in rainfall critically affects subsistence agriculture, water management, and whole ecosystem stability in tribal communities. Spatial change analysis using the Inverse Distance Weighted interpolation method reveals geographical variations in seasonal rainfall and temperature distribution. The main concern is that some areas in the Hoshangabad and Balaghat districts of Madhya Pradesh, which received higher precipitation, more than 1300 mm earlier, ultimately decreased after 1998. The maximum average monsoonal rainfall decreased from 1623 mm to 1311 mm after 1998, implying that water availability drastically declined. It is a critical issue to hint to the policymakers because the water-intensive cropping area, namely wheat, rice and soyabean is increasing while the average rainfall is reducing. These findings suggest that Madhya Pradesh experienced a significant shift in its seasonal rainfall distribution after 1998, which requires further attention and investigation. Temperature distribution experienced a shift towards higher ranges, particularly after 2004 for T_{mean} and 2010 for T_{max}, indicating increased heat stress in this region. These climatic changes pose significant challenges to the livelihoods of tribal communities, demanding urgent adaptive measures to mitigate adverse impacts. This study highlights the importance of developing drought-resilient crops, efficient water management techniques, and improving community preparation for climate resilience. Policymakers must focus on these strategies to guarantee sustainable development and adaptability in changing climate dynamics.

This chapter sets the foundation for the next chapter, providing essential knowledge of the local environment in which climate vulnerability occurs. The insights gathered here on marginalized communities' specific challenges are necessary for the future district-level assessment of climate vulnerability across Madhya Pradesh. The next chapter discusses the 2nd objective, i.e. assessing district-wise climate vulnerability in Madhya Pradesh using environmental and socioeconomic indicators, which expands upon the core information presented in this chapter.

Chapter 3

Assessing District-Level Climate Vulnerability in Madhya Pradesh Using Environmental and Socioeconomic Factors

Madhya Pradesh, a central Indian state, is highly vulnerable to climate change due to its dependence on natural resources, socioeconomic disparities, and frequent exposure to extreme weather events such as droughts, floods, and hailstorms. Previous studies highlight its vulnerability, lacking comprehensive integration of environmental and socioeconomic dimensions in assessing climate vulnerability. This chapter evaluates district-level climate vulnerability using a composite index integrating environmental and socioeconomic factors. By categorizing and analyzing these indices, it recognizes the most and least vulnerable districts and the major factors influencing vulnerability. Furthermore, hierarchical cluster analysis was used to validate the composite index results.

3.1 Introduction

Climate change (CC) is a global phenomenon that extensively challenges human society and natural ecosystems (Kuniyal et al., 2021; Rautela et al., 2022, 2023; Singh et al., 2023). The detrimental effects of CC on both human and natural systems (Sengupta & Thangavel, 2023) arise from the interaction between physical climate-related hazards, such as extreme weather events, droughts, floods, rising sea levels, and the vulnerability of local human and natural systems (Oppenheimer et al., 2015; Saikh & Mondal, 2023). Marginalized populations disproportionately feel these impacts (Ahmad et al., 2023; Huong et al., 2019), particularly in developing countries (Blasiak et al., 2017), due to their increased exposure to climatic events and limited adaptive strategies (Schröter et al., 2005; Turner et al., 2003). Communities reliant on subsistence activities are more vulnerable, with poor people in developing nations disproportionately affected (Bohle et al., 1994; Stern et al., 2006). The far-reaching effects of CC are evident across various sectors, particularly in densely populated and developing nations like India (George et al., 2023; Iqbal & Ghauri, 2011). Changing climatic patterns have led to water scarcity, decreased agriculture productivity (Saravanakumar et al., 2022), and disruptions in ecosystem services (Yadava & Sinha, 2020).

CC vulnerability refers to the degree to which systems are susceptible to adverse consequences (Sarun et al., 2018), influenced by the level of exposure to climatic events and their ability to respond. Sensitivity reflects how effectively these systems can manage and adapt to current and future climate changes over a long period (Hahn et al., 2009). Climate vulnerability is multi-faceted, encompassing social, economic, environmental, institutional, and cultural dimensions (IPCC, 2012). Loss of biodiversity and concurrent stressors often exacerbate climate risks (Oppenheimer et al., 2015), underlining the need to understand regional vulnerabilities to inform adaptation strategies (Olmos, 2001). Climate vulnerability assessments using a composite index are essential to understanding present vulnerabilities. It identifies factors underlying varying degrees of vulnerability across regions, informing superficial decision-making processes and guiding the selection and evaluation of adaptive strategies (Hahn et al., 2009; IPCC, 2012). These assessments usually focus on three main aspects: exposure, sensitivity, and adaptive capacity (Rehman et al., 2022; Venus et al., 2022). Vulnerability assessments combine relevant environmental and socioeconomic indicators into a composite index (Eakin & Luers, 2006; Gbetibouo et al., 2010; Yohe & Tol, 2002). These indices merge physical and economic characteristics based on proxy indicators to quantify vulnerability, offering a comprehensive understanding of climate impacts (Kelly & Adger, 2000). However, the composition and construction of vulnerability indices vary across studies, posing challenges for standardization and comparability (Joint Research Centre-European Commission, 2008). Despite the importance of vulnerability assessments, the integration of socioeconomic and environmental factors within them remains limited. The IPCC's 5th assessment report acknowledges five essential criteria for identifying climate vulnerabilities: exposure, system importance, adaptive capacity, persistence of vulnerable conditions, and susceptibility to cumulative stressors.

Previous research consistently identifies Madhya Pradesh as highly vulnerable to climate-related challenges. This susceptibility includes climate sensitivity, population growth, marginalized communities, agriculture reliance, unemployment, poverty, and inadequate amenities (Chakraborty & Joshi, 2016). Madhya Pradesh, characterized by its predominantly agricultural economy and a population heavily dependent on natural resources for their livelihood, is vulnerable to the uncertain impacts of CC (Anand et al., 2019). The districts within the state have been identified as socially highly vulnerable due to their susceptibility to CC and economic globalization (GMPCCC, 2012). The geographical area frequently encounters various natural calamities, including droughts, floods, and hailstorms (Kapur, 2010). Drought-like conditions are encountered in some regions of the state annually, resulting in distress migration despite the implementation of diverse developmental initiatives (Sharma, 2023). Moreover, the state's forest and environmental resources are facing significant pressure. Observable patterns include the pollution of rivers and wetlands, the degradation of forests, and the decline in biodiversity (Anjali & Aditi, 2013). The relationship between poverty and the environment affects the human development index and worsens the burden of diseases (Rai, 2019) within the region. Specific districts within Madhya Pradesh, like Dindori, Jhabua, and others, are noted as highly vulnerable to climate impacts (GMPCCC, 2012). Research conducted by Azhar et al. (2017) and MPSKMCCC (2018) specifically identified Alirajpur, Barwani, Jhabua, Panna, Rewa, Sidhi, and Singrauli as regions of heightened vulnerability to heat stress and the impacts of CC. MPSKMCCC

(2018) found a state-wide vulnerability increase in 2050 and a decline in 2100. The projected climatic changes over the next few decades indicate Madhya Pradesh's high vulnerability to CC, as shown by existing literature, highlighting the need for a comprehensive study. Furthermore, George et al. (2023) observed a significant decrease in overall social vulnerability and its components over several decades (1991-2011) in Madhya Pradesh. Simultaneously, the Climate Index demonstrated a significant increase during the time frame, leading to a statistically insignificant increase in climate vulnerability in the past decade. Yenneti et al. (2016) reported that urban areas of Madhya Pradesh have exhibited the highest levels of social vulnerability to CC in the last 20 years. Das (2013) also presented that Madhya Pradesh has a very high socioeconomic vulnerability.

A research gap exists in comprehensively evaluating CC vulnerability at the regional level in Madhya Pradesh, India. While the region is recognized for its high vulnerability to climate impacts (George et al., 2023), there is limited research that comprehensively incorporates environmental, socioeconomic, and cultural factors. This research assesses district-level CC vulnerability in Madhya Pradesh utilizing composite vulnerability indices combining Environmental Vulnerability Index (EVI) and Socioeconomic Vulnerability Index (SVI), categorizing them to identify the most vulnerable aspects. Hierarchical cluster analysis validates findings, identifying dominant influences on vulnerability. Considering the observed CC vulnerability of the state, it is imperative to understand the regional differences in vulnerability and the underlying factors that contribute to it. The primary objectives of this chapter are (a) evaluating the CC vulnerability of districts in Madhya Pradesh by integrating environmental and socioeconomic dimensions, (b) classifying districts based on their vulnerability levels and identifying the most and least vulnerable regions, and (c) employing hierarchical cluster analysis for validating the categorization of vulnerability levels and identifying patterns across districts.

3.2 Methodology

3.2.1 Study Area

Madhya Pradesh is called the "heart of India" due to its geographical location in central India (Shama & Roy, 2016). It is surrounded by five states, i.e., Rajasthan in the northwest, Gujarat in the west, Maharashtra in the south, Chhattisgarh in the east, and Uttar Pradesh in the northeast. Currently, the state comprises 55 districts (2023); however, this study encompasses a collective consideration of 51 districts (Fig. 3.1), aligning with data availability. The elevation of this state varies from 56 to 1333m above mean sea level (highest elevation in Dhupgarh), which is collected from SRTM-DEM (Shuttle Radar Topography Mission-Digital Elevation Models). The southern region of Madhya Pradesh exhibits a higher elevation than the northern parts, with the land gradually decreasing in height as one moves towards the north. The north and some parts of the west also have very low elevations. As per the forest survey of India (2021), the total forest cover in this state is 77491 km^2, which covers 25.14% of the total geographical area and 10.86% of India's forest area.

Madhya Pradesh, an agricultural state (74 % arable area), cultivates various crops, including rice, wheat, jowar, soya bean, cotton, and more (Nagesh, 2020). The climatic pattern of Madhya Pradesh was discussed in Chapter 2. The monsoon season, which is a distinctive aspect of the climate across India, plays a crucial role in providing ample rainfall for agricultural activities. Due to uncertainty and irregular rainfall, this state faces floods and drought frequently. Mishra & Singh (2010) have highlighted the profound impact of droughts on the livelihoods of the rural poor in Madhya Pradesh. Droughts not only contribute to water scarcity but also exacerbate the challenges of poverty and the degradation of forest resources. Moreover, with the looming threat of CC, these issues will likely worsen, posing a significant risk to the livelihoods of communities residing in forest fringe villages (Yadava & Sinha, 2020).

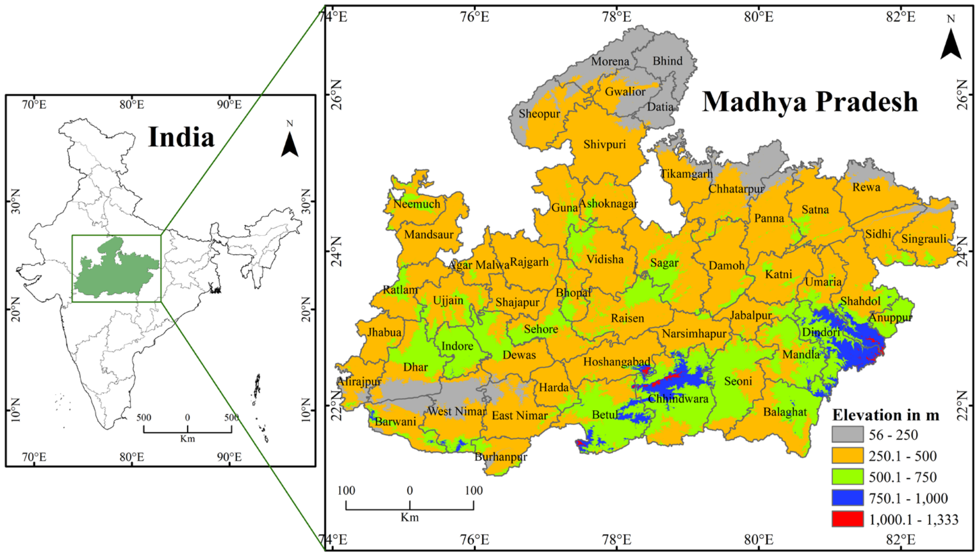


Fig. 3.1: District-wise geographical location map of Madhya Pradesh

Madhya Pradesh exhibits a diverse social composition, with people from various cultural and ethnic backgrounds. The state's economy is primarily agrarian (30.34% of people depend on agricultural activities), playing a central role in its development. The challenging and hilly terrain and scattered settlements spread across a vast area often result in limited access to mainstream development opportunities. Consequently, certain regions remain relatively isolated. Moreover, Madhya Pradesh faces the challenge of a low human development index (Chothodi et al., 2022), reflected by indicators such as education, healthcare, and overall well-being, which need significant improvement (with a current index of 0.596 as per UNDP, 2021). This state has a population of 72,597,565 (5^{th} largest state of India), according to the Census of India 2011. The density of this state is 236 per km^2, and the sex ratio and literacy rate are 931 and 70.6%, respectively. Tribal populations dominate Madhya Pradesh, accounting for 20.27% of the state's population. These tribal communities predominantly reside in rural areas and areas near forests. Unfortunately, the state faces significant socioeconomic challenges, as approximately half of the rural population lives below the poverty line (Mehta & Shah, 2003; Yadava & Sinha, 2020).

3.2.2 Selection of Indicators

Indicators are easily accessible data points that measure system behaviour derived from meaningful and perceivable attributes (Holling, 2003; Yadava & Sinha, 2020). A universally recognized set of indicators or a standardized approach for combining these indicators into a vulnerability index remains absent. When performing a climate vulnerability assessment, using a composite index results in comparative outcomes rather than absolute values. These outcomes are measured on a scale ranging from 0 (representing the least vulnerable) to 1 (representing the most vulnerable) (Shukla et al., 2017). The indicators selected for this study are based on the specific characteristics of CC vulnerability profiles in Madhya Pradesh, determined by a thorough literature review and preliminary investigation. The first phase of the methodology involves identifying key environmental variables (rainfall, maximum and minimum temperature, dense forest cover, agricultural area, floods, droughts, and forest fires) and socioeconomic variables (human development index, population density, socially deprived populations, cultivators, and agricultural labourers) crucial in understanding CC vulnerability in Madhya Pradesh. These variables are plotted in Fig. 3.2 & Fig. 3.3. The identification of primary climate vulnerabilities has been conducted following the Working Group II contribution to the IPCC Sixth Assessment Report.

3.2.3 Data collection

This study was based on two factors, i.e., environmental and socioeconomic factors, to compute the composite vulnerability index. The environmental factors (Fig. 3.2 and Table 3.1) included rainfall, maximum and minimum temperature, dense forest cover, agricultural area, floods, droughts, and forest fires. In contrast, socioeconomic factors (Fig. 3.3 and Table 3.1) included the Human Development Index (HDI), population density, socially deprived populations (Schedule caste and schedule tribe), cultivators, and agricultural labourers.

Table 3.1: Selection of the indicators for computing the composite vulnerability index

SI. No.	Environmental indicators	Data Sources	Cell size
1	Annual rainfall	https://www.imdpune.gov.in/	0.25°×0.25°
2	Maximum Temperature	https://www.imdpune.gov.in/	1°×1°
3	Minimum Temperature	https://www.imdpune.gov.in/	1°×1°
4	Dense forest cover	https://fsi.nic.in/forest-report-2021-details	
5	Agricultural area	https://earthexplorer.usgs.gov/	500 meters
6	Floods	http://www.mpsdma.mp.gov.in/uploads/media/MP-SDMP-2307141.pdf	
7	Droughts	http://www.mpsdma.mp.gov.in/uploads/media/MP-SDMP-2307141.pdf	
8	Forest fires	https://www.earthdata.nasa.gov/learn/find-data/near-real-time/firms	1000 meters
Socio-economic indicators			
9	Population density	http://www.censusmp.gov.in	
10	Socially deprived populations	http://www.censusmp.gov.in	
11	Cultivators	http://www.censusmp.gov.in	
12	Agricultural labourers	http://www.censusmp.gov.in	
13	HDI	Singh & Keshari (2016)	

The daily gridded data for annual rainfall and annual maximum and minimum temperature of the last ten years were obtained from the India Meteorological Department. District-wise, dense forest cover data in percentage of total geographical area was collected from the Forest Survey of India, State of Forest Report 2021. Flood- and drought-affected districts of Madhya Pradesh were acquired from the State Disaster Management Plan – Madhya Pradesh. This study used data generated by collecting 6 MODIS active fire products based on the active fire detection algorithm (Giglio et al., 2016) provided by the Fire Information for Resource Management System (FIRMS). MODIS land use land cover data collected from NASA

Earth Explorer for 2022. The land use land cover (LULC) map of MODIS (MCD12Q1) is created using the supervised classification of MODIS reflectance data (Friedl et al., 2010). All the socioeconomic data except HDI were gathered from the Census of India 2011; the primary census abstract data highlighted Madhya Pradesh, whereas HDI was collected from Singh & Keshari (2016).

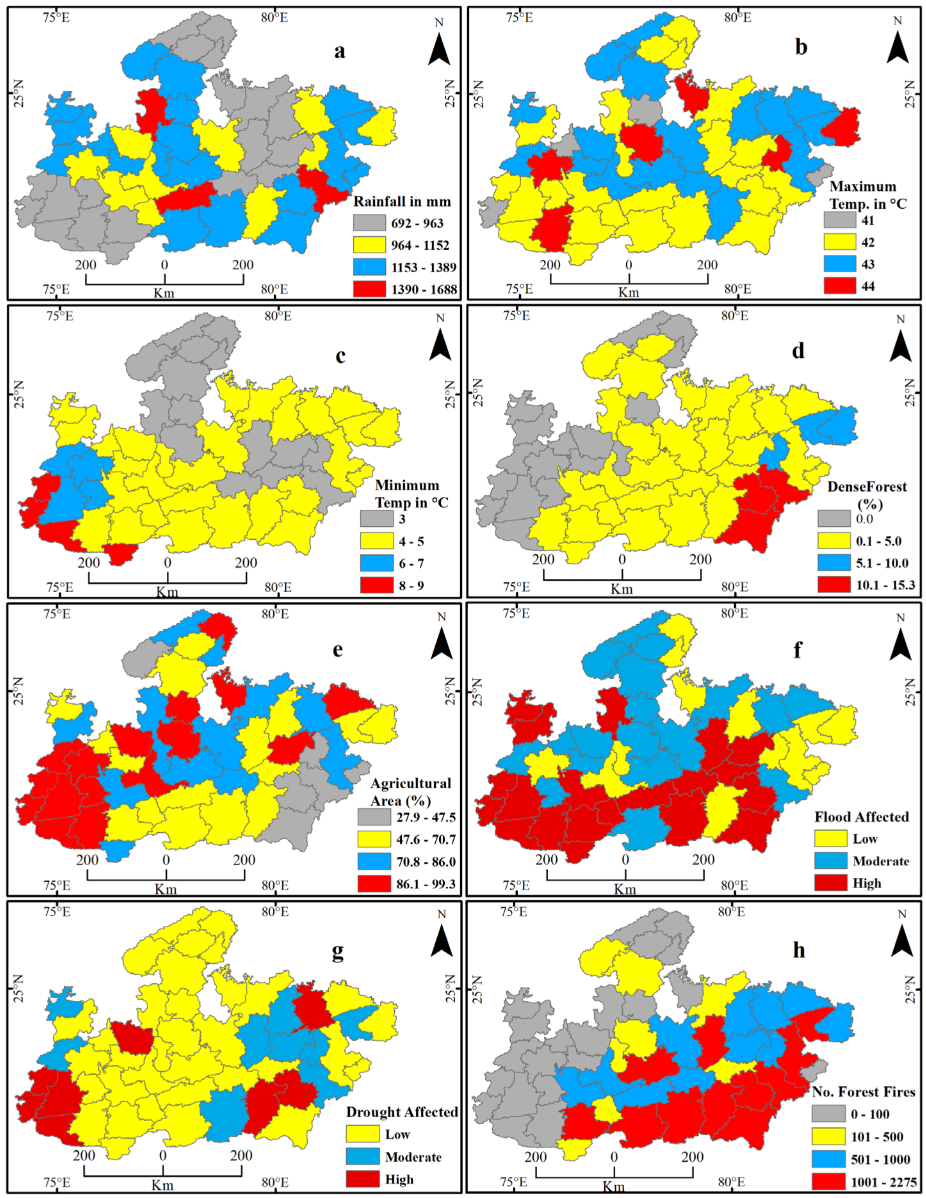


Fig. 3.2: District-wise distribution of environmental factors

Note: Here, (a) Rainfall, (b) Maximum temperature, (c) Minimum temperature, (d) Dense Forest cover, (e) Agricultural area, (f) Flood affected area, (g) Drought affected areas, and (h) Number of forest fire points

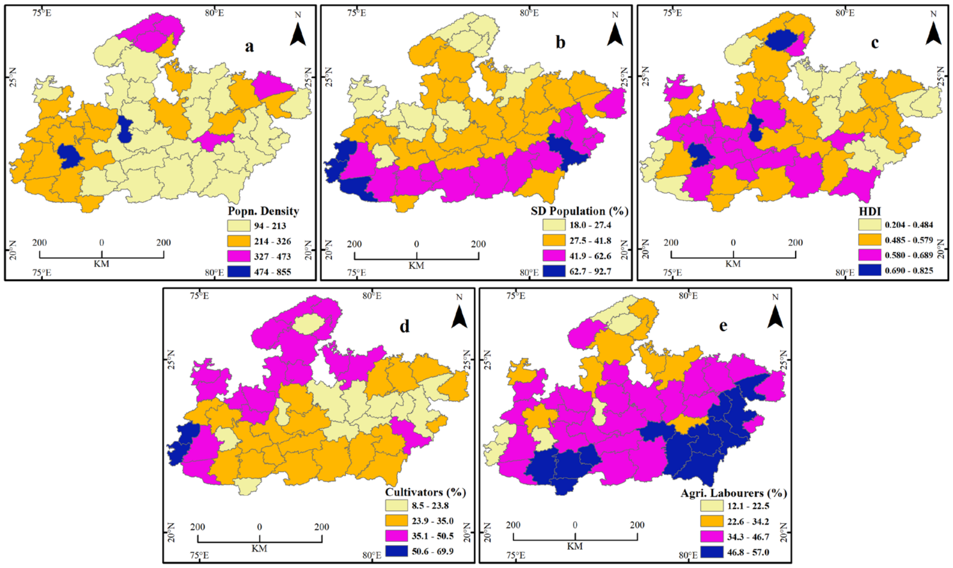


Fig. 3.3: District-wise distribution of socioeconomic factors

Note: Here, (a) Population density, (b) Socially deprived population, (c) HDI, (d) Cultivators, and (e) Agricultural labourers

3.2.4 Data Analysis

The methodology assumes that CC vulnerability is influenced by the susceptibility of a region's existing socioeconomic factors and environmental conditions to CC hazards. The primary challenge lies in identifying the region-specific socioeconomic and environmental parameters. An indicator-based approach has been adopted to construct vulnerability sub-indices at the district level, focusing on specific domains to address this. It allows us to create a composite vulnerability index for the study region, enabling the identification, assessment, and ranking of the vulnerable districts in Madhya Pradesh. The study employed the normalization method (Iyengar & Sudarshan, 1982), which proposed to ensure comparability among indicators measured in different units, as depicted in Equation 3.1.

$$Indicator\ Index\ Score_d = \frac{X(i) - X(min)}{X(max) - X(min)} \qquad (3.1)$$

where *X(i)*= the actual value for the district concerned.

X(max) = the maximum value for the district concerned.

X(min) = the minimum value for the district concerned and,

in the indicator index score, *d* is for the district concerned.

The indicator's numerical value indicates the relative vulnerability status of the selected districts. The above equation considers maximum and minimum values in the expression and ensures vulnerability values lie within [0,1] interval and are non-negative.

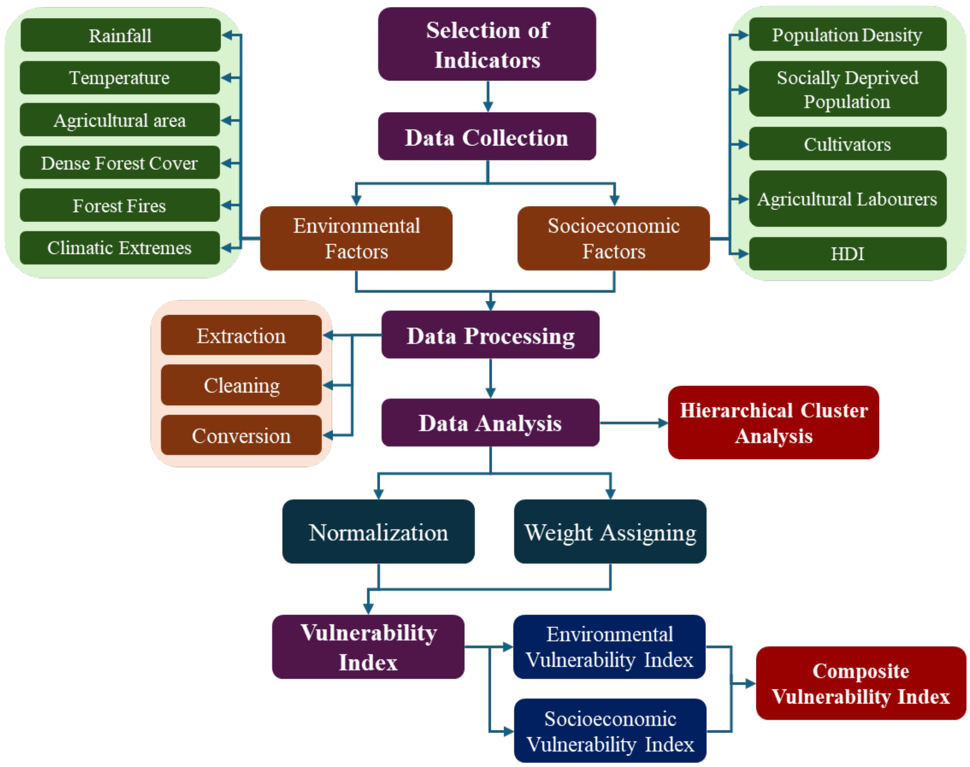


Fig. 3.4: Comprehensive methodology flowchart

The next stage involved allocating weights to each district's indicators, considering the vulnerability's significance. After normalizing each indicator, an equal weight was assigned to each indicator (Bahinipati, 2014; Balica & Wright, 2010; Cutter et al., 2012; Eakin & Bojórquez-Tapia, 2008; Kantamaneni et al., 2020). These weights were established based on an amalgamation of diverse sources, including the Census Report 2011, the Madhya Pradesh State Action Plan on Climate Change, the State Disaster Management Plan, the Human Development Report 2016, and the State Economic Review. The effectiveness of the composite CC vulnerability index was examined by subjecting it to varying normalization techniques and employing diverse weight factors for the selected indicators. The essential characteristics of the outcomes remained unchanged across these variations, thus affirming the robustness of the index. The comprehensive methodological framework for this study is shown in Fig. 3.4.

3.2.1.1 Computation of Environmental Vulnerability Index (EVI)

The environmental vulnerability index has been estimated by taking the simple average of the eight indicators of 13 variables (Rainfall, Maximum Temperature, Minimum Temperature, Dense Forest, Agricultural area, Flood, Drought, and Forest Fires). Hence, the EVI is calculated using Equation 3.2.

$$EVI_{D=}\frac{1}{8}\left(RF_d + T_{maxd} + T_{mind} + DF_d + AA_d + FL_d + DR_d + FF_d\right) \quad (3.2)$$

where RF= Rainfall, T_{max} = Maximum Temperature, T_{min} = Minimum Temperature, DF= Dense Forest, AA= Agriculture Area, FL= Flood, DR= Drought, FF = Forest Fires.

3.2.1.2 Computation of Socioeconomic Vulnerability Index (SVI)

The vulnerability index has been estimated by taking the simple average of the five indicators of 13 variables (HDI, Population Density, Socially Deprived Population, Cultivators, and Agricultural Labourers). Hence, the SVI is calculated using Equation 3.3.

$$SVI_d = \frac{1}{5}\left(HDI_d + PD_d + SD_d + CV_d + AL_d\right) \quad (3.3)$$

where HDI= Human Development Index, PD= Population Density, SD= Socially Deprived Population, CV = Cultivators, AL = Agricultural labourers

3.2.1.3 Calculation of Composite Vulnerability Index (CVI)

A composite vulnerability index of CC was established involving the simple additive weighting applied to the environmental and socioeconomic vulnerability indices (Sarun et al., 2018). Specifically, a weight of 0.70 was assigned to socioeconomic vulnerability because socioeconomic factors are more sensitive to CC, while environmental vulnerability received a weight of 0.30 (Sarun et al., 2018; Yusuf & Francisco, 2009). Hence, CVI was calculated using Equation 3.4.

$$CVI_d = (0.70 \times SVI_d) + (0.30 \times EVI_d) \tag{3.4}$$

Based on this CVI, a clustering process categorized the 51 districts into four distinctive classes. These classes were classified based on the degree of relative vulnerability to environmental and socioeconomic factors (Deressa et al., 2009), indicating the very high, high, medium, and low vulnerability levels present within each district. Subsequently, distinct maps representing the socioeconomic, environmental, and composite vulnerabilities at the district level were generated using ArcGIS 10.8.

3.2.1.4 Hierarchical Cluster Analysis

The hierarchical cluster analysis was performed using OriginPro 2023b (Learning Edition) software to validate the findings. The categorization of districts was conducted using cluster analysis. Cluster analysis is used in exploratory data analysis to categorize problems (Benderskaya, 2017). The primary goal is to group monitoring points based on the strength of their association. Members within the same cluster exhibit a strong association, while those in different clusters have a weak association (Sheela et al., 2015). Hierarchical clustering was employed in this study using Euclidean distance and Ward's linkage methods. Hierarchical clustering is a widely recognized and extensively employed scientific methodology that finds application in various fields, including but not limited to biology, computer science, and social sciences (Shi et al., 2021). Similar data points are grouped based on their attributes to identify patterns and relationships within datasets. The approach described in this study produces a graphical depiction known as a **Dendrogram**, which exhibits a hierarchical arrangement resembling a tree, illustrating the organization of data points within nested clusters (Ma et al., 2020). In general, hierarchical clustering is a reliable methodology that yields significant observations regarding the organization and trends within data through the identification of similarities and dissimilarities among data points (Xie et al., 2020).

3.4 Results and Discussion

A comprehensive assessment was conducted to gain an inclusive understanding of the vulnerabilities caused by CC within the state. The evaluation aimed to broadly understand the climate-induced vulnerabilities specific to Madhya Pradesh by considering a range of socioeconomic and environmental indicators. There is significant variation in the socioeconomic and environmental variables across the districts of Madhya Pradesh. The highest range among the environmental indicators is recorded for rainfall, dense forest cover, agricultural area, and forest fire points. For example, Guna, Hoshangabad, and Dindori received the highest rainfall, while West Nimar, Dhar, and Morena received the least. The comprehensive spatiotemporal climatic dynamics of Madhya Pradesh using rainfall and temperature data were presented in Chapter 2 for better understanding.

The southeastern part of the state has the highest percentage of dense forest. Meanwhile, the western and northeast areas show the unavailability of dense forests, supporting the distribution of forest fire points. The variation in socioeconomic indicators is also observed. For example, HDI and population density are shown to be lowest in Dindori and highest in Indore and Bhopal. Regarding the percentage of the socially deprived population, cultivators and agricultural labourers, Bhopal shows the lowest rate. Whereas Alirajpur shows the highest percentage of socially deprived population and cultivators, Mandla has the highest percentage of agricultural labourers to total workers. This study employs a comprehensive vulnerability assessment to reveal intricate patterns in environmental and socioeconomic vulnerabilities across Madhya Pradesh's districts. Adopting the spatial vulnerability method proposed by Borden et al., 2007 and the Composite Vulnerability Index (CVI) approach by Sarun et al. (2018) and Yusuf & Francisco (2009), the study integrates the Environmental Vulnerability Index (EVI) and Socioeconomic Vulnerability Index (SVI) to offer a comprehensive perspective on climate vulnerability.

3.4.1 Evolution of Composite Vulnerability Index

3.4.1.1 Environmental Vulnerability Index (EVI)

Table 3.2 shows the district-wise index value of environmental factors, calculated using Equation 3.2. The lowest EVI value is 0.21and the highest value is 0.59. The districts are classified based on their estimated EVI quantile to low (0.214 - 0.364), medium (0.365 - 0.425), high (0.426 - 0.487) and very high (0.488 - 0.593) (Fig. 3.5). The analysis reveals various patterns of environmental vulnerability across districts. Districts with the lowest vulnerability - such as Anuppur, Tikamgarh, Datia, Sheopur, Jabalpur, Bhopal, Gwalior, Bhind, Shahdol, Sehore, Ujjain, Morena, and Shajapur—benefit from factors like lower minimum temperatures, limited dense forest coverage, fewer forest fires, and minimal drought-affected areas. These factors imply a higher level of preparedness for environmental changes.

Similarly, districts such as Indore, Panna, Agar Malwa, Shivpuri, Harda, Narsimhapur, West Nimar, Sagar, Umaria, Singrauli, Seoni, Ashoknagar, and Alirajpur exhibit moderate levels of environmental vulnerability. These areas encounter challenges such as variations in rainfall distribution, moderately dense forest coverage, drought occurrences, and forest fires. Implementing strategies to enhance resilience in these districts can effectively mitigate environmental vulnerabilities.

Table 3.2: Environmental vulnerability index

District	RF	T_{max}	T_{min}	DF	AA	FL	DR	FF	EVI	District	RF	T_{max}	T_{min}	DF	AA	FL	DR	FF	EVI
Dindori	1.0	0.4	0.1	1.0	0.1	0.7	0.7	0.9	0.6	Ashoknagar	0.6	0.8	0.1	0.0	0.8	0.7	0.3	0.0	0.4
Mandla	0.5	0.2	0.4	0.8	0.2	1.0	1.0	0.5	0.6	Seoni	0.3	0.2	0.2	0.2	0.5	0.3	1.0	0.6	0.4
Satna	0.4	0.9	0.2	0.0	0.7	0.7	1.0	0.4	0.5	Singrauli	0.5	0.5	0.2	0.5	0.6	0.3	0.3	0.4	0.4
Barwani	0.2	0.3	0.9	0.0	1.0	1.0	1.0	0.0	0.5	Umaria	0.4	0.4	0.1	0.6	0.3	0.3	0.7	0.4	0.4
Balaghat	0.5	0.4	0.4	1.0	0.2	1.0	0.3	0.5	0.5	Sagar	0.4	0.7	0.2	0.0	0.7	0.7	0.3	0.3	0.4
Jhabua	0.2	0.0	1.0	0.0	0.9	1.0	1.0	0.0	0.5	West Nimar	0.0	0.4	0.4	0.0	0.9	1.0	0.3	0.0	0.4
Chhindwara	0.5	0.3	0.2	0.3	0.5	1.0	0.7	0.7	0.5	Narsimhapur	0.2	0.4	0.1	0.1	0.7	1.0	0.3	0.3	0.4
Rajgarh	0.7	0.6	0.2	0.0	1.0	0.7	1.0	0.0	0.5	Harda	0.4	0.3	0.2	0.0	0.6	1.0	0.3	0.2	0.4
Sidhi	0.6	0.7	0.3	0.4	0.6	0.3	0.7	0.4	0.5	Shivpuri	0.6	0.9	0.0	0.0	0.5	0.7	0.3	0.1	0.4
Raisen	0.5	0.7	0.2	0.0	0.7	0.7	0.3	1.0	0.5	Agar Malwa	0.7	0.6	0.2	0.0	0.6	0.7	0.3	0.0	0.4
Damoh	0.2	1.0	0.1	0.0	0.5	1.0	0.7	0.5	0.5	Panna	0.1	0.9	0.2	0.1	0.4	0.3	0.7	0.4	0.4
Guna	0.8	0.8	0.1	0.0	0.8	1.0	0.3	0.0	0.5	Indore	0.3	0.2	0.7	0.0	0.9	0.7	0.3	0.0	0.4
Dhar	0.1	0.2	0.7	0.0	1.0	1.0	1.0	0.0	0.5	Shajapur	0.6	0.6	0.2	0.0	0.6	0.7	0.3	0.0	0.4
Rewa	0.6	0.7	0.3	0.1	0.9	0.7	0.3	0.3	0.5	Morena	0.1	1.0	0.1	0.0	0.7	0.7	0.3	0.0	0.4
Ratlam	0.5	0.4	0.5	0.0	1.0	0.7	0.7	0.0	0.5	Ujjain	0.4	0.4	0.5	0.0	1.0	0.3	0.3	0.0	0.4
Burhanpur	0.2	0.4	0.8	0.1	0.7	1.0	0.3	0.1	0.5	Sehore	0.4	0.3	0.2	0.0	0.9	0.3	0.3	0.4	0.4
Katni	0.1	0.4	0.1	0.1	0.9	1.0	0.7	0.4	0.5	Shahdol	0.6	0.0	0.1	0.1	0.8	0.3	0.3	0.5	0.3
Hoshangabad	0.7	0.3	0.2	0.3	0.5	1.0	0.3	0.3	0.5	Bhind	0.1	1.0	0.1	0.0	1.0	0.3	0.3	0.0	0.3
Dewas	0.4	0.4	0.4	0.0	0.8	1.0	0.3	0.2	0.5	Gwalior	0.3	1.0	0.1	0.0	0.4	0.7	0.3	0.0	0.3
East Nimar	0.2	0.4	0.4	0.1	0.5	1.0	0.3	0.5	0.4	Bhopal	0.5	0.6	0.2	0.0	0.8	0.3	0.3	0.1	0.3
Betul	0.6	0.4	0.2	0.2	0.5	0.7	0.3	0.7	0.4	Jabalpur	0.2	0.4	0.1	0.1	0.4	1.0	0.3	0.2	0.3
Neemuch	0.5	0.6	0.3	0.0	0.4	1.0	0.7	0.0	0.4	Sheopur	0.6	0.9	0.0	0.0	0.0	0.7	0.3	0.1	0.3
Vidisha	0.6	0.8	0.1	0.0	0.9	0.7	0.3	0.1	0.4	Datia	0.2	1.0	0.1	0.0	0.8	0.3	0.3	0.0	0.3
Mandsaur	0.6	0.6	0.3	0.0	0.8	1.0	0.3	0.0	0.4	Tikamgarh	0.2	0.5	0.2	0.0	1.0	0.3	0.3	0.0	0.3
Chhatarpur	0.2	1.0	0.2	0.1	0.7	0.7	0.3	0.2	0.4	Anuppur	0.5	0.0	0.1	0.2	0.3	0.3	0.3	0.0	0.2
Alirajpur	0.2	0.0	1.0	0.0	0.9	0.3	1.0	0.0	0.4										

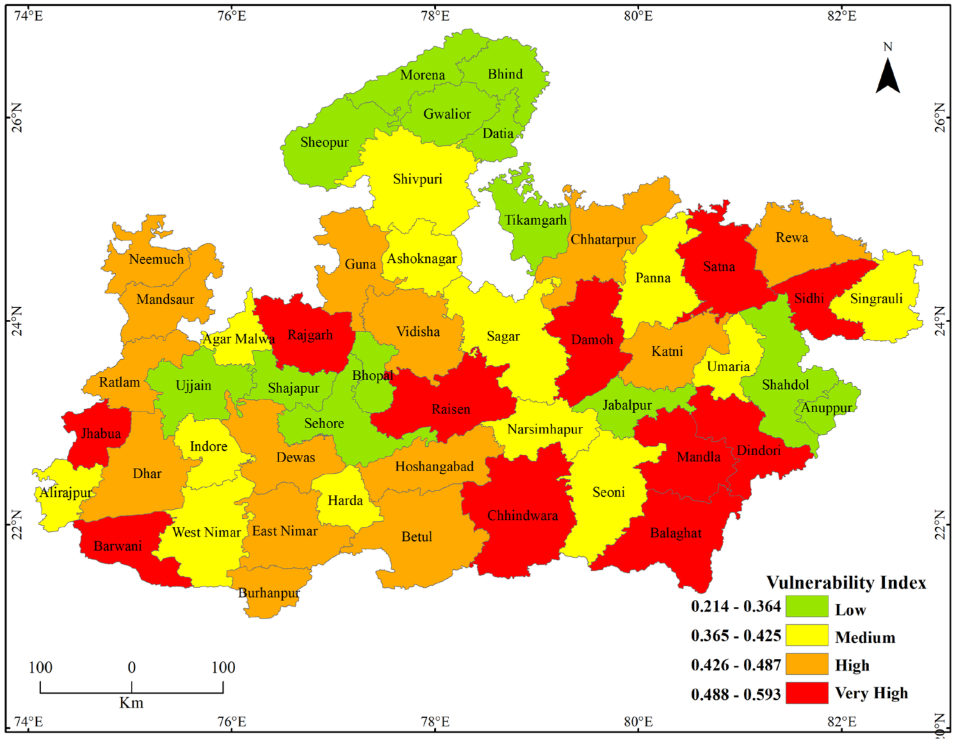


Fig. 3.5: District wise environmental vulnerability map

Districts exhibiting an EVI value, namely Chhatarpur, Mandsaur, Vidisha, Neemuch, Betul, East Nimar, Dewas, Hoshangabad, Katni, Burhanpur, Ratlam, Rewa, Dhar, and Guna, demonstrate higher levels of vulnerability. These districts experience increased rainfall, higher maximum temperatures, expansive agricultural areas, and frequent floods and droughts. As a result, immediate attention must be given to this issue, along with developing and implementing comprehensive strategies for climate adaptation and disaster management.

The districts with the highest EVI scores, namely Damoh, Raisen, Sidhi, Rajgarh, Chhindwara, Jhabua, Balaghat, Barwani, Satna, Mandla, and Dindori, are the most vulnerable to environmental challenges. Significant precipitation, extreme temperatures, extensive dense forestation, expansive agricultural regions, frequent floods, droughts, and forest fires characterize these regions. Comprehensive and diverse interventions are essential to improve adaptive capacity, sustainable resource management, and disaster resilience.

3.4.1.2 Socioeconomic Vulnerability Index (SVI)

The district-wise SVI was calculated using Equation 3.3, presented in Table 3.3. The districts have been divided based on their SVI quantile into low (0.309 - 0.372), medium (0.373 - 0.401), high (0.405 - 0.432), and very high (0.441 - 0.552) (Fig. 3.6). The socioeconomic vulnerability assessment of districts in Madhya Pradesh reveals important insights with significant implications for policy and development strategies.

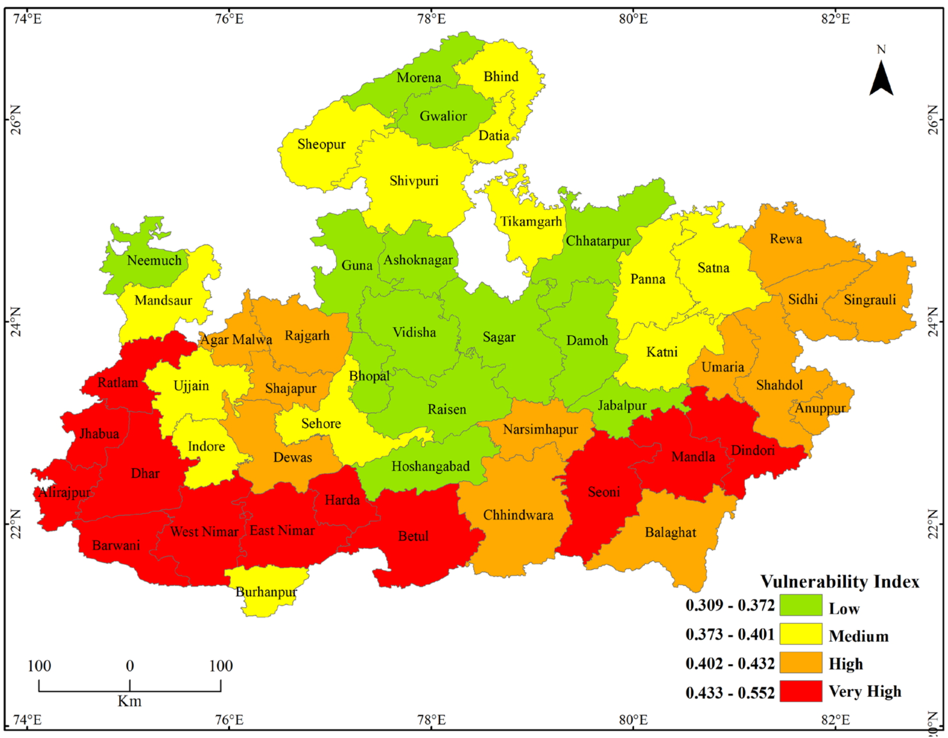


Fig. 3.6: Socio-economic vulnerability map

The districts with the least socioeconomic vulnerability, such as Ashoknagar, Bhopal, Chhatarpur, Damoh, Guna, Gwalior, Hoshangabad, Jabalpur, Morena, Neemuch, Raisen, Sagar, Vidisha, demonstrate favourable attributes like lower population densities and decreased proportions of socially disadvantaged populations. It suggests that these regions possess a comparatively higher level of socioeconomic resilience, enabling them to manage the consequences of CC effectively. Utilizing these strengths can guide the formulation of sustainable development strategies, allocating resources, and implementing disaster preparedness

Table 3.3: Socioeconomic vulnerability index

District	HDI	PD	SD	CV	AL	SVI
Alirajpur	0.4	0.2	1.0	1.0	0.2	0.6
Jhabua	0.4	0.3	0.9	0.9	0.2	0.5
Barwani	0.5	0.2	0.8	0.6	0.6	0.5
Dhar	0.6	0.2	0.6	0.5	0.7	0.5
Mandla	0.5	0.1	0.6	0.3	1.0	0.5
West Nimar	0.6	0.2	0.4	0.4	0.8	0.5
Ratlam	0.7	0.3	0.3	0.4	0.7	0.5
Seoni	0.6	0.1	0.4	0.3	1.0	0.5
Betul	0.6	0.1	0.5	0.4	0.7	0.5
Dindori	0.2	0.0	0.7	0.5	0.8	0.4
Harda	0.6	0.1	0.4	0.3	0.8	0.4
East Nimar	0.5	0.1	0.4	0.3	0.8	0.4
Sidhi	0.5	0.2	0.3	0.2	1.0	0.4
Umaria	0.5	0.1	0.5	0.2	0.9	0.4
Shahdol	0.5	0.1	0.5	0.2	0.9	0.4
Chhindwara	0.6	0.1	0.4	0.3	0.7	0.4
Anuppur	0.5	0.1	0.5	0.4	0.6	0.4
Agar Malwa	0.7	0.2	0.1	0.5	0.7	0.4
Shajapur	0.7	0.2	0.1	0.5	0.7	0.4
Dewas	0.6	0.2	0.2	0.4	0.7	0.4
Rewa	0.5	0.4	0.2	0.3	0.8	0.4
Singrauli	0.5	0.1	0.4	0.3	0.7	0.4
Balaghat	0.6	0.1	0.2	0.3	0.9	0.4
Narsimhapur	0.6	0.2	0.2	0.2	0.9	0.4
Rajgarh	0.6	0.2	0.1	0.5	0.7	0.4
Bhind	0.6	0.4	0.1	0.6	0.4	0.4
Tikamgarh	0.5	0.3	0.2	0.6	0.5	0.4
Datia	0.6	0.2	0.1	0.6	0.4	0.4
Indore	0.8	1.0	0.1	0.1	0.1	0.4
Sehore	0.6	0.1	0.2	0.4	0.6	0.4
Burhanpur	0.5	0.2	0.3	0.2	0.8	0.4
Mandsaur	0.6	0.2	0.0	0.5	0.6	0.4
Ujjain	0.6	0.3	0.1	0.4	0.5	0.4
Satna	0.5	0.3	0.2	0.3	0.6	0.4
Sheopur	0.5	0.0	0.3	0.5	0.7	0.4
Panna	0.4	0.1	0.3	0.4	0.8	0.4
Katni	0.6	0.2	0.3	0.2	0.6	0.4
Shivpuri	0.5	0.1	0.2	0.7	0.4	0.4
Ashoknagar	0.5	0.1	0.2	0.5	0.6	0.4
Guna	0.5	0.1	0.2	0.5	0.5	0.4
Raisen	0.6	0.1	0.2	0.3	0.7	0.4
Vidisha	0.6	0.1	0.1	0.4	0.7	0.4
Neemuch	0.6	0.1	0.1	0.5	0.5	0.4
Morena	0.6	0.4	0.1	0.6	0.2	0.4
Bhopal	0.8	1.0	0.0	0.0	0.0	0.4
Hoshangabad	0.6	0.1	0.2	0.3	0.6	0.4
Jabalpur	0.7	0.5	0.2	0.0	0.4	0.3
Chhatarpur	0.5	0.1	0.1	0.5	0.4	0.3
Damoh	0.5	0.1	0.2	0.2	0.7	0.3
Sagar	0.5	0.2	0.2	0.2	0.6	0.3
Gwalior	0.7	0.5	0.1	0.2	0.1	0.3

initiatives.

Among the medium SVI category, districts such as Indore, Ujjain, Katni, Satna, etc, exhibit comparatively higher HDI and population densities with lower socially deprived populations. These districts are more strategically situated to utilize human and infrastructural resources to counter climate-induced vulnerabilities effectively. Strategic allocations of resources towards agriculture, livelihood diversification, and healthcare sectors can enhance their adaptive capacity.

High SVI districts, such as Rajgarh, Narsimhapur, and other similar regions, highlight the intricate relationship between reliance on agricultural labour and the HDI. The high prevalence of these factors highlights the urgent need for targeted interventions to reduce dependence on agriculture and improve socioeconomic conditions. Strategies focused on alternative livelihood opportunities and promoting human development indicators can mitigate CC impacts.

Districts with the highest SVI value, including Alirajpur, Barwani, Betul, Dhar, Dindori, East Nimar, Harda, Jhabua, Mandla, Ratlam, Seoni, West Nimar, require urgent and thorough attention. The critical necessity for multifaceted strategies is indicated by the convergence of various factors, such as the presence of socially deprived populations, cultivators, and agricultural labourers at high percentages. These strategies should promote socioeconomic development, diversify livelihood, and enhance healthcare services. Furthermore, the low HDI in certain districts further emphasizes the need for comprehensive developmental strategies to improve living standards and promote adaptive capacities. Jha & Negi (2021) reported that the highest vulnerability among socio-ecological systems was observed in the socioeconomic sector.

3.3.1.3. Composite Vulnerability Index (CVI)

Table 3.4 presents district-wise CVI values calculated using Equation 3.4 and shows a district’s ranking based on CVI. As per this table, Gwalior is the least vulnerable district, and Barwani is the most vulnerable. The districts have been classified into four clusters based on their CVI quantile: low, medium, high, and very high, as shown in Fig. 3.7.

Table 3.4: Composite vulnerability Index

District	CVI	Rank	District	CVI	Rank	District	CVI	Rank
Barwani	0.54	1	Satna	0.43	18	Ashoknagar	0.39	35
Jhabua	0.54	2	Harda	0.43	19	Bhind	0.39	36
Mandla	0.52	3	Umaria	0.42	20	Sehore	0.38	37
Alirajpur	0.51	4	Agar Malwa	0.41	21	Damoh	0.38	38
Dhar	0.50	5	Burhanpur	0.41	22	Datia	0.38	39
Dindori	0.49	6	Singrauli	0.41	23	Panna	0.38	40
Ratlam	0.47	7	Shajapur	0.41	24	Ujjain	0.38	41
Chhindwara	0.46	8	Narsimhapur	0.41	25	Shivpuri	0.38	42
West Nimar	0.45	9	Shahdol	0.41	26	Tikamgarh	0.37	43
Sidhi	0.45	10	Raisen	0.41	27	Chhatarpur	0.37	44
Balaghat	0.45	11	Guna	0.41	28	Sheopur	0.37	45
Betul	0.45	12	Mandsaur	0.40	29	Anuppur	0.37	46
East Nimar	0.44	13	Katni	0.40	30	Morena	0.36	47
Seoni	0.44	14	Indore	0.39	31	Bhopal	0.36	48
Rewa	0.44	15	Neemuch	0.39	32	Sagar	0.35	49
Rajgarh	0.44	16	Vidisha	0.39	33	Jabalpur	0.34	50
Dewas	0.43	17	Hoshangabad	0.39	34	Gwalior	0.32	51

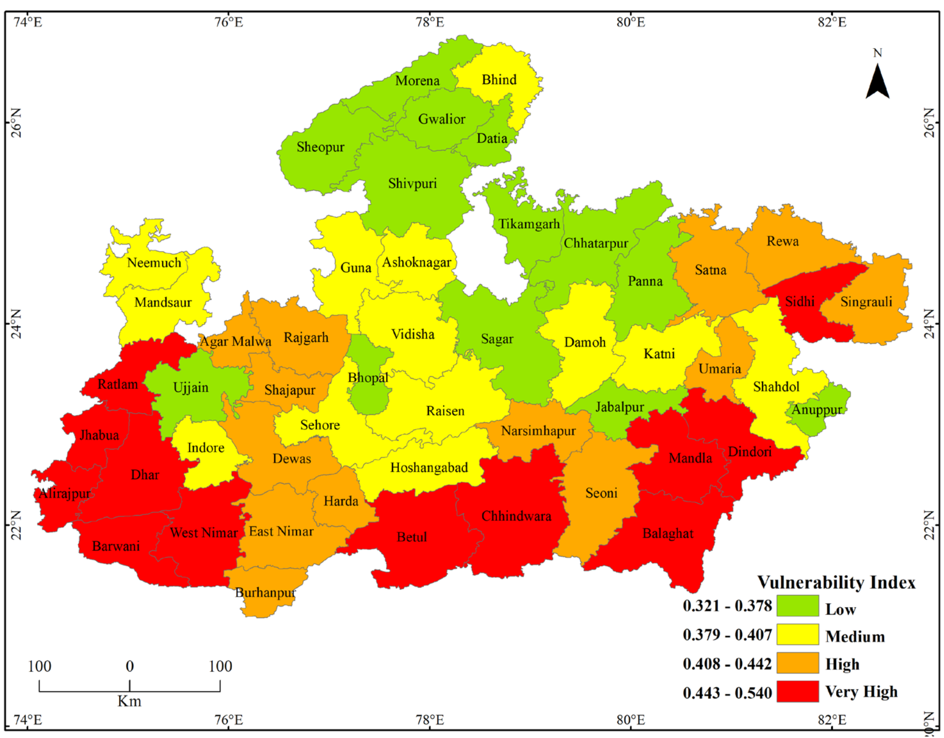


Fig. 3.7: Composite vulnerability map

a) Low vulnerable districts (0.321-0.378)

The districts of Gwalior, Jabalpur, Sagar, Bhopal, Morena, Anuppur, Sheopur, Chhatarpur, Tikamgarh, Shivpuri, Ujjain, Panna, and Datia demonstrate lower CVI values (Fig. 3.8). It results in a decrease in the EVI and SVI values for these districts. This outcome is influenced by multiple factors, including a reduced percentage of dense forest cover, a reduced presence of regions affected by drought, a population with lower levels of social deprivation, and a higher HDI. These findings emphasize the complex dynamics of climate vulnerability. The lower CVI values indicate these districts are less vulnerable to CC impacts, both environmentally and socio-economically. Effective forest management and drought mitigation approaches have played a significant role. Furthermore, lower levels of socially deprived populations and higher HDI values suggest an increased ability to adapt and withstand the impacts of climate-related challenges.

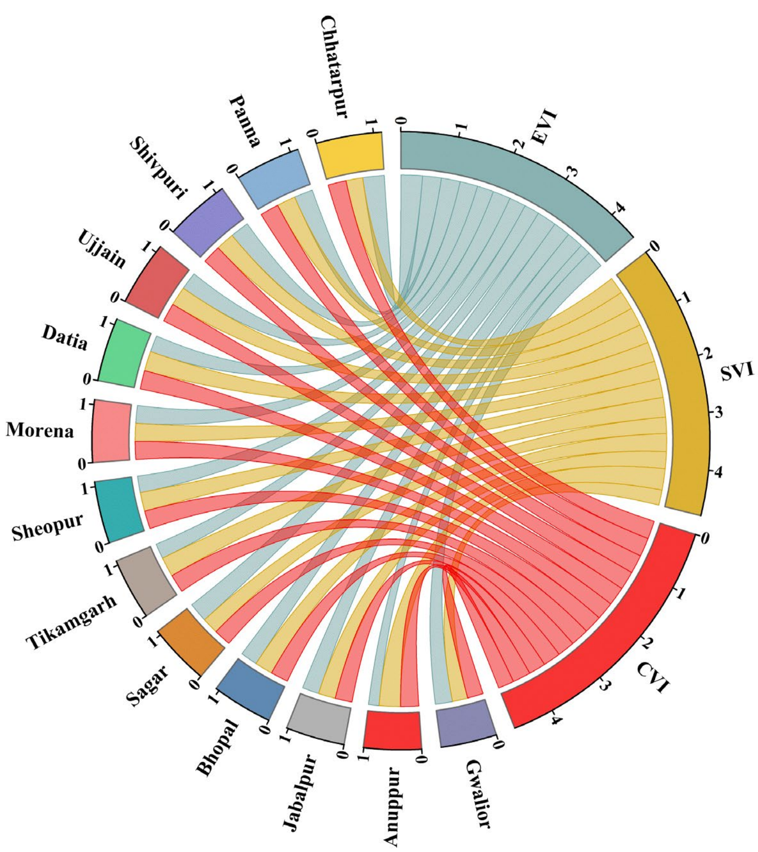


Fig. 3.8: Low vulnerable districts based on CVI

b) Medium vulnerable districts (0.381 - 0.407)

The group comprises the districts of Damoh, Sehore, Bhind, Ashoknagar, Hoshangabad, Vidisha, Neemuch, Indore, Katni, Mandsaur, Guna, Raisen, and Shahdol. The districts demonstrate a decrease in exposure and sensitivity to environmental and socioeconomic factors, as illustrated in Fig. 3.9. The rationale for incorporating these districts is based on their comparatively lower risk profiles, such as extensive forest coverage, population density (except Indore), a smaller proportion of socially marginalized populations, and better performance in the HDI.

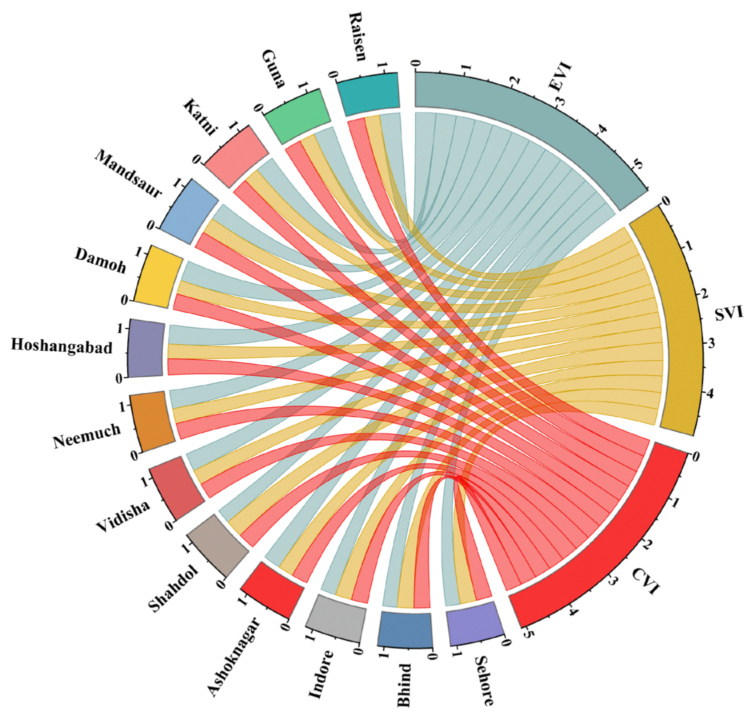


Fig. 3.9: Medium vulnerable district based on CVI

c) High vulnerable districts (0.409 - 0.442)

The heightened vulnerability of districts like Narsimhapur, Shajapur, Singrauli, Burhanpur, Agar Malwa, Umaria, Harda, Satna, Dewas, Rajgarh, Rewa, Seoni, and East Nimar is illustrated in Fig. 3.10. The increased susceptibility is correlated to higher EVI and SVI values, which are mainly due to the high proportion of agricultural areas, regions prone to flooding and droughts, and a noteworthy concentration of agricultural workers. The categorization of these regions as highly vulnerable highlights the urgent need for targeted climate adaptation and mitigation strategies. The heightened EVI and SVI values emphasize the need for a comprehensive approach to address the challenges of extensive agricultural activities, occurrences of flood and drought, and the prevalence of agricultural workers. It becomes necessary to prioritize targeted initiatives to enhance agricultural resilience through effective water management, diversification of crops, and implementation of improved agricultural practices. Employing effective flood and drought mitigation requires establishing resilient early warning systems, streamlined disaster response mechanisms, and adopting nature-based solutions for water retention and regulation.

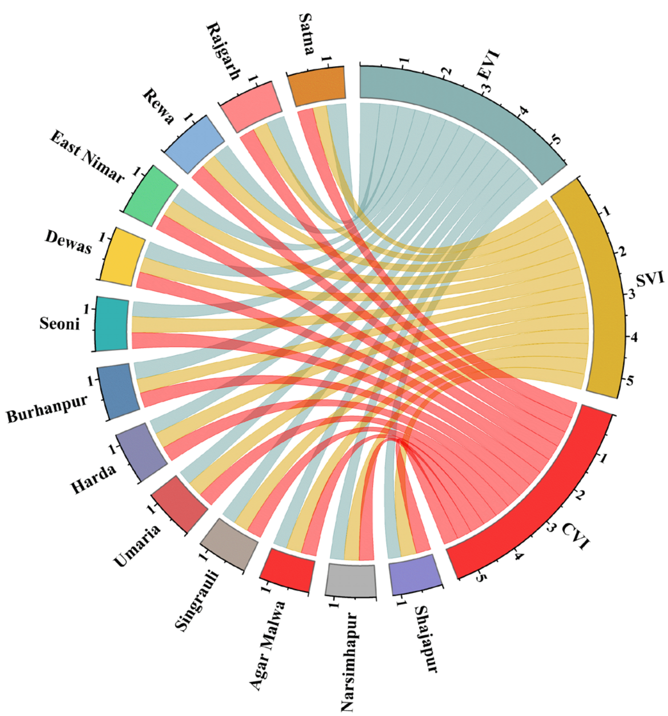


Fig. 3.10: High vulnerable districts based on CVI

d) Very high vulnerable districts (0.448 - 0.540)

The districts of Betul, Balaghat, Sidhi, West Nimar, Chhindwara, Ratlam, Dindori, Dhar, Alirajpur, Mandla, Jhabua, and Barwani exhibit higher levels of the CVI, primarily attributed to their elevated scores on the EVI and SVI (Fig. 3.11). These districts collectively demonstrate an increased awareness and vulnerability to the impacts of CC, although influenced by different factors. Significantly, Balaghat, West Nimar, Chhindwara, Dhar, Mandla, Jhabua, and Barwani exhibit a notable frequency of flood events, whereas the districts of Dhar, Alirajpur, Mandla, Jhabua, and Barwani recurrently affected by droughts.

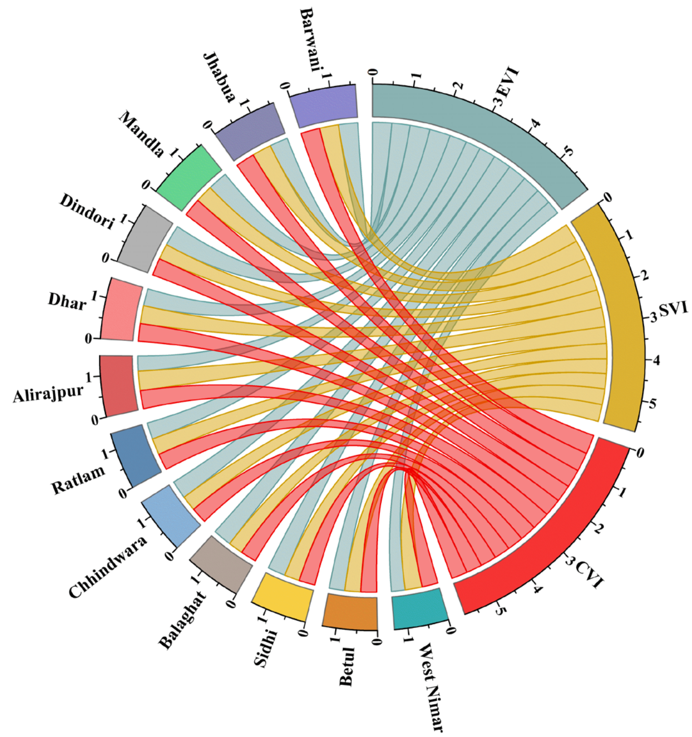


Fig. 3.11: Very high vulnerable districts based on CVI

Dindori exhibits the highest precipitation, dense forests, frequent forest fires, and extensive agricultural land. On the other hand, the districts of Sidhi, West Nimar, Ratlam, Dhar, Alirajpur, Jhabua, and Barwani have the largest agricultural areas, which directly influence their CVI values. Except for Alirajpur and Jhabua, all districts within this group have a higher percentage of agricultural labourers. Moreover, the Dindori, Alirajpur, Mandla, Jhabua, and Barwani districts exhibit the highest levels of vulnerability, as evidenced by their low HDI and the higher percentage of socially marginalized populations.

Districts with low CVI exhibit higher resilience due to favourable environmental conditions and lower socioeconomic challenges. However, districts with higher CVI values face severe challenges driven by environmental and socioeconomic factors, imposing urgent interventions. The findings emphasize the need for tailored strategies that address various patterns of vulnerabilities in districts like Damoh, Rajgarh, and Betul. Even districts with medium CVI values need current monitoring and adaptive policies to maintain their resilience due to CC. The relationship between environmental factors, socioeconomic conditions, and human development demands a nuanced, regional-level approach to vulnerability mitigation and adaptation.

The district-level CVI offers policymakers a valuable understanding of the root causes of regional vulnerability (Jha & Gundimeda, 2019). However, it is essential to recognize that while this index simplifies communication, it can cause some ambiguity due to its simplification (Abson et al., 2012). The results align with studies by Patri et al. (2022) and Ge et al. (2021), demonstrating the role of urbanization in reducing vulnerability in India. Azhar et al. (2017) emphasize the increased vulnerability in tribal regions. These studies support the conclusions of our analysis. As CC continues to impact more areas, specific actions are required to decrease current environmental and socioeconomic vulnerabilities. Marginalized populations, workers and communities are identified as having increased vulnerability, influenced by climate-induced migration and agricultural losses (Pradhan & Narayanan, 2022). Our study's identification of vulnerable districts in Madhya Pradesh is further validated by other research on CC vulnerability in India (Azhar et al., 2017; Chakraborty & Joshi, 2016). The results of the climate index by George et al. (2023), indicating a significant increase over decades, align with MPSKMCCC (2018) observation of heightened vulnerability toward mid-century (2050). Policies should promote sustainable land and forest management practices to enhance climate resilience, such as reforestation, soil conservation, and fire management strategies (Amoak et al., 2022). Improving forest regeneration, incorporating native species, and restricting human disturbances to forests are essential to protecting biodiversity and enhancing ecosystem services (Seidl et al., 2009). Engaging local communities in forest management guarantees the sustainable use of forest resources and reduces deforestation (Haji et al., 2020). The vulnerable districts identified in our research correspond to the present climatic scenario, validating our findings.

3.4.2 Validation of the Composite Vulnerability Index through Cluster Analysis

An essential step in this study involves applying cluster analysis to validate the outcomes extracted from the vulnerability index map. The present method explores the intricate relationship between environmental and socioeconomic variables contributing to CC vulnerability. The aim is to identify latent patterns and connections that may not be immediately evident from individual observations. The results of this analytical procedure are shown in the form of a dendrogram map (Fig. 3.12), which visually depicts the hierarchical clustering of the examined districts. The dendrogram illustrates the level of similarity or dissimilarity (Nguyen et al., 2019) among the districts based on the chosen variables. Districts exhibiting similar attributes concerning their vulnerability profiles are categorized into coherent clusters (Fig. 3.13), which are hierarchically structured.

This study's hierarchical cluster analysis effectively classifies the districts into a comprehensive set of 25 discrete clusters (Table 3.5). The clustering process enables the identification of complex nuances in vulnerability patterns throughout the study area. This approach systematically elucidates the interactions and interdependencies among various environmental and socioeconomic factors (Fernandez et al., 2016).

The hierarchical clustering analysis supports and reinforces the initial findings obtained from the composite vulnerability index by exposing hidden connections and discrepancies. This methodology adds a layer of verification and comprehensiveness to evaluating CC vulnerability,

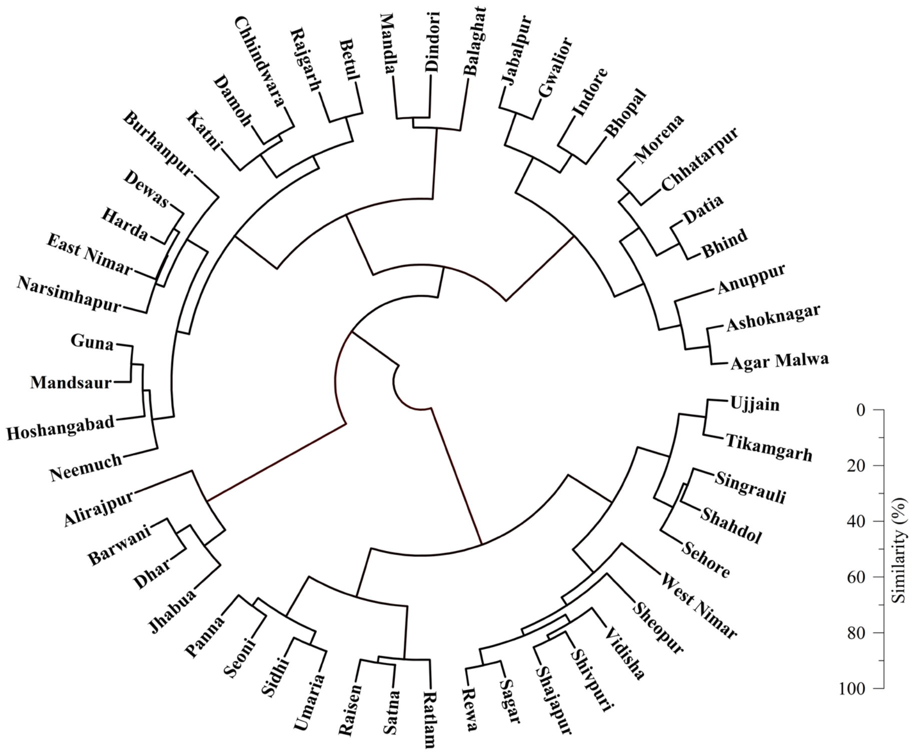


Fig. 3.12: Dendrogram map

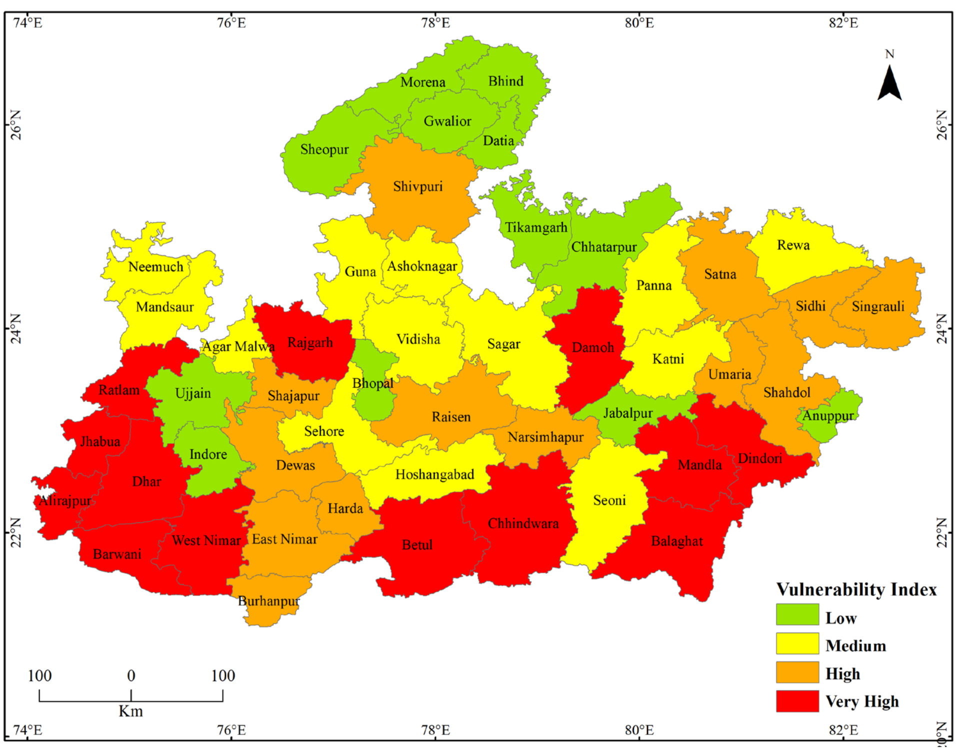


Fig. 3.13: Cluster map

Table 3.5: District classification using cluster analysis of environmental and socio-economic factors

Cluster	Districts	Vulnerability status with explanations
1	Anuppur	low vulnerability due to minimal maximum temperature, limited flood and drought-affected areas, exceedingly low percentage of dense forest, and a lower count of forest fire points
2	Bhind, Datia, Chhatarpur, and Morena	low vulnerability attributed to decreased rainfall, significantly lower dense forest coverage, fewer forest fires, minor drought-affected regions, and a modest proportion of socially disadvantaged populations
3	Bhopal and Indore	low vulnerability due to the absence of dense forest, minimal drought-affected areas, scarce forest fire occurrences, robust Human Development Index (HDI) performance, and a reduced percentage of socially marginalised populations, cultivators, and agricultural labourers
4	Gwalior and Jabalpur	low vulnerability due to reduced rainfall, limited dense forest presence, minor drought-affected regions, robust HDI performance, and a decreased percentage of socially deprived populations, cultivators, and agricultural labourers
5	Sheopur	low vulnerability attributed to modest dense forest and agricultural area percentages, limited drought-affected regions, and population density considerations
6	Tikamgarh and Ujjain	low vulnerability due to an exceptionally low percentage of dense forest, an absence of forest fires, minimal impact from climatic extremes, and a reduced percentage of socially disadvantaged populations
7	Agar Malwa and Ashoknagar	moderately vulnerable due to comparatively higher rainfall, expanded agricultural areas, and population dependent on the agricultural sector; moderate flood-affected levels
8	Katni	moderately vulnerable due to a comparatively extensive agricultural area, areas affected by climatic extremes, and an elevated count of forest fire points
9	Guna, Mandsaur, Hoshangabad, and Neemuch	moderately vulnerable due to substantial rainfall, limited dense forest coverage and forest points, a relatively extensive agricultural area, and a population reliant on the agricultural sector
10	Panna and Seoni	moderately vulnerable due to comparatively higher maximum temperature, minor minimum temperature levels, a moderate percentage of agricultural area, socially disadvantaged population, cultivators, and agricultural labourers
11	Rewa and Sagar	moderately vulnerable due to substantial agricultural area extent, forest fire points, population density, and moderate flood impact
12	Vidisha	moderately vulnerable due to relatively high rainfall and maximum temperature, expansive agricultural area and labourer numbers, and moderate minimum temperature levels

13	Sehore	moderately vulnerable due to relatively high maximum and low minimum temperatures, extensive agricultural area and forest fire points, and a strong HDI performance
14	Sidhi and Umaria	high vulnerability due to significantly elevated maximum and minimum temperatures, a higher count of forest fire points, lower HDI percentages, and a substantial percentage of agricultural labourers
15	Burhanpur, Dewas, Harda, East Nimar, Narsimhapur	high vulnerability due to a comparatively large agricultural area extent, regions impacted by floods, and a notable proportion of agricultural labourers
16	Raisen and Satna	high vulnerability due to elevated maximum temperatures, extensive agricultural areas and labourers, and significant climatic extremes impact
17	Shajapur and Shivpuri	high vulnerability due to relatively high rainfall, maximum temperatures, and a lower minimum temperature, expansive agricultural area, and population dependency on this sector
18	Shahdol and Singrauli	high vulnerability due to elevated rainfall, a sizable agricultural area and labourer population, forest fires, and a lower HDI performance
19	Balaghat, Dindori, and Mandla	very high vulnerability due to extensive dense forest presence and forest fire points, high climatic extremes impact, lower HDI performance, and a substantial percentage of agricultural labourers
20	Betul and Rajgarh	very high vulnerability due to elevated rainfall, minor minimum temperature levels, an extensive forest fire count, expansive agricultural land, and a significant agricultural labourer population
21	Alirajpur	very high vulnerability due to a substantial agricultural land extent and population dependence on this sector, socially disadvantaged population, drought impact, and extremely low HDI performance
22	Barwani, Dhar, and Jhabua	very high vulnerability due to an expansive agricultural land extent and population dependency on this sector, socially disadvantaged population, significant climatic extremes impact, and HDI performance
23	Chhindwara and Damoh	very high vulnerability due to notably low minimum temperatures, substantial climatic extremes and forest fires impact, a substantial percentage of socially disadvantaged populations and agricultural labourers
24	Ratlam	very high vulnerability due to an extensive agricultural area, socially disadvantaged population, and population dependency on agricultural activities
25	West Nimar	very high vulnerability due to elevated maximum temperatures and flood impact, expansive agricultural area, socially dependent population, and reliance on the agricultural sector

ensuring that the outcomes are not dependent on individual indicators but are validated by a comprehensive analysis of the various contributing factors (Feng et al., 2022). The findings provide valuable insights for policymakers and stakeholders involved in climate resilience. Targeted interventions in highly vulnerable districts are imperative, addressing agricultural challenges, flood and drought occurrences, and the prevalence of agricultural labour. Comprehensive strategies must encompass environmental, socioeconomic, and community-oriented approaches to effectively address identified challenges and enhance resilience. Ultimately, the study offers a robust framework for vulnerability assessment, integrating environmental and socioeconomic dimensions. The nuanced understanding of district-level vulnerabilities facilitates informed decision-making, which is essential for climate adaptation and disaster management in the different districts of Madhya Pradesh.

3.5 Conclusions

This research comprehensively analyses climate vulnerability in Madhya Pradesh, classifying districts into four vulnerability groups based on CVI values. Districts like Gwalior, Jabalpur, Bhopal, and Ujjain show low vulnerability (0.321-0.378) due to lower climatic extremes affected areas, reduced percentage of socially deprived population, and higher HDI values. Medium vulnerability (0.381-0.407) districts, including Damoh, Hoshangabad, and Indore, exhibit moderate susceptibility, indicating their capacity to manage climate stressors. High vulnerability (0.409-0.42) districts like Narsimhapur and Rewa are at increased risk, imposing targeted interventions. Very high vulnerability (0.448-0.540) districts, including Betul, Balaghat, and Alirajpur, encounter major challenges due to environmental exposure and socioeconomic disparities, mainly in socially marginalized populations. The categorization of districts into different vulnerability groups offers a granular perspective that goes beyond a simplistic classification. Moreover, the study used hierarchical cluster analysis to validate the CVI, strengthening the credibility of the findings and affirming the complex relationships between environmental and socioeconomic variables that influence vulnerability. This analytical approach enhances the credibility of the study's recommendations and strengthens the foundation for evidence-based policy formulation.

However, this chapter found that the districts where marginalized people are in the majority those districts are highly vulnerable. Moving away from analyzing at the district level to obtaining understanding at the community level would provide a deep knowledge of Madhya Pradesh's climate vulnerability. So, a study on the impact of climate on marginalized communities, particularly tribal communities, is necessary. Based on the results of this chapter, Dhar and Chhindwara districts were selected for the 3rd and 4th objective, i.e. tribal people's perceptions on CC and its impacts in Dhar and Chhindwara District will be discussed in the next chapter.

Chapter 4

Climate Change and Tribal Livelihoods: Perceptions, Impacts, and Determinants in Dhar and Chhindwara Districts of Madhya Pradesh

Dhar and Chhindwara districts are tribal-dominated districts with higher vulnerability to climate change based on environmental and socioeconomic factors. Tribal communities face increased vulnerability due to their dependence on rain-fed agriculture and limited resources in these regions. This chapter examines their perceptions on climate change, its livelihood impacts, and the sociodemographic determinants influencing their perceptions. Combining local perceptions with observed climatic trends offers valuable insights to strengthen adaptive capacities and inform targeted policies.

4.1 Introduction

As seen in the previous chapter, climate change (CC) has begun as a severe challenge globally, with profound impacts on ecosystems, livelihoods, and marginal communities (Tugjamba et al., 2023). According to the Intergovernmental Panel on Climate Change (IPCC), vulnerable communities that rely on climate-sensitive sectors like agriculture, forestry, and fisheries face uneven threats (Makondo & Thomas, 2024). These threats are further exacerbated in developing countries like India, Bangladesh, Sri Lanka, and Nepal, where socioeconomic determinants frequently regulate adaptation capacities (Patel et al., 2020). CC significantly challenges agricultural sustainability, water resources, and rural livelihoods in India (Praveen & Sharma, 2020), where over 70% of the population is still directly or indirectly dependent on agriculture (Harsh et al., 2024). Variations in rainfall, increasing temperatures, and rising droughts and flood events severely affect food security and economic stability (Shukla et al., 2016). The India Meteorological Department (IMD) reports that climate anomalies have been particularly severe in central and western India, where agriculture remains the primary livelihood for millions of people (Todmal, 2024). India's tribal population constitutes 8.6%, while in Madhya Pradesh, 21.1% belongs to scheduled tribes (Fig. 4.1), with 43 distinct tribal groups living there (Census, 2011). Major tribal communities in the research include the Bhil, Gond, Pardhan, Bharia, Mawasi, and Kharia. The Bhil tribe is the most populous (37.7%), followed by the Gond at 35.6% of the total scheduled tribal population. These tribal communities are severely impacted by CC, worsening their current social and economic issues.

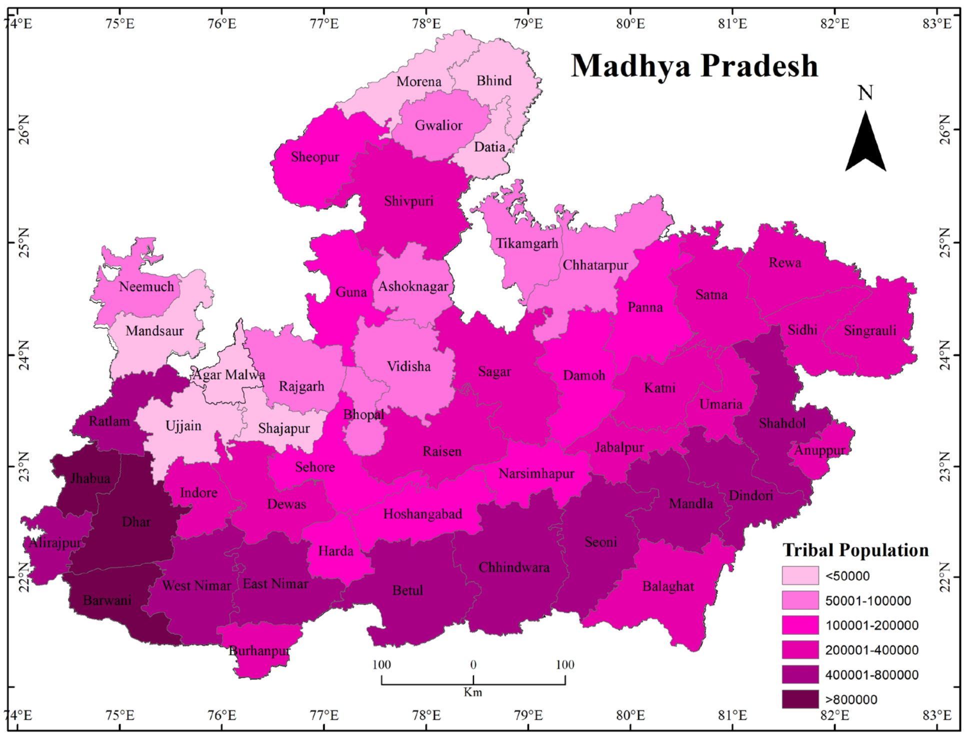


Fig. 4.1: District-wise tribal population in Madhya Pradesh

Dhar and Chhindwara districts, located in Madhya Pradesh state, India, were selected for this study. The state's tribal population is highly vulnerable to CC. While rich in traditional ecological knowledge, tribal communities face major challenges due to their socioeconomic marginalization, limited access to basic infrastructure, and high dependence on rain-fed agriculture (George et al., 2023). The unpredictable monsoon patterns, declining water resources, and rising temperatures in the region have intensified their vulnerability, making it necessary to understand their perceptions of CC and its impacts on their livelihoods. Tribal communities worldwide are known for their strong connection to natural resources and conventional knowledge systems that support their livelihoods (S. Mehta, 2024). Tribal communities in Dhar and Chhindwara, reliant on agriculture and forests, face increased vulnerability due to CC, which is demonstrated by irregular rainfall, prolonged droughts, and increasing temperature trends. These environmental changes directly influence agricultural productivity, water availability, and forest resources, compounded by socioeconomic problems such as inadequate access to modern agricultural technologies, lack of infrastructure, and poor health services (Anser et al., 2023; Shamshad et al., 2024; Stavi et al., 2021). Their perceptions and adaptive responses to CC are affected by gender, education, occupation, and infrastructure access, highlighting the need for a nuanced approach to adopting these vulnerabilities.

Various previous studies have been conducted on local people's perceptions of CC. Brechin & Bhandari (2011) recognized global variations in public perceptions of CC, which are affected by factors such as willingness to pay for environmental protection and views on government initiatives. It is also observed by Capstick et al. (2015) over the past 25 years, particularly in developed countries, because of economic and sociopolitical indicators, with a remarkable gap in longitudinal studies outside Western countries. Around 78% of respondents in China documented the detrimental impact of CC on society (Yu et al., 2013). In Bangladesh, 72.2% of Khasia and 60% of Tripura communities perceived increasing temperatures, with a significant percentage also experiencing decreasing rainfall patterns (Ahmed & Atiqul Haq, 2019). In the Chakma community, 61% of the population perceived moderate CC, with education emerging as the robust awareness indicator (Huda, 2013). Rai et al. (2022) noticed significant CC perceptions in the Chepang community in Nepal, with 97.3% reporting a reduction in pre-monsoon rainfall and adverse effects on agriculture, water sources, and food security. Furthermore, about 80% of the Tharu community reported higher flood incidents, 60% recorded increased windstorms, and 50% observed higher drought incidents in Nepal (Devkota et al., 2011). In India, over 80% of transhumant herders in the Himalayas perceived increasing summer temperatures and decreasing snowfall, leading to disruptions in the transhumance system (Aryal et al., 2014). In the Indian Himalayas' Pangi Valley, Meena et al. (2019) found that nearly all tribal communities (98.3%) observed a decrease in snowfall alongside rising temperatures. This shift has led to shorter growing seasons and declining crop yields, threatening the region's agricultural stability. Similar worries emerged in Uttarakhand, where 76% of farmers reported declining summer and winter rainfall, while 85% documented a rise in summer temperatures (Shukla et al., 2019). Low-resource farmers expressed greater anxiety over food security, as their livelihoods are more vulnerable to these climatic changes. In Bundelkhand, Jatav (2022) revealed that over 80% of farmers perceived significant changes in rainfall patterns, with 90% reporting increased heat waves. However, these farmers' perceptions and meteorological data showed a negative correlation, highlighting the complexities of localized CC awareness. Similarly, in the Kanchandzonga Biosphere Reserve, Shukla et al. (2016) reported that 85% of respondents had experienced temperature increases, while 3% remained sceptical of these changes.

Despite various research on CC impacts on agriculture and livelihoods in India, major gaps persist. Many studies focus on general perceptions of temperature rise, rainfall variations, and agricultural challenges, but few integrate indigenous knowledge with scientific data to develop region-specific adaptation strategies. Discrepancies between local perceptions and meteorological data remain underexplored in this region. Additionally, the influence of socioeconomic factors on climate perceptions and adaptive capacities among marginalized groups is not well understood. This chapter is essential since it offers region-specific insights into climate variability and addresses the critical role of local perceptions in climate adaptation by concentrating on tribal communities in the Dhar and Chhindwara districts. The primary objectives of this chapter are which fill the above-mentioned gaps are to (a) analyse tribal perceptions of CC and its impacts on their livelihoods in Dhar and Chhindwara, (b) assess observed regional climatic variations using rainfall and temperature data and link them to local perceptions, and (c) identify sociodemographic factors influencing climate awareness and its impacts. This chapter bridges the gap between indigenous knowledge and scientific analysis, offering actionable insights for policymakers to design targeted climate adaptation strategies for vulnerable tribal communities.

4.2 Methodology

4.2.1 Study Area

Dhar: Dhar district is situated in the southwestern part of Madhya Pradesh and lies between longitudes 75°00’E and 75°26’E and latitudes 22°42’N and 23°10’N (Fig. 4.2). The district is surrounded by Indore, Ujjain, Ratlam, Khargone, Barwani, Jhabua, and Alirajpur districts. Dhar comprises 8,153 km² (2.64% of Madhya Pradesh’s total area), forming the 13th biggest district in Madhya Pradesh. The district is separated into 3 physiographic divisions: the Malwa, Vindhyachal range, and Narmada valley. The southern part lies in the Narmada catchment zone, while the Chambal and Mahi rivers drain to the north. Dhar has 7.9% (644 km²) of forest cover to the total geographical area (Forest Survey of India, 2021), mostly containing dry teak forest. The district receives a typically dry climate, with May being the warmest month (average T_{max} 40 °C) and January the coldest (average T_{min} 10 °C). The average annual rainfall is 854 mm. The total population of this district is 2,185,793, with a decadal growth rate of 25.6%. The rural population represents 81.1% of the total, with a population density of 268 persons/km². The sex ratio is 964 women per 1000 men, while the literacy rate is 59.0%. Scheduled tribes comprise 55.9% of the total population (1,222,814 persons, highest in the state).

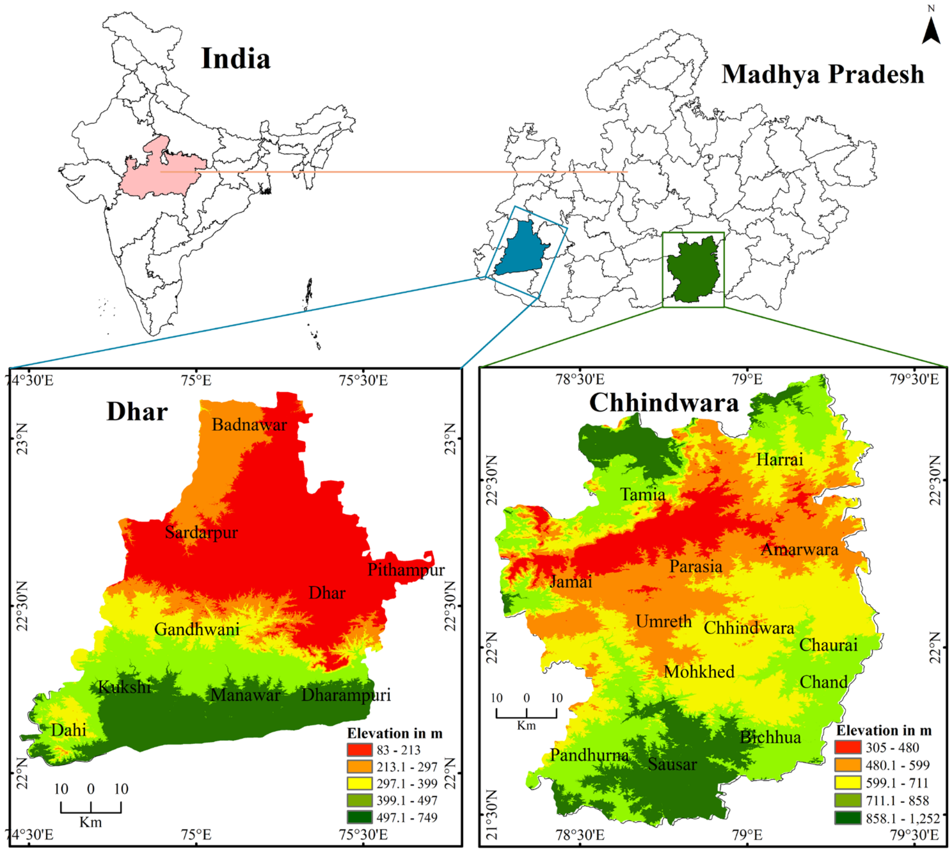


Fig. 4.2: Study area map

Chhindwara: Chhindwara district is situated in the southern-central part of Madhya Pradesh (Fig. 4.2). It is a part of the Vindhyachal-Baghelkhand area, which is located between longitudes 78°01’E and 79°23’E and latitudes 21°27’N and 22°49’N. It is the biggest district in Madhya Pradesh, with an area of 11,815 km² (3.83% of the state’s total area). Narsimhapur, Nagpur, Amravati, Seoni, Hoshangabad, and Betul border it. The district is geographically subdivided into the Satpura Range, Chhindwara Plateau, and Sausar Forested Upland. The tributaries mainly drain it off the Narmada and Godavari rivers, namely the Kanhan, Pench, and Wardha rivers. Chhindwara has ample forest cover, making up over 39% (4608 km²) of its total area, according to the Forest Survey of India in 2021. These forests are mostly composed of Southern Tropical Dry Deciduous Forest. The climate is milder than the surrounding districts, characterized by four distinct seasons (summer, winter, monsoon, and post-monsoon) and average temperatures varying from 26 °C to 29 °C. The mean annual precipitation is 1159 mm. The total population is 2,090,922, with a prevalent rural majority of 75.8% and a population density of 177 people/km^2. The district has a sex ratio of 964 females per 1000 males, a literacy rate of 71.2%, and scheduled tribes form 36.8% (769,778 persons) of the total population.

4.2.2 Rationale of the Study Area

Dhar and Chhindwara districts were selected as the study areas based on various aspects. Both districts emerged as among the most vulnerable to climate change in Madhya Pradesh when integrating environmental and socio-economic indicators, as identified in Chapter 3. While districts like Barwani and Jhabua have a higher proportion of tribal population and rank first and second in terms of CVI values, the selection of Dhar and Chhindwara is not solely based on tribal population. It also considers regional variation, ecological diversity, and the availability of consistent data related to climate and socioeconomic variables. Dhar district has the highest number of tribal population (12,22,814) and is situated in the southwestern part of Madhya Pradesh. It is characterized by a semi-arid climate, predominantly rain-fed agriculture, and lower forest cover (7.9%), making it highly sensitive to climatic variability. Chhindwara, the largest district of Madhya Pradesh in terms of area, lies in the southern-central part of the state. It has a little lower percentage of tribal population (36.8%) but 4th highest tribal population (7,69,778), a sub-humid climate, higher average rainfall (1159 mm), and significant forest cover (39%). Despite these natural advantages, Chhindwara faces socio-economic vulnerabilities due to its livelihood dependencies and occupational patterns. This ecological and socio-economic difference offers a robust comparative framework to understand tribal people's perceptions of climate change and vulnerability assessment of tribal livelihood. However, it is also recognised that such perceptions are shaped by multiple factors, including traditional ecological knowledge, previous experiences with climate extremes, cultural and institutional influences, access to early warning systems, and awareness and education. Therefore, selecting these two districts allows a comprehensive understanding of how multiple interrelated factors influence climate change perception and adaptive responses among tribal communities. Their selection ensures that the study findings are relevant for broader policy implications in tribal-dominated regions of Madhya Pradesh.

4.2.3 Data Collection

This study combines both primary and secondary data for analysis, focusing on all Tehsils within Chhindwara (13) and Dhar (9) districts in Central India. Primary data were collected using a multistage sampling design. In the first, the study districts were selected purposively due to their significant tribal populations and very high vulnerability to CC (Kumar et al., 2024; Kumar & Mohanasundari, 2024). All 22 Tehsils were included in the second stage. Third, tribal residential villages (26 from Chhindwara and 27 from Dhar) were chosen randomly from each Tehsil (Fig. 4.3), and finally, approximately 10 tribal households from each village were randomly selected. The identification of eligible tribal households was facilitated by local resource persons, such as Panchayat members, Anganwadi workers, ASHA workers, and village elders. From this pool, households were selected randomly to ensure unbiased representation. Cochran's (1977) formula was used to determine the sample size (Jamshed et al., 2020). As per this method, the minimum sample size is 385, with a confidence interval of 95% and an error value of ±5%. The sample was distributed in 2 districts: 261 households from Chhindwara and 274 from Dhar, comprising 535 households. The selected households were surveyed using semi-structured scheduled interviews to evaluate their livelihood vulnerability due to climate variability. A key respondent from each village was also interviewed to verify household responses. Data collection occurred from January to April 2024, including participants of all ages (excluding <18 years) and genders. For their convenience, interviews were conducted in Hindi, and all information was documented in writing. Verbal informed consent was obtained from all respondents before proceeding with the survey questions.

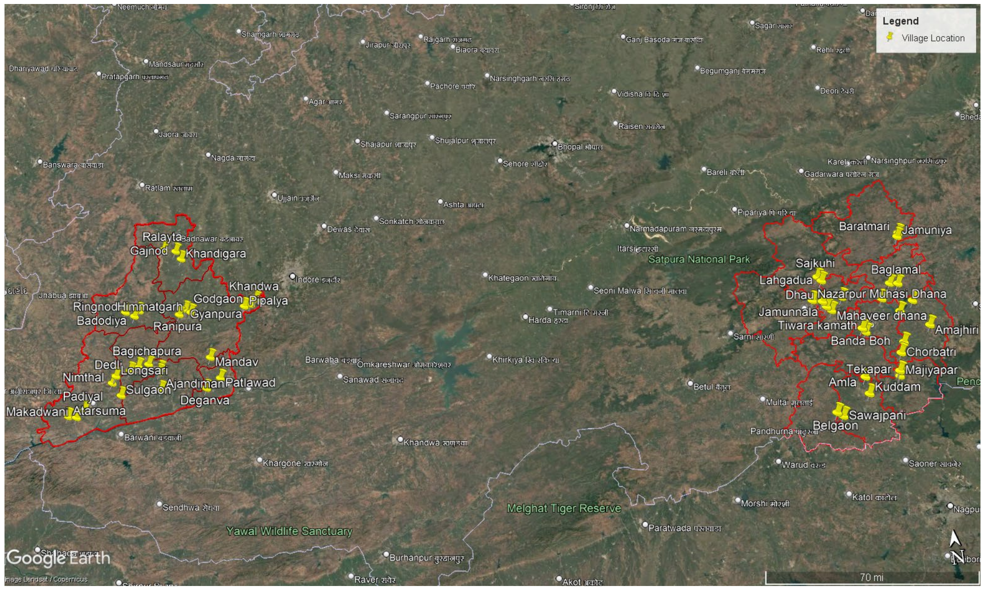


Fig. 4.3: Location of visited villages. The maps were generated using Google Earth Pro (version 7.3) on desktop software (https://www.google.com/intl/en_in/earth/about/versions/#earth-pro).

The scheduled interviews encompassed three parts: (1) respondents' personal and household characteristics, access to essential utilities such as water, schools, healthcare facilities, drainage systems, transport facilities, banks, and the main market, and livelihood strategy; (2) perceptions of CC and variability; and (3) perceived environmental and socioeconomic impacts of CC. These impacts were recognized through group discussions during a pilot survey with tribal people. To ensure clarity, the authors explained the difference between short-term weather variability and long-term CC (over 10–30 years) to respondents aged 18 and above, reducing bias. Perception-based questions used a binary 0 (No) and 1 (Yes) format. At the same time, statements on CC impacts were rated on a 5-point Likert scale, as follows: 1= "Strongly disagree", 2= "Disagree", 3= "Neutral", 4= "Agree", 5= "Strongly agree". Climate data, such as daily gridded rainfall (0.25° × 0.25°) and temperature (1° × 1°) data were obtained for 70 years (1954-2023) from the India Meteorological Department.

4.2.4 Data Analysis

This chapter employed several techniques to analyse the gathered data, ensuring robust and accurate results (Fig. 4.4). Innovative Trend Analysis (ITA) was used to analyse trends (Şen, 2012) in annual rainfall, T_{mean}, T_{max}, and T_{min}. The Standardized Precipitation Index-3 (SPI-3) was applied to evaluate the dry and wet conditions (Mckee et al., 1993) from 1954 to 2023. Descriptive statistics were employed to examine the respondent's sociodemographic characteristics, perception of CC, and CC impacts using frequency and percentage distributions of categorized responses. The binary logistic regression model was employed to correlate CC perception (whether the climate is changing or not) with sociodemographic determinants. Further, the Multiple Linear Regression model was used to explore the potential effects of each sociodemographic variable on the perception of CC's environmental and socioeconomic impacts. For applying linear regression, the impact of CC was grouped into 6 categories using normalization, with equal weight assigned and an indexed value created. Following are the indices - climatic extremes (Flood and Drought incidents are increasing), natural resources (Forest and mountainous vegetation and Agricultural lands are decreasing), agriculture (Crop growing seasons are changing, Crop production is reducing, Crop failure and economic loss, Crops are damaging due to pests, and Crops are damaging due to environmental issues), water (Water level is declining and Water shortages), Socioeconomic (Climate extreme incidents affected your livelihood and Led to rural-urban migration), and health (Affects health and creates health issues and Increased water-borne diseases and other diseases). Before regression analysis, multicollinearity and heteroscedasticity assumptions were tested. These data did not show multicollinearity, following Gujarati's (1995) guideline that correlation coefficients above 0.8 indicate a significant multicollinearity issue. Heteroscedasticity was also checked using the Breusch-Pagan test to ensure the model's validity. Data cleaning, conversion, analysis and visualization were done using MS Excel, R-Studio, STATA, Origin 2024b, and ArcGIS 10.8.

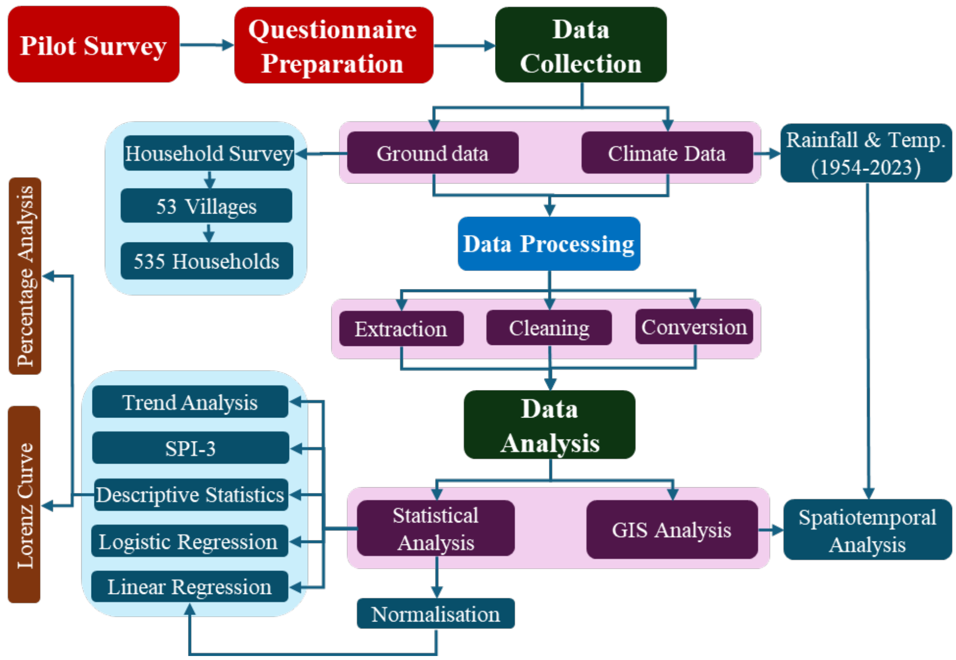


Fig. 4.4: A comprehensive methodological framework

4.2.4.1 Innovative trend analysis (ITA)

ITA is a non-parametric method for trend detection in climate data without distributional norms (Şen, 2012). It involves separating the dataset, such as annual rainfall or temperature (T_{mean}, T_{max}, T_{min}), into two halves and plotting the first half on the x-axis and the second half on the y-axis. For a dataset X with n observations:

$$X_1 = \{x_1, x_2, \dots \dots, x_{n/2}\}, X_2 = \{x_{(n/2)+1}, x_{(n/2)+2}, \dots \dots, x_n\}$$

These subsets are plotted as a scatter plot:

Trend Plot: (X_1, X_2)

- 45° line ($y = x$): indicates no trend.
- Above 45° line ($y > x$): shows an increasing trend.
- Below 45° line ($y < x$): reflects a decreasing trend.

ITA offers a clear visual representation of trends in climate variables, making it a rational choice for analyzing annual changes without complex statistical assumptions. This study applied it to assess trends in rainfall and temperature data from 1954 to 2023, helping to identify changes in climate patterns.

4.2.4.2 Standardized Precipitation Index (SPI)

The SPI evaluates meteorological droughts and rainfall variability over various time scales (Mckee et al., 1993). Fitting long-term precipitation data calculates SPI to a probability distribution, typically the gamma distribution, which is then transformed into a standard normal distribution with a mean of zero. The SPI equation is defined as:

$$SPI = \frac{(X - \mu)}{\sigma}$$

Where X is the observed precipitation, μ is the mean precipitation, and σ is the standard deviation of the historical data. SPI values show deviation from average rainfall conditions rather than absolute water availability, where SPI>0 signifies wet periods, SPI<0 indicates drought, and SPI=0 represents normal conditions. Severity categories range from mild drought (-1.0 to -1.49) to severe drought (≤ -2.0), with positive values indicating wetter-than-average periods (Singh et al, 2023). This study employed SPI-3 (three-month SPI) to evaluate short-term wet and dry conditions from 1954 to 2023, depicting seasonal impacts essential to agriculture and water management.

4.2.4.3 Binary Logistic Regression (BLR)

BLR is a statistical model that explores the correlation between a binary dependent variable and one or more independent variables (Huda, 2013). The model approximates the likelihood $P\,(Y = 1)$ using the logistic function:

$$P\ (Y_i = 1 |\ X) = \frac{exp\left(\beta_0 + \sum_{k=1}^{15} \beta_k X_{ki}\right)}{1 + exp(\beta_0 + \sum_{k=1}^{15} \beta_k X_{ki})}$$

where, Y represents the dependent variable, $X_1, X_2, \ldots, X_{15}$ are the independent variables, β_0 is the intercept, and $\beta_1, \beta_2, \ldots, \beta_{15}$ are the coefficients for each predictor.

For the current study, the perception of CC is the dependent variable (Y), which is coded as 1 if "climate is changing" and zero otherwise ("no change"). We have used 15 different independent variables namely gender, age, education, family size, annual household income, economic status, housing structure, occupation, land holdings, access to electricity, LPG connection, toilets, drinking water sources, communication media and distance to the nearest health centre. Hence the maximum value of k is 15. The model's coefficients were estimated using the maximum likelihood estimation method.

4.2.4.4 Multiple Linear Regression (MLR)

The MLR model was used to detect the primary factors most significantly affecting household perceptions on CC impacts. This method is commonly used in empirical studies and predictive models that involve multiple independent variables (Phuong et al., 2023). It constructs an optimal regression equation by choosing independent variables with a significant linear impact on the dependent variable, making it a popular choice in CC research (Ghosh & Ghosal, 2020; Phuong et al., 2023). The MLR was applied using given equations.

$$Y_i = \beta_0 + \sum_{k=1}^{15} \beta_k X_{ki} + u_i$$

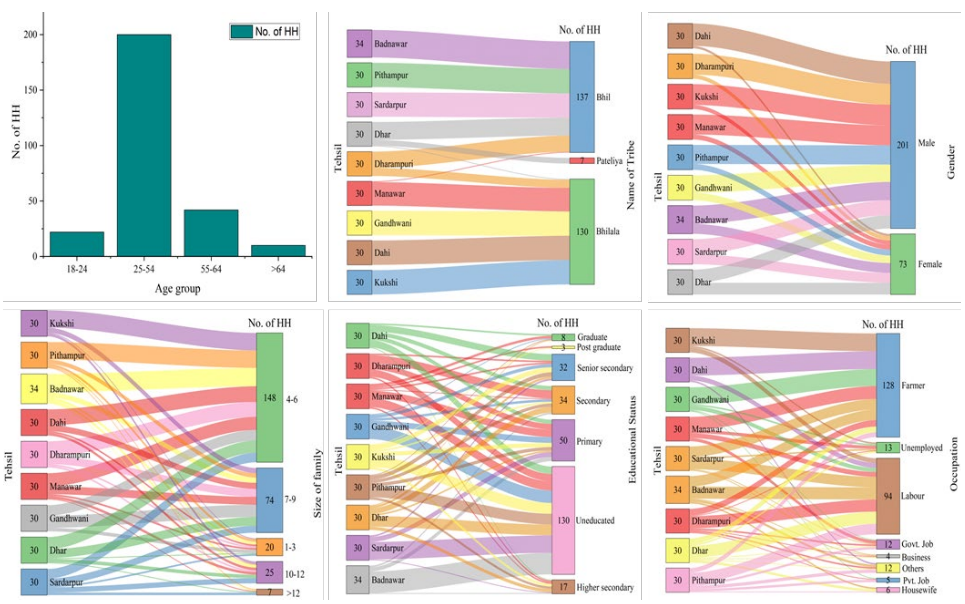
where Y is the dependent variable. In the current study we have used various dependent variables namely, "flood incidents are increasing", "drought incidents are increasing", "forest and mountainous vegetation are reducing", "crop growing season is changing", "crop failure and economic loss", "damage to crops due to pests, water shortages", "loss of livestock", "led to rural-urban migration", "affecting health and creating health issues", and "increasing waterborne diseases". β_0 is the intercept, $\beta_1, \beta_2, \ldots, \beta_{15}$ are partial regression coefficients, u is the regression error term, and $\boldsymbol{X}$ is the set of independent variables already discussed in the previous section. This method explored how sociodemographic factors influence perceptions of CC impacts among respondents, allowing for valuable insights into their beliefs on environmental and socioeconomic effects.

4.3 Results and Discussion

4.3.1 Sociodemographic Characteristics of the Respondents

The sociodemographic attributes of households examined in the Dhar (Fig. 4.5(a)) and Chhindwara (Fig. 4.5(b)) districts reveal significant disparities in age distribution, tribal community, gender ratio, family size, educational status, occupation, and income. Female respondents had a low percentage in both districts, representing only 27% in Dhar and 29% in Chhindwara. In Dhar, 73% of respondents belong to the 25-54 age group, whereas 77% in Chhindwara. Bhil and Bhilala communities constitute 50% and 47% of the tribal population in Dhar; however, the Gond tribe comprises the majority at 77% in Chhindwara. Chhindwara's family sizes were predominantly larger, with 76% of families including 4-6 persons, rather than 54% in Dhar. Educational status showed variation, with 54% of Dhar families possessing

(a)



(b)

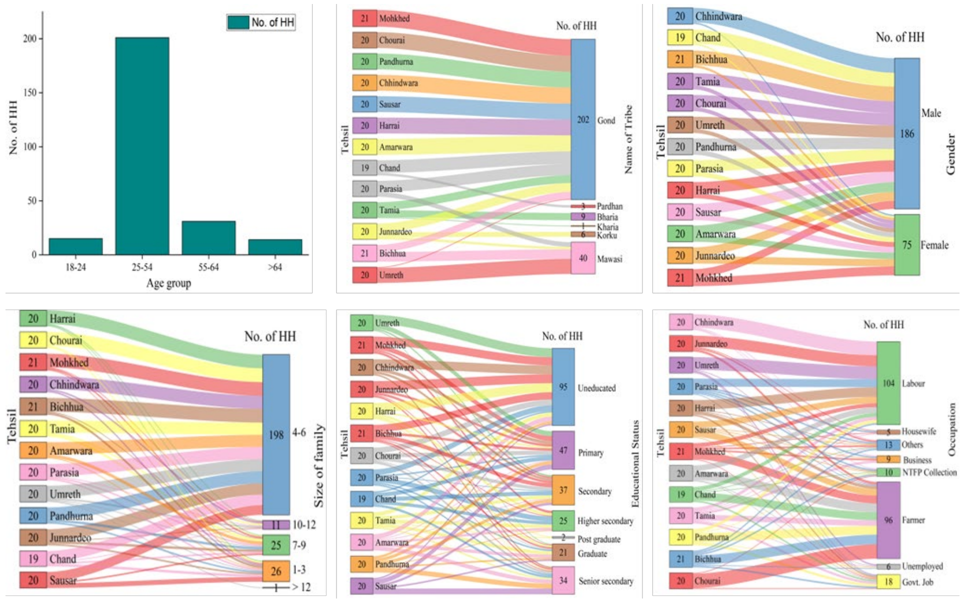


Fig. 4.5: Respondent's age, community, gender, family size, education, and primary occupation (a) Dhar (b) Chhindwara

at least a primary education (Class 1-5), instead of 76% in Chhindwara. In both districts, agriculture constituted the most common occupation, being more prominent in Dhar (47%) compared to Chhindwara (37%), whilst alternative occupations included farming and non-farming labour, business, non-timber forest product (NTFP), and other work. Income statistics indicated that a higher percentage of families in Chhindwara (45%) earned less than 50,000 rupees yearly, compared to 36% in Dhar (Fig. 4.6(a)). The Lorenz curve revealed relatively homogeneous distribution of income in both districts (Fig. 4.6(b)), indicating similar degrees of income inequality. Targeted poverty alleviation and livelihood enhancement initiatives for tribal groups are essential to mitigate socioeconomic disparities and promote inclusive development (Jernigan et al., 2020).

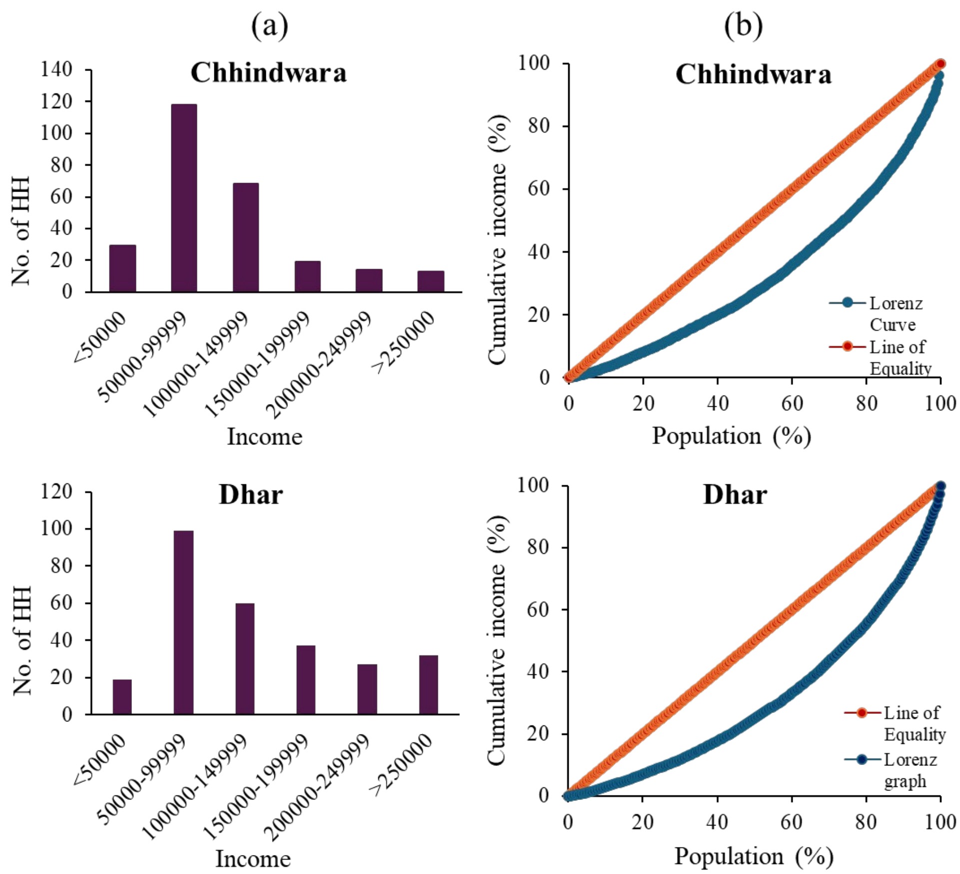


Fig. 4.6: Households (a) annual income and (b) Lorenz curve of income inequality for Chhindwara and Dhar districts

4.3.2 Observed Climate Change and Impacts

Table 4.1 presents the results of ITA in climate variables for Dhar and Chhindwara, concentrating on critical climatic variables such as rainfall, Tmax, and Tmin. In Chhindwara, rainfall exhibits a negative trend (-0.072) (Fig. 4.7) with a non-significant slope (-0.239), showing consistency in rainfall patterns. Conversely, Dhar demonstrates a non-significant decreasing trend in rainfall (-0.193) (Fig. 4.7) with a higher slope (-0.476). The decline in rainfall can influence agricultural production, livestock production, and affect water availability, which is essential for the subsistence of tribal communities. This situation highlights the vulnerability of tribal communities to variations in rainfall patterns, necessitating adaptive measures such as water conservation, implementation of effective irrigation technologies, and crop diversification to mitigate the challenges posed by rainfall variability (Hazarika et al., 2024). These findings are consistent with Devi et al. (2020), Jain et al. (2023), Kundu et al. (2017), Pal & Al-Tabbaa (2011), and Rai et al. (2014), who have reported a long-term decrease in annual rainfall across Central and Central West India over the last century.

Table 4.1: Results of trend analysis

Variables	**ITA**		**Trend slope**		**95% Upper-level Confidence**	
	Dhar	**Chhindwara**	**Dhar**	**Chhindwara**	**Dhar**	**Chhindwara**
Rainfall	-0.193	-0.072	-0.476	-0.239	0.235	0.412
T_{mean}	0.058	0.075	0.004	0.005	0.001	0.001
T_{max}	0.07	0.106	0.009	0.013	0.001	0.001
T_{min}	0.805	-0.253	0.015	-0.005	0.003	0.002

T_{mean} implies an increasing trend in Dhar (ITA= 0.058) and Chhindwara (ITA= 0.075), indicating a warming climate that could exacerbate crop heat stress and reduce yields. The T_{max} trend reveals a more significant rise in Chhindwara (ITA= 0.106) than in Dhar (0.07). Elevated T_{max} increases evapotranspiration, reduces soil moisture and exacerbates agricultural water stress, especially during essential crop growth stages (Sadok et al., 2021). The T_{min} reveals a dramatic divergence, with Dhar witnessing an increase (ITA= 0.805) while Chhindwara shows a decrease (ITA= -0.253). The temperature variations disrupt the phenological cycles of crops, modify insect populations and disease spreads, and shift harvesting seasons, creating difficulties for conventional agricultural practices and indigenous knowledge systems (Skendžić et al., 2021). It also interrupts important components of tribal livelihoods, including gathering NTFPs and other seasonal activities closely related to climatic patterns (Asamoah et al., 2024). Tribal people, who depend primarily on subsistence agriculture and animal husbandry, are vulnerable to these climate-induced difficulties, which endanger food security and economic stability (Sushant, 2013).

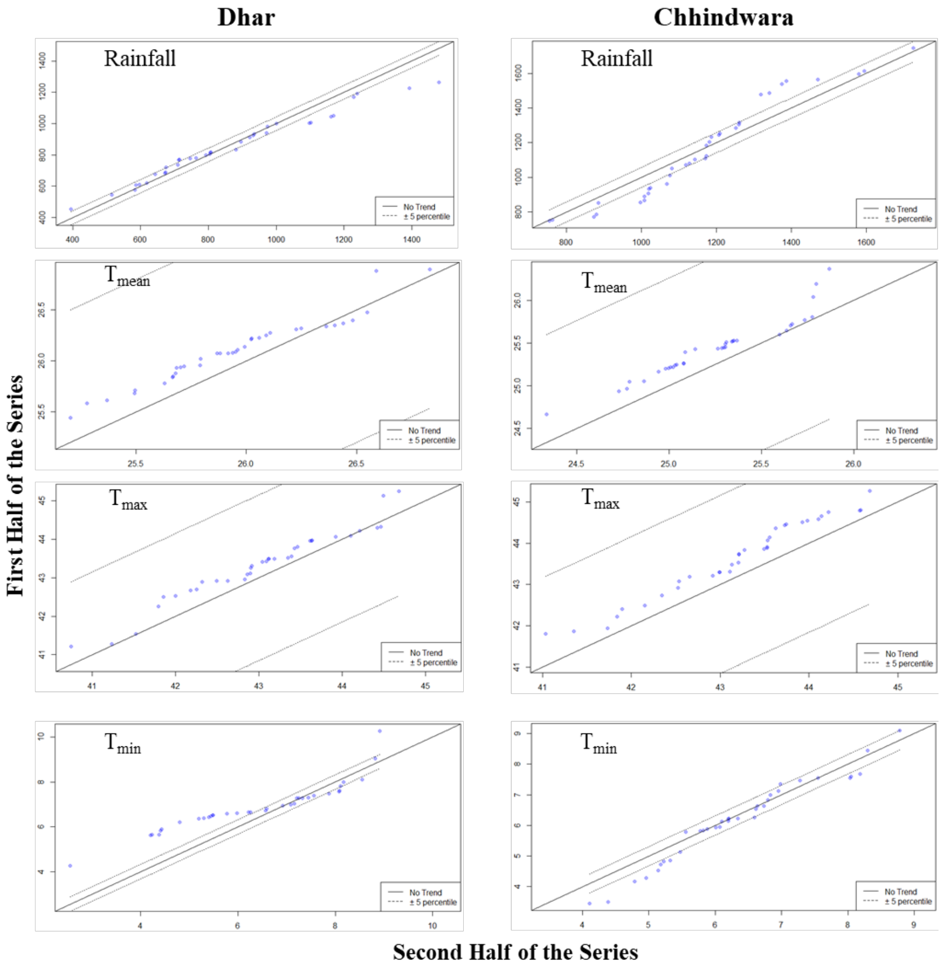


Fig. 4.7: Graphical results of ITA

Furthermore, increasing temperatures aggravate heat stress on cattle, significantly affecting their health and production (Herbut et al., 2018). These findings align with Devi et al. (2020), Shukla et al. (2017), Kundu et al. (2017), Duhan et al. (2013), and Shukla & Khare (2013), who documented significant increases in T_{max} and T_{min} across Madhya Pradesh and Central India over the period from 45 to 105 years. For a better understanding, the spatiotemporal changes of climatic variables for both districts were presented in Fig. 4.8. Enhancing the resilience of tribal people to climatic variability and change needs promoting agroecological practices, protecting biodiversity-rich places, and rehabilitating traditional ecological knowledge systems (Kala, 2022). Climatic changes emphasize the urgent need for adaptive strategies and resilience-building initiatives tailored to the vulnerabilities faced by tribal populations, as shifts in rainfall and temperature patterns directly threaten their traditional livelihoods and cultural practices. Addressing these problems is essential for encouraging sustainable development and preserving the well-being of these communities to cope with CC.

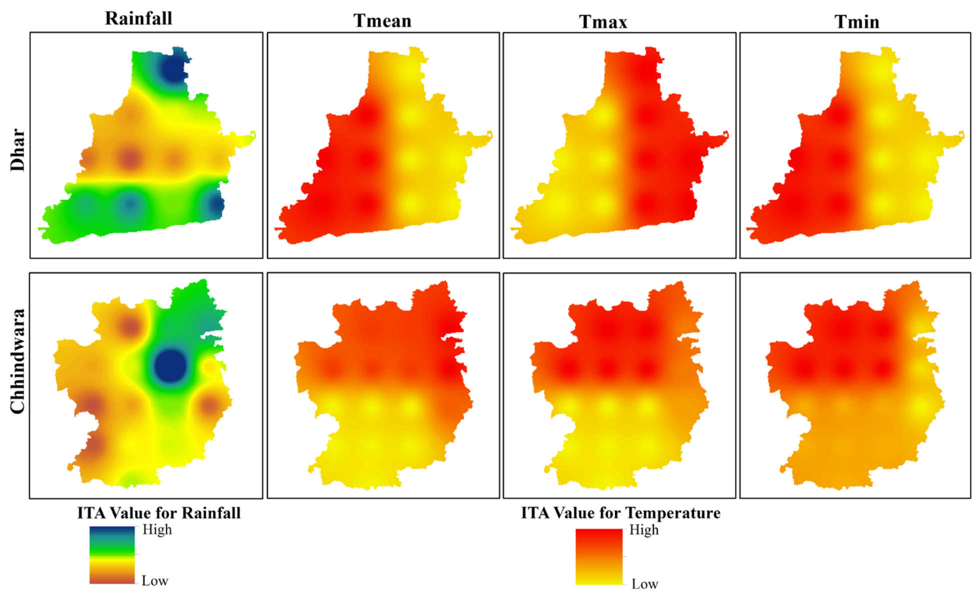


Fig. 4.8: Visual representation of spatiotemporal analysis

The SPI-3 results for the Dhar and Chhindwara districts (Fig. 4.9) give essential insights into the meteorological conditions affecting the tribal livelihood. It is important to note that SPI reflects rainfall deviations from local averages rather than absolute water availability. In regions receiving ample rainfall, negative SPI values can represent adequate water supply, whereas in drier regions, even positive SPI values might coincide with limited water availability. Thus, local climatic context is essential when interpreting SPI values. SPI-3 evaluates three-month rainfall variations as a significant drought indicator, with positive values indicating wet conditions and negative ones showing dry conditions. These changes significantly impact rainfed agriculture, water availability, and ecosystem health, which are important to tribal livelihood (Kumar et al., 2009). Periods of negative SPI-3 are often associated with an increased risk of crop failure and water stress, contributing to heightened vulnerability among subsistence tribal farmers (Bhunia et al., 2020). The inconsistent rainfall patterns recorded by SPI-3 data underline the issues caused by periodic rainfall, which exacerbates food insecurity and poverty (Wahla et al., 2022). While negative SPI values indicate drier-than-average conditions, actual impacts on livelihoods depend on community adaptive capacity and local environmental factors. These findings highlight the necessity for adaptive strategies to address climate risks. Integrating SPI-3 analysis into the nexus between CC and tribal livelihood enhances our understanding, supporting targeted resilience-building. The SPI-3 results provide essential evidence for policymakers to develop targeted adaptation strategies that address vulnerabilities, ensuring sustainable development and climate resilience in marginalized communities.

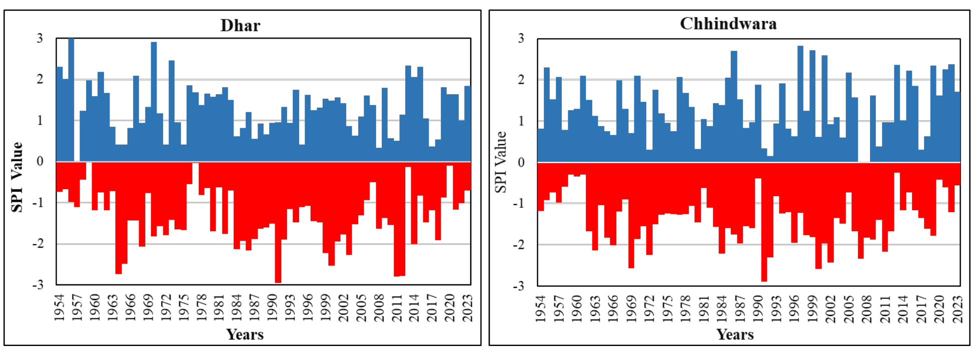


Fig. 4.9: Results of SPI-3

4.3.3 Tribal Communities' Perception on Climate Change

Local communities have their own ways of explaining CC (Boillat & Berkes, 2013). The perception of CC among respondents in the Dhar and Chhindwara districts suggests a strong agreement on changes in rainfall and temperature patterns (Fig. 4.10). In Chhindwara, 88.9% of respondents observed a decrease in rainfall amounts, compared to 69.7% in Dhar. The perception of irregular rainfall patterns is nearly identical, with 98.5% in Chhindwara and 96.7% in Dhar reporting changes. Most respondents in both districts admitted a temperature rise, with 98.5% in Dhar and 96.6% in Chhindwara confirming this trend. Almost 97% of respondents in both districts agreed that summer days are becoming hotter. A study by

Srivastava et al. (2021) in the Bundelkhand Agroclimatic zone of Madhya Pradesh reported the hot days have increased during the last decade (2001-10). These perceptions supported the observed changes in climatic variables, which suggests a decreasing trend in rainfall and an increasing trend in T_{mean} and T_{max}. It also aligns with the studies conducted in India by Jatav (2024), Shukla et al. (2019), Sam et al. (2020), and Shukla et al. (2016).

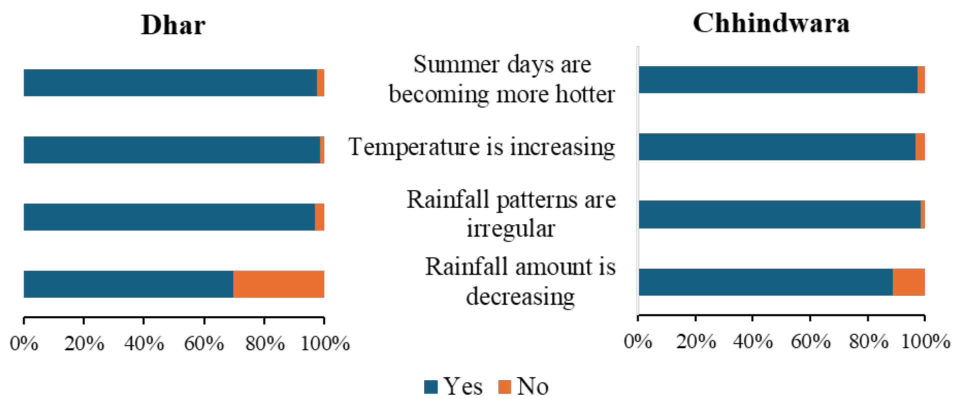


Fig. 4.10: Tribal people's perception of climate variability

For major consequences of CC, people mainly notice shifts in rainfall patterns, temperature fluctuations, and agricultural productivity (Varadan & Kumar, 2014). The tribal communities have been particularly vulnerable to the impacts of CC due to their heavy reliance on natural resources and traditional agricultural practices, placing them at the central stage of experiencing climate-induced challenges (Khanal et al., 2019). Their perceptions are essential for enhancing our understanding of CC and guiding the development of adaptation strategies (Brugnach et al., 2017; Rai et al., 2022). Understanding tribal communities' perceptions of CC is essential for policymakers and stakeholders to draft culturally sensitive and active adaptation strategies that report the vulnerabilities of these marginalized communities while promoting sustainable development on a broader scale.

4.3.4 Determinants of Perception on Climate Change

Binary logistic regression was applied to predict the perception of CC. The dependent variable for this model was whether the household observed CC or not, and the independent variables comprised the socioeconomic factors (Table 4.2). The logistic regression results demonstrate significant variations and similarities in the sociodemographic parameters impacting CC understanding across the Dhar and Chhindwara districts (Table 4.3). Model statistics like Pseudo R^2 justified around 26 % for Dhar and 33 % for Chhindwara regarding the goodness of fit. Also, Wald Chi^2 values signify that the model is statistically significant at 1%, 5%, and 10%. Gender differences are significant in Dhar (OR= 0.42, $p<0.05$) and Chhindwara (OR= 0.5, $p<0.1$), with males more likely to perceive CC. These results align with the study by Jatav (2024). In both districts, education plays an important role, with families in Dhar (OR= 2.48, $p<0.01$) and Chhindwara (OR= 6.09, $p<0.01$) much more likely to perceive CC if they have higher education levels, highlighting the relevance of educational outreach in promoting awareness and supported a study conducted by Hasan & Akhter (2011).

Table 4.2: Explanation and descriptive statistics of explanatory independent variables

Variables	**Explanation**	**Mean**		**Standard Deviation**	
		Dhar	**Chhindwara**	**Dhar**	**Chhindwara**
Gender	1= Female 0= Otherwise	0.27	0.29	0.44	0.45
Age	Continuous (Years)	42.65	41.37	11.74	12.28
Education	1= Household head is educated 0= Otherwise	0.53	0.64	0.5	0.48
Family Size	Continuous (No. of family members)	6.46	5.15	2.92	1.89
Annual household income	Continuous (log)	11.72	11.4	0.66	.82
Economic status	1= Below Poverty Line 0= Otherwise	0.68	0.65	0.47	0.48

Housing structure	1= Kutcha 2= Semi-pucca 3= Pucca	2.21	1.46	0.88	0.78
Occupation	1= Farmer 0= non-farmer	0.76	0.70	0.43	0.46
Land holdings	Continuous (Acre)	2.38	2.97	3.01	3.60
Electricity	1= access to electricity 0= Otherwise	0.99	0.95	0.12	0.21
LPG Connection	1= Access to LPG Connection 0= Otherwise	0.67	0.68	0.47	0.47
Toilets	1= Access to Toilets 0= Otherwise	0.6	0.61	0.49	0.49
Drinking water sources	1= Access to Safe drinking water 0= Otherwise	0.62	0.52	0.48	0.50
Distance to the nearest health center	Continuous (Km)	3.33	8.64	2.69	5.53
Access to communication media	1= Yes 0= No	0.43	0.34	0.5	0.47

In Chhindwara, wealthier families were less likely to perceive CC (OR= 0.32, $p<0.01$), probably because of their decreased dependence on natural resources, which is supported by Kelly & Adger (2000). However, in Dhar, income level had no significant influence. Occupation is more important in Chhindwara (OR= 2.45, $p<0.05$), showing that families with farming as their primary occupation are more exposed to climate change than Dhar, where occupation is not a significant factor. Hasan & Kumar (2020) observed that people engaged in agricultural activities perceived more about CC. Access to basic infrastructure also shows variation: in Chhindwara, access to electricity greatly enhances perception (OR= 5.62, $p<0.01$), whereas in Dhar, improved access to drinking water sources is an important determinant (OR= 2.69, $p<0.01$). These differences imply that infrastructure facilities impact climate awareness differently in these regions. Puri et al. (2022) revealed a positive and significant relationship between access to infrastructure and CC perception. Access to communication media is essential in both districts, raising CC perception by 4.12 times in Dhar and

5.50 times in Chhindwara, indicating that media exposure promotes awareness. Media played an important role in raising tribal people's knowledge and understanding of CC by providing essential information (Huda, 2013). Overall, enhancing education, communication, and utility access while addressing gender and economic inequality is necessary for raising CC awareness among indigenous groups in both districts.

Table 4.3: Results of binary logistic regression on household's perception of CC

Determinants	Dhar (n=274)			Chhindwara (n=261)		
	Coefficient	Robust std. errs.	Odds Ratio	Coefficient	Robust std. errs.	Odds Ratio
Gender	-0.862**	0.351	0.42	-0.688*	0.375	0.50
Age	-0.006	0.016	0.99	0.038**	0.015	1.04
Education	0.906***	0.327	2.48	1.807***	0.389	6.09
Family Size	-0.032	0.070	0.97	-0.084	0.102	0.92
Annual household income	0.307	0.296	1.36	0.055	0.296	1.06
Economic status	0.023	0.350	1.02	-1.155***	0.377	0.32
Housing structure	-0.093	0.354	0.91	-0.232	0.389	0.79
Occupation	0.128	0.374	1.14	0.898**	0.441	2.45
Land holdings	0.081	0.067	1.08	0.069	0.068	1.07
Electricity	-0.244	1.046	0.78	1.726***	0.670	5.62
LPG Connection	0.465	0.339	1.59	0.142	0.406	1.15
Toilets	0.019	0.344	1.02	0.186	0.385	1.20
Drinking water sources	0.989***	0.342	2.69	0.560*	0.341	1.75
Distance to health center	-0.082	0.057	0.92	-0.018	0.032	0.98
Access to communication media	1.415***	0.369	4.12	1.704***	0.452	5.50
Constant	-4.138	3.576	0.02	-4.207	3.416	0.01
Log pseudolikelihood	-137.17			-112.44		
Wald chi^2	63.85			77.13		
Pseudo R^2	0.258			0.329		

*** p<0.01, ** p<0.05, * p<0.1

4.3.5 Tribal Communities' Perception on Impacts of Climate Change

The perceptions of CC impacts among tribal communities in Dhar and Chhindwara demonstrate diverse patterns (Fig. 4.11). In Dhar, 50.7% of respondents agree that drought occurrences are increasing, while 36.9% express strong agreement, showing major concern over water scarcity. Similarly, 41.2% agree that agricultural productivity is decreasing, and 46% agree about crop failure and economic loss in Dhar. In Chhindwara, the perceptions vary. 39.5% strongly agree that drought incidents are increasing. The pattern of drought occurrence is inconsistent, impacting the entire state at times while at other times affecting only specific regions or areas (Tiwari et al., 2024). The incidence of drought at the micro level has significantly increased in Madhya Pradesh over the past decade, impacting soybean and paddy yields across the region (Srivastava et al., 2021). A higher proportion (85.1%) of respondents strongly agree that water levels are declining, and 72% strongly agree that water shortages are becoming severe. Tiwari et al. (2024) reported that extreme hydro-meteorological events, including floods and droughts, are significantly affecting water and groundwater resources in Madhya Pradesh. Both districts report increasing incidents of crop damage due to pests and environmental factors like heat and cold waves, untimely rainfall, and hailstorms, with over 39% in both regions agreeing and strongly agreeing with this issue. These results align with the study conducted by Atta et al. (2023) in India, who reported that increasing the spread of weeds and pest attacks and rainfall events during the crop-growing cycle damaged the crops.

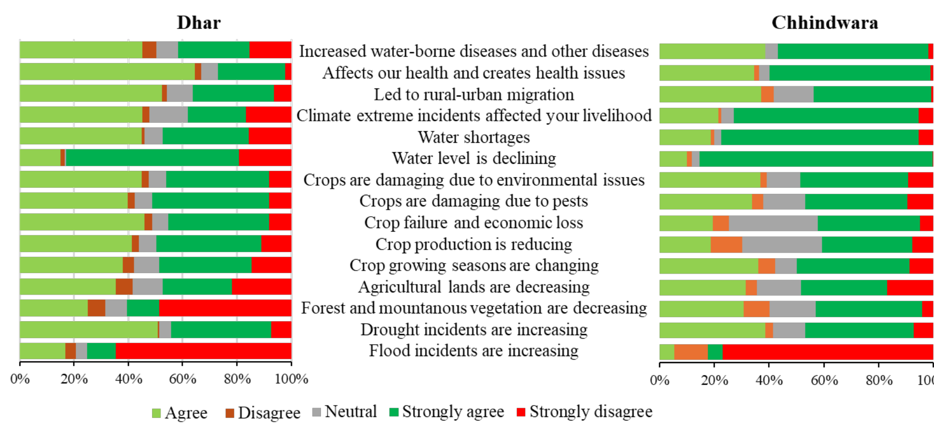


Fig. 4.11: Tribal people’s perception of CC impacts

The results indicate that CC is augmenting water shortages, modifying agricultural output, and increasing the vulnerability of tribal livelihoods, mainly because of crop failure and economic loss. These impacts are acutely perceived in Chhindwara, where water shortages and declining water levels pose enormous challenges. Furthermore, health-related issues, such as the rise of water-borne diseases and other diseases (diarrhea, dysentery, malaria, allergies, skin, and itching), are an increasing worry in Chhindwara, where 54.8% strongly agree with this statement. Ashrafuzzaman et al. (2023) reported that more than 70% of respondents reported gastrointestinal issues, hypertension, diarrhea, malnutrition, and skin diseases as the primary water-borne health risks linked to salinity and inadequate access to safe water in Bangladesh. The increasing occurrence of climatic extremes, reduced agricultural yield, and rising health risks emphasize the need for targeted adaptation strategies. Enhancing water management systems, promoting climate-resilient crops, and improving healthcare access are essential for strengthening tribal communities' resilience to CC. Moreover, practical measures to address rural-urban migration, which is perceived as a growing trend in both districts, are needed to mitigate the socioeconomic displacement triggered by environmental challenges. Understanding tribal communities' perceptions of CC impacts is essential for policymakers and stakeholders, as it allows the design of targeted interventions that align with local knowledge and priorities, confirming effective and culturally applicable adaptation strategies that can be scaled globally.

4.3.6 Determinants of Perception on Impacts of Climate Change

Multiple Linear Regression (MLR) was applied to understand CC's environmental and socioeconomic impacts (Table 4.2) on tribal livelihood (Table 4.4). The results of the MLR on households' perceptions of CC impacts in the Dhar and Chhindwara districts highlight the varying influence of sociodemographic factors across different domains, such as climatic extremes (flood and drought incidents are increasing), natural resources (forest and mountainous vegetation and agricultural lands are decreasing), agriculture (crop growing seasons are changing, crop production is reducing, crop failure and economic loss, crops are damaging due to pests, and crops are damaging due to environmental issues), water

Table 4.4: Results of multiple linear regression on household's perception of CC impacts

Determinants	**Coefficient (β) with Robust standard errors**											
	Climatic extremes		**Natural resources**		**Agriculture**		**Water**		**Socioeconomic**		**Health**	
	Dhar	**Chhindwara**	**Dhar**	**Chhindwara**	**Dhar**	**Chhindwara**	**Dhar**	**Chhindwara**	**Dhar**	**Chhindwara**	**Dhar**	**Chhindwara**
Gender	-0.023	-0.008	-0.091**	-0.013	-0.065*	0.013	0.021	0.005	-0.012	-0.026	-0.079**	-0.009
	(0.034)	(0.027)	(0.040)	(0.032)	(0.036)	(0.026)	(0.039)	(0.023)	(0.032)	(0.025)	(0.035)	(0.022)
Age	0.000	0.001	-0.002	0.002	0.000	0.002*	-0.002	0.000	-0.002	0.002	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education	-0.054*	-0.044	-0.019	0.054	0.026	-0.007	-0.052	0.011	-0.002	0.009	0.013	0.022
	(0.029)	(0.027)	(0.041)	(0.033)	(0.031)	(0.026)	(0.042)	(0.026)	(0.032)	(0.027)	(0.028)	(0.025)
Family Size	-0.003	0.003	-0.007	-0.004	0.000	-0.005	0.005	0.005	0.001	-0.009	0.003	-0.016**
	(0.007)	(0.006)	(0.006)	(0.008)	(0.005)	(0.007)	(0.006)	(0.006)	(0.006)	(0.008)	(0.006)	(0.007)
Annual household income	0.006	-0.009	0.08***	-0.011	0.065***	0.002	-0.037	-0.022*	-0.002	-0.033***	0.010	-0.025*
	(0.024)	(0.010)	(0.031)	(0.015)	(0.024)	(0.02)	(0.032)	(0.012)	(0.026)	(0.012)	(0.025)	(0.015)
Economic status	-0.011	-0.019	0.032	-0.097***	0.052*	0.004	-0.140***	-0.033	-0.069**	-0.029	-0.101***	-0.079***
	(0.029)	(0.025)	(0.041)	(0.028)	(0.031)	(0.025)	(0.038)	(0.021)	(0.03)	(0.025)	(0.030)	(0.023)
Housing structure	-0.035	0.007	0.112***	-0.011	-0.021	-0.027	0.006	0.007	-0.048	0.024	0.003	-0.013
	(0.03)	(0.033)	(0.042)	(0.034)	(0.033)	(0.026)	(0.042)	(0.026)	(0.033)	(0.029)	(0.031)	(0.026)
Occupation	0.036	0.079***	-0.015	0.103***	0.303***	0.267***	0.083*	-0.019	0.048	0.018	-0.015	0.021
	(0.033)	(0.026)	(0.047)	(0.038)	(0.048)	(0.035)	(0.045)	(0.025)	(0.034)	(0.027)	(0.033)	(0.027)

Landholdings	-0.008*	0.000	0.009	0.013***	-0.002	0.006	-0.014*	0.002	-0.008*	0.003	-0.001	0.002
	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)	(0.008)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)
Electricity	0.116	0.035	-0.191	-0.053	0.048	-0.084	0.189	-0.003	0.027	-0.051	0.187	-0.066**
	(0.114)	(0.055)	(0.133)	(0.060)	(0.155)	(0.059)	(0.167)	(0.057)	(0.151)	(0.041)	(0.117)	(0.03)
LPG Connection	-0.031	-0.002	-0.005	0.039	-0.032	0.072**	-0.009	-0.014	-0.079**	-0.009	-0.048	0.042
	(0.03)	(0.027)	(0.04)	(0.032)	(0.030)	(0.031)	(0.04)	(0.023)	(0.032)	(0.029)	(0.029)	(0.028)
Toilets	0.040	-0.043	0.031	-0.037	0.026	-0.031	-0.017	-0.021	0.038	-0.013	-0.034	-0.025
	(0.032)	(0.027)	(0.04)	(0.032)	(0.032)	(0.027)	(0.041)	(0.024)	(0.033)	(0.025)	(0.031)	(0.023)
Drinking water source	-0.039	-0.066***	0.010	-0.061**	0.07**	0.005	-0.170***	-0.032	-0.117***	-0.049**	-0.024	-0.031
	(0.028)	(0.023)	(0.04)	(0.029)	(0.032)	(0.024)	(0.033)	(0.021)	(0.028)	(0.024)	(0.029)	(0.024)
Distance to health center	0.017***	-0.001	-0.007	-0.006**	0.007	-0.009***	-0.039***	-0.003	-0.011*	-0.003	-0.014**	-0.003
	(0.006)	(0.002)	(0.007)	(0.003)	(0.005)	(0.003)	(0.008)	(0.002)	(0.006)	(0.002)	(0.006)	(0.003)
Access to communication media	-0.004	0.065**	0.061	0.086**	-0.004	0.213***	0.040	-0.023	0.043	0.042	0.053*	-0.005
	(0.031)	(0.029)	(0.040)	(0.033)	(0.032)	(0.026)	(0.041)	(0.027)	(0.030)	(0.027)	(0.03)	(0.023)
Constant	0.368	0.494***	-0.184	0.790***	-0.375	0.493**	1.352***	1.235***	0.908***	1.270***	0.610*	1.299***
	(0.283)	(0.160)	(0.408)	(0.201)	(0.334)	(0.228)	(0.398)	(0.157)	(0.306)	(0.168)	(0.318)	(0.181)
R-squared	0.104	0.113	0.116	0.216	0.369	0.498	0.300	0.058	0.180	0.088	0.141	0.121
Root MSE	0.203	0.187	0.285	0.219	0.220	0.185	0.282	0.170	0.209	0.177	0.214	0.170

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(water level is declining and water shortages), socioeconomic (climate extreme incidents affected your livelihood and led to rural-urban migration), and health (affects health and creates health issues and increased water-borne diseases and other diseases). Although the forest is an important resource for tribal communities, the Dhar district tribes are not very dependent on the forest due to less or no access or availability. Hence, we have not included forests in this categorization. The impacts of CC differ based on topography, economic conditions, and institutional functioning (Rai et al., 2022).

Gender significantly influenced perceptions of natural resources (β= -0.091, $p<0.05$) and health (β= -0.079, $p<0.05$) in Dhar but not in Chhindwara. These results align with the study by Badmos (2018). Age and education showed limited influence, although education negatively affected perceptions of climatic extremes in Dhar (β= -0.054, $p<0.1$). Family size negatively impacted livelihood perceptions in Chhindwara (β= -0.016, $p<0.05$). Haq & Ahmed (2020) reported that age, education and family size affect the perception of CC impacts on climatic extremes and livelihood. Household income displayed a significant positive relationship with perceptions of natural resource depletion (β= 0.079, $p<0.01$) and agricultural challenges (β= 0.065, $p<0.01$) in Dhar while negatively affecting water (β= -0.022, $p<0.1$), livelihood (β= -0.033, $p<0.01$), and health (β= -0.033, $p<0.1$) perceptions in Chhindwara. Economic status was also important in shaping perceptions, especially regarding agriculture and health in both districts, where lower economic status correlated with increased concerns about these impacts. The result aligns with the study conducted by Howard et al. (2020). The occupation of respondents (agriculture as primary occupation) had a significant association with perceptions of agricultural changes in both districts, particularly in Dhar (β= 0.303, $p<0.01$), reflecting the dependence of tribal communities on agriculture for their livelihoods. Agriculture serves as the primary occupation for marginal communities (Mekonnen et al., 2019). Decreasing and unpredictable rainfall directly impacts agricultural yields, water availability, and forest-based livelihoods, essential to these people's economic and cultural survival (Rai et al., 2022). Rising temperatures and harsh summers can augment drought conditions, diminish agricultural production, and lead to higher heat stress, further challenging the adaptive capacity of these communities (Steiner et al., 2018). Access to safe drinking water and health services influenced perceptions of water scarcity and health risks in Dhar, negatively associated with perceptions of water and health challenges (β= -0.066, $p<0.01$ and β= -0.049, $p<0.05$, respectively). A study by Ashrafuzzaman et al. (2023) supports these findings.

These results highlight the vulnerability of tribal communities to CC in terms of agriculture, water scarcity, and health. As these communities depend highly on natural resources and subsistence farming, declining crop yields, water shortages, and increased health risks could exacerbate poverty and force rural-urban migration. Indigenous knowledge should be integrated with individual household-level scientific equipment to boost agricultural productivity in these changing climatic scenarios (Manandhar et al., 2011). Targeted interventions that address these vulnerabilities, such as improving access to safe drinking water, promoting climate-resilient agriculture, and enhancing healthcare and basic infrastructure facilities, are essential to preserving the livelihoods and well-being of these marginalized communities.

4.4 Conclusions

The study investigates the sociodemographic characteristics, CC perceptions, and its impacts on the livelihood of tribal communities in Dhar and Chhindwara districts of Madhya Pradesh. The major findings indicate significant household characteristics, educational levels, and income variations, with both districts highly dependent on agriculture. The ITA result found a decreasing trend in rainfall and an increase in T_{mean}, worsening agricultural vulnerability and water shortages. Tribal communities are highly aware of these climate shifts, with over 90% of respondents revealing irregular rainfall and increased summer temperature, supporting observed climate data analysis. The binary logistic regression analysis illustrates that education, occupation, and access to infrastructure significantly affect CC perceptions, with education being a critical determinant in both districts. Gender differences, specifically in Dhar, also influenced CC perception. The linear regression model further explained that sociodemographic factors, such as income and occupation, significantly affected perceptions of the impact of climate on agricultural productivity, water availability, and health. Chhindwara's respondents described more significant concerns over water shortages and decreasing agricultural yields, while Dhar's respondents focused more on natural resource depletion. All this climate variability evidence and people's perceptions denote that CC is an important issue that needs to be addressed urgently by policymakers. To conclude, CC is diminishing the income from agriculture, the primary livelihood of these communities. Despite government efforts to double farmers' income, declining crop yields and the increasing frequency of droughts are causing significant financial losses for the farming community.

Moreover, this chapter comprehensively explains the tribal communities' perceptions of CC and its impact on their livelihood, emphasizing their lived experiences and adaptive challenges. The findings, such as declining rainfall, rising temperatures, and their adverse effects on this region's agriculture and water resources, have been discussed in chapters 2 and 3, providing the environmental background for assessing livelihood vulnerability for tribal communities. The influence of sociodemographic factors, such as education, income, and occupation, on climate perceptions underlines their adaptive capabilities within these communities. Chapter 5 discusses the 4th objective, i.e. the integrated assessment of livelihood vulnerability to climate variability among tribal communities in Dhar and Chhindwara districts, Madhya Pradesh.

Chapter 5

Integrated Assessment of Livelihood Vulnerability to Climate Variability among Tribal Communities in Dhar and Chhindwara Districts, Madhya Pradesh

The previous chapter discussed how tribal communities in Chhindwara and Dhar districts have noticed climate changes. The results showed that these weather shifts are affecting their livelihoods. Since they rely on natural resources and have limited adaptation methods, they are highly vulnerable to climate change (CC). This chapter employs the Livelihood Vulnerability Index - Intergovernmental Panel on Climate Change (LVI-IPCC) framework to assess tribal livelihood vulnerability, considering exposure, sensitivity, and adaptive capacity. It also identifies determinants influencing vulnerability and highlights regional differences between the districts.

5.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) 6th Assessment Report predicts a worldwide temperature rise of 1.5 °C, which is expected to intensify climatic threats and disasters (Phuong et al., 2023; Pörtner et al., 2022). Temperature rise is associated with more severe climate events, such as higher storm surges, flash flooding, severe droughts, land erosion, forest degradation, and relocation of indigenous communities (Kuniyal et al., 2021; Shivam et al., 2017). These occurrences significantly challenge the livelihoods of millions of indigenous people (Phuong et al., 2023). Developing nations like India, which heavily rely on agriculture and climate-sensitive resources such as water, biodiversity, and forestry, confront additional difficulties because of CC (Rautela et al., 2023; Venus et al., 2022). These issues include increasing demand for agriculture, ensuring food security, improving infrastructure, maintaining public health, and preserving forest ecosystems (IPCC, 2007). Several climatic and non-climatic factors impact food security and vulnerability. These factors include increasing temperatures, shifting rainfall patterns (Singh et al., 2024), the accessibility of natural resources, socioeconomic changes, gender inequality, social networks, government interferences, geopolitical shifts, loss of traditional knowledge, innovation, and the adoption of new information (Joshi & Rawat, 2021; Panthi et al., 2016).

The repercussions of CC have a higher effect on marginalised populations, incorporating poor, young, old, sick, and tribal communities (Hahn et al., 2009). Tribal communities, which mainly depend on regional natural resources like forests, are more exposed to the effects of CC than urban people (Sushant, 2013). Their close relationship with nature for livelihoods, culture, and health intensifies their susceptibility (Das & Basu, 2022). Forest ecosystems provide diverse economic and social benefits, including job opportunities, forest resources, and cultural protection (FAO, 2012). Approximately 100 million people in India reside in forested areas, mostly tribal communities that sustain themselves by collecting and selling non-timber forest products (NTFPs) (Das & Basu, 2022; Pandey et al., 2016). These items play a crucial part in their lives globally. Forest-dependent populations, such as nomadic tribes, are among the most vulnerable to the impacts of CC on forests (Pandey & Kori, 2011; Shackleton et al., 2015).

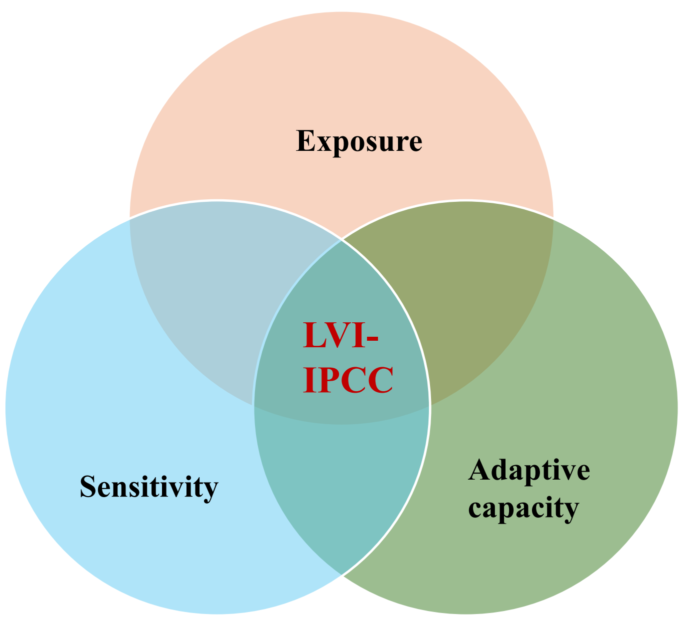


Fig. 5.1: Contributing factors of LVI-IPCC

It is important to comprehend the factors contributing to livelihood vulnerability to address the local climate-related concerns (Ngu et al., 2023). A comprehensive and complex method is important to evaluate vulnerability, concentrating on three components: exposure, sensitivity, and adaptive capacity (Hahn et al., 2009; Joshi & Rawat, 2021; Rehman et al., 2022; Venus et al., 2022) (Fig. 5.1). ***Exposure*** consists of variations in climate and extreme natural events, and ***sensitivity*** encompasses land and infrastructure, food security, social security, water access, and health, and ***adaptive capacity*** includes awareness, socio-demographic profiles, financial stability, livelihood strategies, and social networks. Birkmann et al. (2022) also developed the World Risk Index, which assesses risk by combining exposure to natural hazards with vulnerability factors, including susceptibility, lack of coping, and adaptive capacities. An indicator-based method is commonly taken to quantify these factors, suggesting context-based understandings of socially controlled causes of vulnerability, community requirements, and adaptive solutions. Several approaches exist for measuring vulnerability: quantitative model-based techniques (Wisner, 2016), qualitative participatory models (Wisner, 2016), and indicator-based methods. These methodologies may be coupled to offer thorough vulnerability evaluations. Qualitative techniques depend on interviews and focus group discussions to reflect regional perceptions of vulnerability (Smit & Wandel, 2006), whereas quantitative analysis-based models employ methodologies such as the Ricardian method and GIS-based tools to analyse risk from a natural sciences viewpoint (Panda, 2017). Indicator-based methods integrate qualitative and quantitative methodologies, including data from censuses, surveys, and climatic records (Hahn et al., 2009; Phuong et al., 2023). Indices like the Agricultural Vulnerability Index, Socioeconomic Vulnerability Index, Climate Change Vulnerability Index, Livelihood Vulnerability Index, Multidimensional Livelihood Vulnerability Index, and Human Development Index are essential tools in climate vulnerability analysis (Hahn et al., 2009). Methods for the improvement of the vulnerability assessment framework aim to enhance the understanding of vulnerability by considering key factors like exposure, susceptibility, and lack of resilience while addressing multidimensional aspects, including physical, social, ecological, economic, cultural, and institutional themes (Birkmann et al., 2013).

Recent researchers have directed climate vulnerability measurements in India using various indices, such as the Socioeconomic Vulnerability Index (George et al., 2023; George & Sharma, 2022), Socio-ecological vulnerability (Jha & Negi, 2021), Infrastructural Vulnerability Index (George & Sharma, 2022), Climate Change Vulnerability Index (Ghosh & Ghosal, 2021), Composite Vulnerability Index (George et al., 2023; Sarun et al., 2018), Livelihood Vulnerability Index (Ahmad et al., 2023; Das & Basu, 2022; Jha et al., 2018; Joshi & Rawat, 2021; Rehman et al., 2022; Roy et al., 2023; Venus et al., 2022), the Potential Livelihood Vulnerability Index (Jatav, 2024), Household Vulnerability Index (Deb & Mukherjee, 2022; Ghosh & Ghosal, 2020), and Composite Livelihood Vulnerability Index (Das et al., 2020). However, research focused on the susceptibility and variables impacting the vulnerability of tribal households in India is quite rare. Kumar et al. (2023) employed eight primary components of the LVI to estimate tribal family livelihood vulnerability in Himachal Pradesh, revealing variances in vulnerability due to differences in adaptation, sensitivity, and exposure to CC. Roy et al. (2023) utilised the LVI-IPCC method to estimate climate vulnerability across tribal and non-tribal communities in Tripura, observing that tribal households were more exposed and susceptible owing to higher sensitivity and weaker adaptation capability. Deb & Mukherjee (2022) used the vulnerability index at the household level among major tribal groups (Santal, Munda, and Oraon) in the Himalayan region of West Bengal, report variables including the lack of basic infrastructure, absence of ration, and poor medical services as increasing family vulnerability. Das & Basu (2022) assessed the CC livelihood vulnerability of Munda, Santal, Lodha, and Bhumij tribal communities in West Bengal, India, using the LVI and Beta regression model to find its determining factor. The study found that the Lodha community had the highest LVI, indicating greater vulnerability than the other tribes. Yadava & Sinha (2020) investigated CC vulnerability in Madhya Pradesh, showing that economic circumstances, educational status, and professions effectively affected household susceptibility.

Existing studies on CC primarily focus on rural and agricultural communities, frequently ignoring the specific vulnerabilities of tribal populations. Birkmann et al. (2022) assessed vulnerability through global indices but have often missed the cultural, social, and economic factors that increase vulnerability in tribal communities. This study addresses the gap by concentrating on tribal households and their nuanced association with climate variability. Furthermore, limited research uses trend analysis or composite indices (Ghosh & Ghosal, 2021; Hahn et al., 2009; Phuong et al., 2023; Venus et al., 2022), and few incorporate methods such as trend analysis, drought index, the LVI-IPCC framework, and the multiple linear regression model to provide a more robust and holistic view of vulnerability. By integrating these approaches, this study offers a more comprehensive assessment of socioeconomic and environmental factors. Moreover, it presents a convenient methodological framework, encompassing local circumstances to inform global research on vulnerability in rural and tribal populations. The study contributes not only to the Indian context but also to international debates on CC adaptation, facilitating targeted policy actions to minimise vulnerability and promote sustainable development among tribal communities. Despite using micro-level samples, this study can be generalised to the macro level, particularly in Asia and Africa, where a significant proportion of the indigenous population exists. This study focuses on these research gaps by measuring tribal livelihood vulnerability in the Central Indian region of Chhindwara and Dhar districts using the LVI-IPCC methodology. This chapter address the following objectives: a) assess the livelihood vulnerability of tribal households in Chhindwara and

Dhar districts using the LVI-IPCC framework, b) validate the LVI-IPCC results, c) determine the important factors affecting the vulnerability of tribal households in the study areas using multiple linear regression model, d) compare the vulnerability levels between the two districts to understand regional differences and e) provide policy recommendations to enhance adaptive capacity and resilience among tribal communities.

5.2 Methodology

5.2.1 Selection of Indicators

Selecting suitable indicators for assessing climate vulnerability is critically important, though there is no universally recognised set or uniform method (Yadava & Sinha, 2020). Indicators must be relevant, easily quantifiable, and capable of reflecting exposure, sensitivity, and adaptive capacity levels (Doorn, 2017). A participatory technique is frequently employed to recognise contextually suitable components involving stakeholders (Salter et al., 2010). Once identified, indicators are merged into a composite index, providing a single measure of vulnerability normally scaled from 0 to 1 (Balica et al., 2012). These indicators should be associated with research goals, data availability, and the characteristics of the studied system.

Following a comprehensive literature review, a pilot survey, and an initial assessment of climatic variability, a set of household vulnerability dimensions and indicators was established. Initially several studies (Baffoe & Matsuda, 2018; Das & Basu, 2022; Ghosh & Ghosal, 2020; Hahn et al., 2009; Ha-Mim et al., 2020; Huong et al., 2019; Joshi & Rawat, 2021; Panthi et al., 2016; Phuong et al., 2023; Rehman et al., 2022; Venus et al., 2022) were reviewed which provided 10 major components and 40 sub-components. These components were used to construct the base for a pilot survey. However, following conversations with local environmentalists, agronomists, and economists and further questionnaire examination via pilot survey, revisions were made to represent the socioeconomic conditions of the study area. This study estimated tribal livelihood vulnerability in response to CC and several socioeconomic indicators. We adopted a technique proposed by Hahn et al. (2009), which provides a comprehensive approach for scientifically analysing the connections between people and their social, environmental, and physical perspectives. The vulnerability assessment follows the IPCC's framework, which explains vulnerabilities as a combination of exposure, sensitivity, and adaptive capacity. Twelve major components and 54 sub-components were chosen for this research (Table 5.1), categorised into LVI-IPCC contributing factors to tribal household vulnerability (Fig. 5.2).

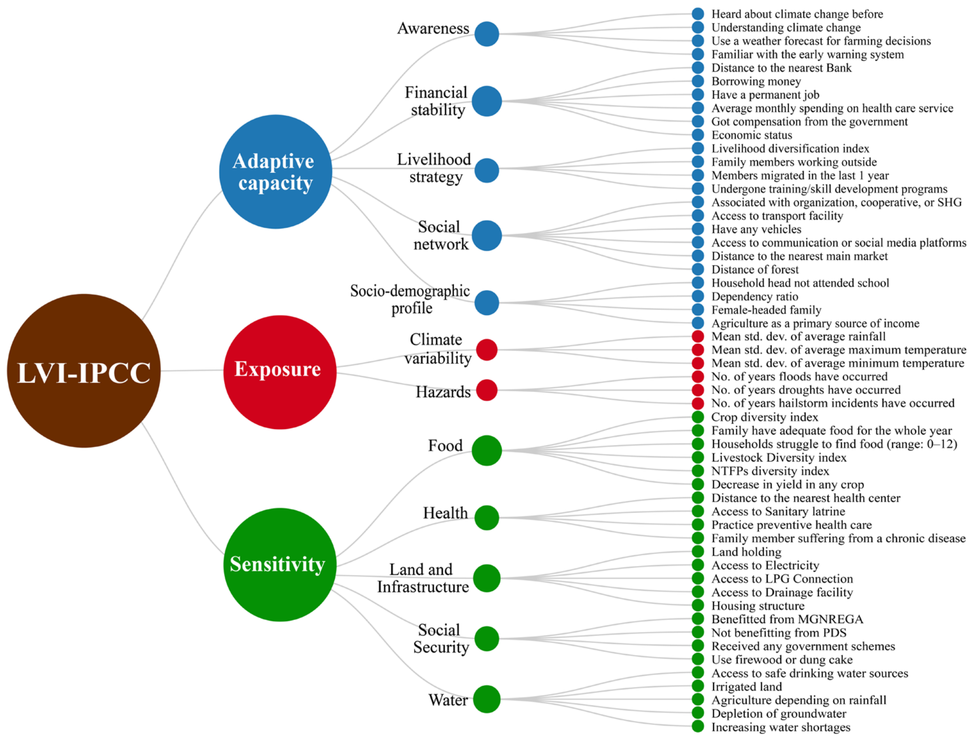


Fig. 5.2: Indicators of LVI-IPCC

The selected indicators comprehensively represent tribal livelihoods. Exposure included the years of floods, droughts, hailstorms they observed, and climate variability over the past decade (2014-2023). Sensitivity was assessed using land and infrastructure, food security, social security, water access, and health. The five major components evaluated adaptive capacity through awareness, socio-demographic profiles, financial stability, livelihood strategies, and social networks. This structured approach allows

Table 5.1: The indicators of the LVI-IPCC for Chhindwara and Dhar

Major components	Indicators	Explanation	Source
Climate variability	Mean std. dev. of average rainfall by month	Standard deviation of the average monthly rainfall between 1951 and 2023 was averaged for both district	Hahn et al. (2009)
	Mean std. dev. of average T_{max} by month	Standard deviation of the average daily maximum temperature by month between 1951 and 2023 was averaged for both district	Hahn et al. (2009)
	Mean std. dev. of average T_{min} by month	Standard deviation of the average daily minimum temperature by month between 1951 and 2023 was averaged for both district	Hahn et al. (2009)
Hazards	Floods	Total number of floods that were reported by the households in the past 10 years (range 0–10)	Hahn et al. (2009)
	Droughts	Total number of droughts that were reported by the households in the past 10 years (range 0–10)	Hahn et al. (2009)
	Hailstorms	Total number of hailstorms that were reported by the households in the past 10 years (range 0–10)	Joshi and Rawat (2021)
Land and Infrastructure	Land holding	In hectare	Joshi and Rawat (2021)
	Not access to electricity	% of households not having access to electricity	Joshi and Rawat (2021)
	Not access to LPG connection	% of households not having access to LPG connection	Yadava & Sinha (2019)
	Not access to Drainage facility	% of households not having access to Drainage facility	Rehman et al. (2022)
	Housing structure (Kutcha house)	% of households not having cemented house	Rehman et al. (2022)
Food	Crop diversity index	The inverse of (the number of crops grown by a household + 1) reported by a household	Hahn et al. (2009)
	Food availability	% of households not having adequate food for the whole year	Joshi and Rawat (2021)

	Households struggle to find food (range: 0–12)	Average number of months households struggle to find food for their family	Hahn et al. (2009)
	Livestock Diversity index	The inverse of (the number of livestock species by a household + 1) reported by a household	Venus et al. (2021)
	NTFPs diversity index	The inverse of (the number of NTFPs collected by a household + 1) reported by a household	Das and Basu (2022)
	Decrease in yield in any crops in last 10 years	% of households observed decrease in yield in any crops in last 10 years	Rehman et al. (2022)
Water	Not access to safe drinking water sources	% of households not having access to safe drinking water sources	Joshi and Rawat (2021)
	Irrigated land	In hectare	Joshi and Rawat (2021)
	Agriculture depending on rainfall	% of households entirely dependent on rainfall for irrigation	Venus et al. (2021)
	Depletion of groundwater	% of households observed depletion of groundwater	Rehman et al. (2022)
	Increasing water shortages	% of households noticed increasing water shortages	Venus et al. (2021)
Health	Distance to the nearest health center	Average distance to the nearest health center from household's home	Hahn et al. (2009)
	Not access to Sanitary latrine	% of households not having access Sanitary latrine	Venus et al. (2021)
	Doesn't practice preventive health care	% of households not practicing preventive health care to reduce the impact of natural disasters	Venus et al. (2021)
	Family member suffering from a chronic disease	% of households' family member suffering from a chronic disease (Diabetes/cardiovascular diseases /tuberculosis/cancer/asthma/ mental disorders/ others)	Hahn et al. (2009)
Social Security	Not benefitted from MGNREGA	% of households not benefitting from MGNREGA	Das and Basu (2022)
	Not benefitted from PDS	% of households not benefitting from PDS	Das and Basu (2022)
	Not received any government schemes	% of households not receiving any government schemes	Das and Basu (2022)
	Use firewood or dung cake	% of households using firewood or dung cake as your primary energy source for cooking	Venus et al. (2021)

Socio-demographic profile	Household head not attended school	% of households where the household head have not attended school	Hahn et al. (2009)
	Dependency ratio	Ratio of the dependent population under 18 and over 65 years of age to working age group population	Hahn et al. (2009)
	Female-headed family	% of households where the household head is female	Hahn et al. (2009)
	Agriculture as a primary source of income	% of households where primary occupation is agriculture	Hahn et al. (2009)
Awareness	Heard about climate change before	% of households heard about climate change before	Venus et al. (2021)
	Understanding climate change	% of households understanding climate change	Venus et al. (2021)
	Use a weather forecast for making farming decisions	% of households using a weather forecast for making farming decisions	Venus et al. (2021)
	Familiar with the early warning system for natural disasters	% of households familiar with the early warning system for natural disasters	Rehman et al. (2022)
Livelihood strategy	Livelihood diversification index	The inverse of livelihood sources (the number of major livelihood sources + 1) reported by a household	Hahn et al. (2009)
	Family members working outside	% of households' members working outside the local area	Hahn et al. (2009)
	Members migrated in the last 1 year	Number of households' members have migrated in the last 1 year for work/education	Joshi and Rawat (2021)
	Not undergone training/skill development programs	% of households' members of your household undergone training or skill development programs to enhance their ability to generate income	Venus et al. (2021)
Financial stability	Distance to the nearest Bank	Average distance to the nearest bank from their home	Ghosh and Ghosal (2020)
	Borrowing money	% of households borrowing money	Hahn et al. (2009)
	Don't have a permanent job	% of household head haven't a permanent job	Ghosh and Ghosal (2020)
	Average monthly spending on health care service	average monthly spending on health care services (doctor's fees, medicine)	Venus et al. (2021)

	Didn't get compensation from the government	% of households didn't get compensation from the government	Hahn et al. (2009)
	Economic status (Below poverty line)	% of households living below poverty line	Venus et al. (2021)
Social network	Not associated with organisation, cooperative, or SHG	% of households not associated with organisation, cooperative, or SHG	Venus et al. (2021)
	Not access to transport facility	% of households not having access to transport facility	Jamshed et al. (2020)
	Don't have any vehicles	% of households not having any vehicle	Jamshed et al. (2020)
	Not access to communication or social media platforms	% of households not having access to communication or social media platforms	Venus et al. (2021)
	Distance to the nearest main market	Average distance to the nearest main market from their home	Venus et al. (2021)
	Distance of forest	Average distance to the forest from their home	Das and Basu (2022)

for a systematic assessment of livelihood vulnerability due to climate variability tailored to the exclusive requirements and characteristics of the tribal communities studied. The indices for these indicators were constructed so that greater values indicate higher vulnerability.

5.2.2 Data Analysis

Several methods were employed to analyse the collected data in this study (Fig. 5.3), ensuring robust and accurate results. The LVI-IPCC framework was applied to assess the field survey data. The LVI-IPCC results were validated using Jamshed et al. (2022)'s vulnerability index (VI) method.

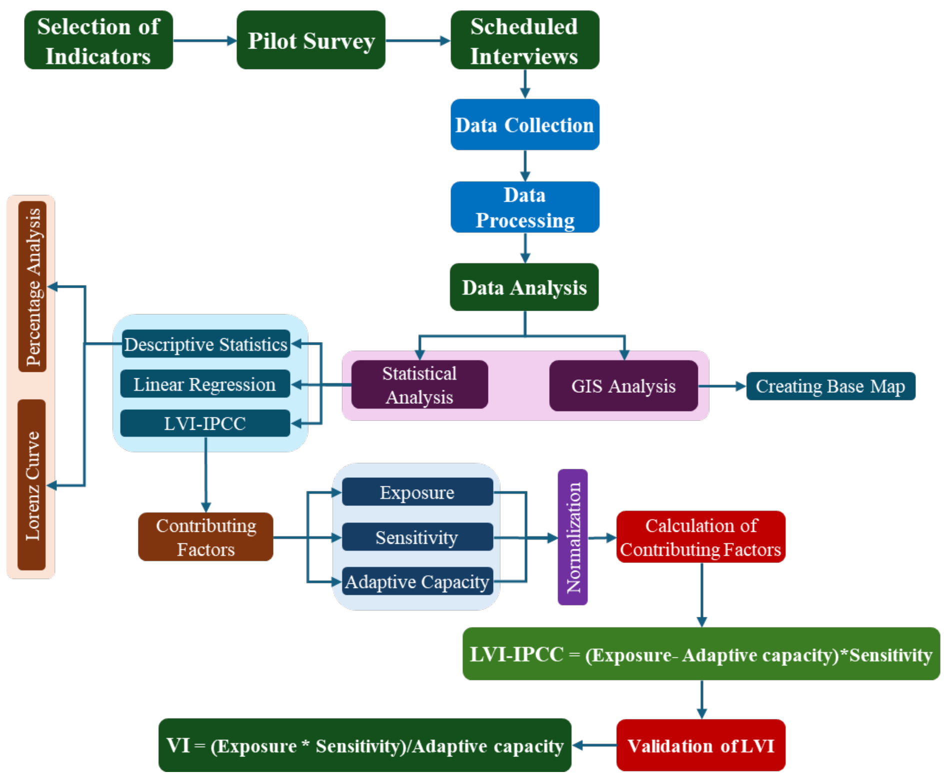


Fig. 5.3: Comprehensive methodology framework

The multiple linear regression (MLR) model defined the most important indicators affecting household vulnerability. Assumptions of multicollinearity and heteroscedasticity were tested before running the vulnerability and regression analysis. The indicators with collinearity of more than 0.8 have been removed, following Gujarati's (1995) guideline that correlation coefficients above 0.8 indicate a significant multicollinearity issue. Heteroscedasticity was also checked using the Breusch-Pagan test to ensure the model's validity. Data cleaning, conversion and preliminary analysis were conducted using MS Excel. Data visualisations were performed using Origin 2024, facilitating a clear understanding of the findings.

5.2.2.1 Calculation of LVI-IPCC and VI

The LVI was computed based on constraints explained by the IPCC framework, incorporating Exposure, sensitivity, and adaptation capacity (Hahn et al., 2009; Phuong et al., 2023; Rehman et al., 2022). All the sub-indicators evaluated on various units (i.e. count, percent, ratio, index) were normalised (0 to 1) using Eq. 5.1.

$$Index_{sc} = \frac{X(a) - X(min)}{X(max) - X(min)}$$

Where $Index_{sc}$ denotes the normalised value of sub-components, X(a), X(max), and X(min) shows the actual, maximum, and minimum values for each household, respectively.

An equal weight was assigned to all sub-components and averaged to calculate the major indicators using Eq. 5.2.

$$M_{sc} = \frac{\sum_{i=1}^{n} Index_{SC}}{n} \tag{5.2}$$

Where n = no. of sub- components, indexed by i,

$Index_{sc}$ = normalised value of sub-indicators,

M_{sc} = index value of sub-components.

After calculating the major components, the contributing factors were computed using Eq. 5.3.

$$CF_{mc} = \frac{\sum_{i=1}^{n} w_i M_{sc}}{\sum_{i=1}^{n} w_i} \tag{5.3}$$

Where CF_{mc} = IPCC-defined contributing factor (adaptation capacity, sensitivity, and Exposure), w_i = weight for each indicator,

M_{sc} = index of the major indicators.

Once contributing factors were calculated, LVI-IPCC was computed by using Eq. 5.4.

$$LVI - IPCC_{mc} = (Exposure_{mc} - Adaptive\ Capacity_{mc}) \times Sensitivity_{mc} \tag{5.4}$$

Where $LVI\text{-}IPCC_{mc}$ is the LVI using the IPCC framework,

The LVI–IPCC value was rescaled from -1 (least vulnerable) to +1 (most vulnerable).

The vulnerability index was calculated using Eq. 5.5.

$$VI \quad \frac{\sum_{i=6}^{n} w_i E_{cf} \times \sum_{i=24}^{n} w_i S_{cf}}{\sum_{i=24}^{n} w_i\, AC_{cf}} \tag{5.5}$$

Where E_{cf} = Exposure, S_{cf} = Sensitivity, and AC_{cf} = Adaptive capacity

5.2.2.2 Multiple Linear Regression (MLR)

In this chapter MLR model was used to detect the primary factors most significantly impacting household vulnerability. The MLR was applied using given equations.

$$Y_i = \beta_0 + \sum_{k=1}^{18} \beta_k X_{ki} + u_i$$

where Y represents the dependent variable, $X_1, X_2 \ldots, X_{15}$ are the independent variables, β_0 is the intercept, and $\beta_1, \beta_2, \ldots, \beta_{15}$ are the coefficients for each predictor.

For the current study, the LVI-IPCC of households is the dependent variable (Y). We have used 18 different independent variables included 4 socio-demographic variables (gender, household head's education level, age, and agriculture as the primary income source); 1 variable for natural disasters (number of extreme weather events); 3 variables related to land and infrastructure (access to electricity, housing structure, and land holdings); 2 variables for livelihood strategies (number of livelihood approaches and participation in skill development programs); and 2 variables related to awareness (use of weather forecasts for farming decisions and awareness of local early warning systems). However, one variable each was considered for food, water, health, social security, social networks, and financial stability. Hence the maximum value of k is 18.

5.3 Results and Discussion

The results of the indexed value (Table 5.2) present a comprehensive categorisation of contributing factors, major components (Fig. 5.4), and sub-components of vulnerability assessment within the Chhindwara and Dhar districts, offering valuable insights into the complex nature of vulnerability among the surveyed households (n=535). The indexed values thoroughly evaluate various factors, including exposure to climatic variability, hazards caused by severe events, and implications for adaptation strategies and resilience-building initiatives.

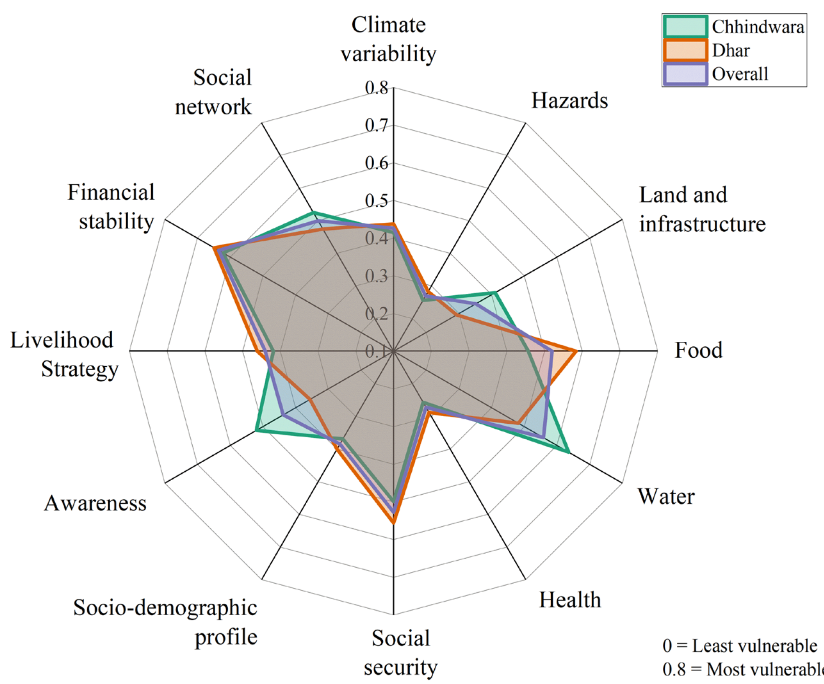


Fig. 5.4: Major components of the LVI-IPCC for Chhindwara and Dhar

Table 5.2: Indexed value of major components and sub-components to the vulnerability among Chhindwara and Dhar

Indicators	Units	Chhindwara (n=261)	Dhar (n=274)	Overall (n=535)
Exposure		0.336	0.360	0.348
Climate variability		0.415	0.438	0.427
Mean std. dev. of average rainfall by month	Millimeters	0.293	0.298	0.296
Mean std. dev. of average T_{max} by month	Celsius	0.376	0.459	0.418
Mean std. dev. of average T_{min} by month	Celsius	0.576	0.557	0.567
Hazards		0.256	0.283	0.270
No. of years floods have occurred in last 10 years	Count	0.051	0.094	0.073
No. of years droughts have occurred in last 10 years	Count	0.314	0.350	0.332
No. of years hailstorm incidents have occurred in last 10 years	Count	0.405	0.405	0.405
Sensitivity		0.452	0.440	0.446
Land and Infrastructure		0.411	0.293	0.352
Land holding	Ha. (count)	0.119	0.095	0.107
No access to electricity	Percent	0.046	0.015	0.031
No access to LPG connection	Percent	0.322	0.332	0.327
No access to Drainage facility	Percent	0.847	0.719	0.783
Housing structure (Kutcha house)	Percent	0.720	0.303	0.512
Food		0.457	0.583	0.520
Crop diversity index	1/ (No. of crops +1)	0.543	0.500	0.522
Family doesn’t have adequate food for the whole year	Percent	0.540	0.657	0.599
Households struggle to find food (range: 0–12)	Count	0.275	0.343	0.309
Livestock Diversity index	1/ (No. of Livestock +1)	0.494	0.481	0.488
NTFPs diversity index	1/ (No. of NTFP +1)	0.560	0.891	0.726
Decrease in yield in any crops in last 10 years	Percent	0.330	0.628	0.479
Water		0.635	0.482	0.559
No access to safe drinking water sources	Percent	0.475	0.376	0.426
Irrigated land	Ha. (count)	0.046	0.077	0.062
Agriculture depends on rainfall	Percent	0.759	0.376	0.568

Depletion of groundwater	Percent	0.977	0.792	0.885
Increasing water shortages	Percent	0.920	0.788	0.854
Health		0.257	0.288	0.273
Distance to the nearest health center	Km (count)	0.432	0.370	0.401
No access to Sanitary latrine	Percent	0.387	0.401	0.394
Doesn't Practice preventive health care	Percent	0.169	0.321	0.245
Family member suffering from a chronic disease	Percent	0.038	0.058	0.048
Social Security		0.499	0.556	0.528
Not Benefitted from MGNREGA	Percent	0.444	0.996	0.720
Not Benefitted from PDS	Percent	0.188	0.102	0.145
Not Received any government schemes	Percent	0.425	0.252	0.339
Use firewood or dung cake	Percent	0.939	0.872	0.906
Adaptive capacity		0.495	0.472	0.483
Socio-demographic profile		0.369	0.400	0.385
Household head not attended school	Percent	0.364	0.474	0.419
Dependency ratio	Ratio	0.499	0.440	0.470
Female-headed family	Percent	0.245	0.219	0.232
Agriculture as a primary source of income	Percent	0.368	0.467	0.418
Awareness		0.520	0.356	0.438
Heard about climate change before	Percent	0.582	0.288	0.435
Understanding climate change	Percent	0.828	0.650	0.739
Use a weather forecast for making farming decisions	Percent	0.494	0.241	0.368
Familiar with the early warning system for natural disasters	Percent	0.176	0.245	0.210
Livelihood strategy		0.419	0.461	0.440
Livelihood diversification index	1/ (Livelihood activities+1)	0.359	0.407	0.383
Family members working outside	Percent	0.261	0.354	0.307
Members migrated in the last 1 year	Count	0.074	0.117	0.096
Not undergone training/skill development programs	Percent	0.981	0.967	0.974
Financial stability		0.622	0.649	0.636
Distance to the nearest Bank	Km (count)	0.382	0.311	0.347
Borrowing money	Percent	0.682	0.766	0.724
Don't have a permanent job	Percent	0.931	0.931	0.931

Average monthly spending on health care service	Rs. (count)	0.185	0.197	0.191
Didn't get compensation from the government	Percent	0.900	0.985	0.943
Economic status (Below poverty line)	Percent	0.651	0.704	0.678
Social network		0.525	0.474	0.500
Not associated with organisation, cooperative, or SHG	Percent	0.613	0.755	0.684
No access to transport facility	Percent	0.425	0.511	0.468
Don't have any vehicles	Count	0.847	0.288	0.568
Not access to communication or social media platforms	Percent	0.663	0.566	0.615
Distance to the nearest main market	Km (count)	0.447	0.355	0.401
Distance of forest	Km (count)	0.154	0.372	0.263
LVI-IPCC		-0.072	-0.049	-0.060
VI		0.309	0.336	0.321

5.3.1 Exposure

The average exposure index of household livelihood to climate variability and hazards is 0.348 in general. The same for Dhar is (0.360) is slightly higher than Chhindwara (0.336), indicating a marginally increased vulnerability to climate-related hazards in the Dhar district. This increased exposure suggests that tribal populations in these regions are particularly vulnerable to environmental stresses such as unpredictable rainfall, temperature variations, and natural hazards, possibly compromising agricultural output, water accessibility, and livelihood stability. It emphasises the increased hazard faced by tribal communities, greatly dependent on rain-fed agriculture and natural resources, thereby accenting the urgent need for targeted adaptation strategies and resilience-building initiatives (Barron et al., 2021). Climatic variability reveals similar levels in both districts, emphasising the variability in rainfall and temperature patterns, which can critically impact rain-fed agriculture, a leading livelihood strategy for tribal communities. The mean standard deviation of average rainfall by month is nearly equal in both districts (Chhindwara= 0.293 mm, Dhar= 0.298 mm), indicating consistent variations in monthly rainfall. The standard deviation of maximum (T_{max}) and minimum (T_{min}) temperatures shows significant variation in Dhar (T_{max}= 0.459 °C, T_{min}= 0.557 °C) compared to Chhindwara (T_{max}= 0.376 °C, T_{min}= 0.576 °C), indicating prominent temperature extremes in Dhar. These variations can poorly affect crop yields and water availability, aggravating the vulnerability of tribal communities, such as Gond, Mahasin, Mawasi, and Bhariya in Chhindwara and Bhil and Bhilala in Dhar who depend greatly on these natural resources.

Further examination of hazards gives insights into the frequency of climatic events such as floods, droughts, and hailstorms from the last 10 years. Dhar reports a low occurrence of floods (0.094) and higher drought (0.350) in the last 10 years compared to Chhindwara (0.051 and 0.314, respectively). Both districts experience the same and a higher frequency of hailstorm incidents (0.405). These hazard indicators imply Dhar is more prone to floods and droughts, which can rigorously interrupt agricultural cycles and food security for tribal households. Dhar's higher exposure and variability indices indicate a need for targeted interventions to improve resilience against climatic events. Initiatives such as introducing drought-resistant crops, developed water management practices, and robust early warning systems could mitigate the impacts of climate variability (Mall et al., 2017). Incorporating traditional knowledge with modern agricultural practices could improve the adaptive capacity of tribal communities (Kala, 2022). While these districts face significant climatic challenges, Dhar's a little higher vulnerability imposes focused efforts to reinforce resilience and adaptive capacity among its tribal populations. Addressing these vulnerabilities through community-based approaches and sustainable practices can advance more resilient and equitable development paths, confirming the long-lasting welfare of these marginalised communities.

5.3.2 Sensitivity

The average sensitivity index within the Chhindwara and Dhar districts is 0.446, providing crucial insights into the vulnerability of tribal communities to various climatic stressors. Chhindwara (0.452) shows slightly higher sensitivity than Dhar (0.440), indicating comparable levels of vulnerability to environmental change. The higher sensitivity of the Chhindwara district is mostly because of the substantial variation in the sub-components of land, infrastructure, and water. Land and infrastructure are important factors in the sensitivity index. Chhindwara has a higher percentage of households who do not have electricity than Dhar (4.6% and 1.5%, respectively) and residing in Kutcha houses (72% and 30.3%, respectively). The inadequate housing and absence of essential services exacerbate the vulnerability of these communities, making them more vulnerable to CC (Ajibade & McBean, 2014). These results are consistent with (Ghosh & Ghosal, 2020) argument that rural households often lack the economic capacity to build a pucca house. Access to basic infrastructure is essential for health, social, and economic development. Investments in water infrastructure, such as rainwater harvesting and community water purification systems, are necessary for enhancing resilience (Wallis-Lage & Erdal, 2022). Food security is a major issue, with 54% of Chhindwara households and 65.7% of Dhar households requiring adequate food for the year. The higher food sensitivity index in Dhar (0.583) compared to Chhindwara (0.457) stresses Dhar's severe food insecurity problem. Tribal households struggling to find food are also greater in Dhar (34.3%) than in Chhindwara (27.5%). These proportions exhibit a precarious food situation, with inferences for health and welfare. The problem of water accessibility exposes extensive challenges, particularly in Chhindwara, where 97.7% of households report groundwater depletion, compared to 79.2% in Dhar. Increasing water shortages are a severe problem, affecting 92% of households in Chhindwara and 78.8% in Dhar. Limited access to safe drinking water sources (such as hand pumps, wells, and tap water through Pradhan Mantri Jal Nal Yojna) and high dependence on rain-fed agriculture (75.9% in Chhindwara and 37.6% in Dhar) further aggravate water insecurity. Agricultural productivity also decreased due to water scarcity in both regions.

Health indicators indicate large discrepancies, with a substantial percentage of families in both districts not having access to sanitary latrines and not practising preventive health care. The distance to the nearest health centre remains a barrier, particularly in Chhindwara, which averages 8.64 km compared to 3.32 km in Dhar. Chronic disease occurrence, although relatively low, includes another level of vulnerability. A study by Cardona et al. (2021) stated that climate-related disasters like storms, floods, heat waves, and wildfires are expected to exacerbate public health risks. The social security index reveals disparities in the benefits of government schemes (such as Indira Gandhi Old Age Pension, Widows Pension, Ladli Bahna Yojna, and Kisan Samman Nidhi). A larger number of households in Dhar (99.6%) did not benefit from the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) than in Chhindwara (44.4%). Similarly, a substantial percentage of households in both districts were not receiving benefits from the Public Distribution System (PDS), which explains the lack of connectivity of the people with the state system. Enhancing programs like MGNREGA, skill development programs, and PDS can improve employment opportunities and mitigate socioeconomic vulnerabilities to promote food security (George et al., 2023). High dependency on firewood or dung cake as the primary energy source for cooking (93.9% in Chhindwara and 87.2% in Dhar) indicates perpetual reliance on traditional and less efficient energy sources, which further deteriorate their health due to indoor pollution (Srivastav, 2021). These results highlight the complex character of sensitivity in tribal communities, encompassing inadequate infrastructure, food and water insecurity, health issues, and limited social security. Addressing these vulnerabilities requires targeted interventions that improve infrastructure and access to essential services and ensure food and water security. Tailored approaches influencing local knowledge and involving tribal communities in decision-making can encourage resilience and promote sustainable development (Musavengane, 2019). Recognising and mitigating these sensitivities are necessary for decreasing vulnerability and improving the livelihood of tribal communities in the study areas.

5.3.3 Adaptive Capacity

The results of adaptive capacity indicators for the study districts give valuable insights into the socioeconomic and livelihood patterns of tribal communities. The average adaptive capacity index is 0.483, indicating only a minor difference between Chhindwara (0.495) and Dhar (0.472) districts, with significant implications for the tribal communities. Chhindwara has a lower percentage of household heads who have not attended school (36.4%) than Dhar (47.4%), indicating a better educational status among tribal people, which is important for adaptive capacity. However, both districts exhibit similar dependency ratios and percentages of female-headed households, implying a similar family structure. Agriculture as a primary source of income is more widespread in Dhar (46.7%) than in Chhindwara (36.8%), reflecting the increased reliance on climate-sensitive livelihoods in Dhar. CC awareness level is noticeably greater in Chhindwara (52.0%) than in Dhar (35.6%). This awareness gap shows Dhar may need specific education and communication strategies to increase CC preparation.

The usage of weather forecasting and familiarity with early warning systems are also higher in Chhindwara, indicating a more robust integration of climate information into agricultural activities. Sen et al. (2021) observed that access to and use of weather forecasting and climate info vary. Livelihood diversification is somewhat greater in Dhar (0.479) than in Chhindwara (0.439), exposing an enormous diversity of income-generating activities. However, more family members work outside Dhar (35.4%) compared to Chhindwara (26.1%), implying greater mobility and possibly better access to outside employment opportunities in Dhar. This mobility could offer extra income sources, enhancing household resilience. However, this also suggests a reliance on migration for income, which can have social implications such as family separation and reduced community cohesion (Chen et al., 2023). Migration in the last year for work or education was almost similar and less in both districts.

Most families have not undertaken training or skill development programs (98.1% in Chhindwara and 96.7% in Dhar). This lack of capacity-building opportunities impedes people’s ability to diversify their livelihoods or strengthen their current abilities, restricting their adaptive capacity and long-term resilience. Phuong et al. (2023) discussed that involving marginal communities in training programs enhances their awareness of CC and improves their adaptability. Both districts reveal comparable financial stability characteristics, with a strong dependence on borrowing (68.2% in Chhindwara and 76.6% in Dhar) and a greater portion of households below the poverty line (65.1% in Chhindwara and 70.4% in Dhar). The absence of permanent jobs is higher in both districts (93.1%), reflecting the unstable nature of employment. Chhindwara has a greater social network index (0.525) than Dhar (0.474), suggesting stronger community cohesiveness and possible support networks. However, access to transport facilities, communication, and the main market is typically higher in Dhar, which may enhance economic activity and access to services. Cong et al. (2016) highlighted that increasing media access fulfils societal accountability by raising awareness and bridging the gap between regional observations and global incidents. Also, Nguyen & Leisz (2021) observed that diverse media sources are important for strengthening social networks, indirectly enhancing household adaptability. A complex interaction of educational status, CC awareness, livelihood diversification, and social networks determines the adaptation capacity of tribal households in both districts. Enhancing adaptive capacity involves a broad strategy, including improving education and climate knowledge, encouraging different livelihood alternatives, and boosting financial stability and social networks. Targeted interventions, such as skill development programs, access to climate information, and infrastructure developments, are essential for developing resilience among these vulnerable communities. Focusing on these characteristics may lead to more sustainable and reasonable development, eventually strengthening the capacity of tribal communities to persist and adapt to climatic change and variability.

5.3.4 LVI-IPCC

The LVI-IPCC offers a synthesised measure of vulnerability, amalgamating various components across exposure, sensitivity, and adaptive capacity for Chhindwara and Dhar districts (Fig. 5.5). The average LVI-IPCC value of -0.060 suggests a moderate level of vulnerability to climate-related risks among the surveyed households. This index provides valuable insights into the nuanced vulnerability profiles of tribal communities and the geographical heterogeneity of vulnerability within the study area (Fig. 5.6). All the Tehsils were categorised into 4 groups based on the quartile value of the index, representing low, medium, high, and very high (Jamshed et al., 2020). Dhar (-0.049) exhibits a higher LVI-IPCC value than Chhindwara (-0.072), indicating a greater vulnerability to CC and its impact among the surveyed households. The same results were also obtained from the Vulnerability Index (VI) for Dhar (0.336) and Chhindwara (0.309). The results underscore the intricate relationship of environmental, socioeconomic, and institutional factors shaping vulnerability dynamics within these districts. The higher LVI-IPCC value in the Dhar district may be attributed to various underlying factors that increase the vulnerability of tribal households. One significant aspect is the region's susceptibility to climate variability and hazards, such as mean maximum temperature, floods, and droughts, exacerbating vulnerabilities (Ghosh & Ghosal, 2021) among tribal communities reliant on agriculture and natural resources for their livelihoods. Dhar's relatively lower adaptive capacity index suggests limited resilience and coping mechanisms among tribal households to respond effectively to these climate variability and hazards.

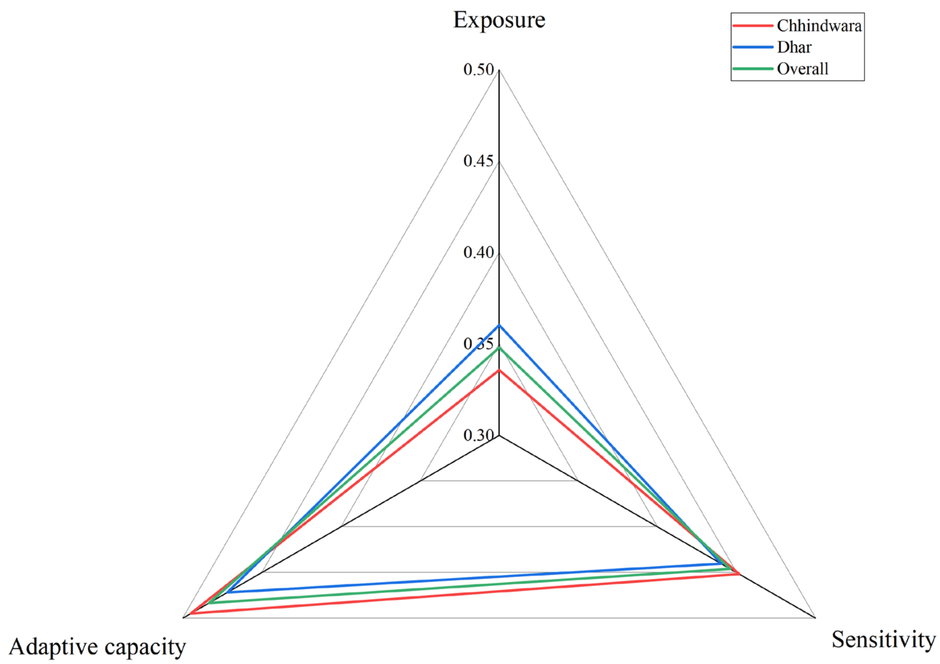


Fig. 5.5: Contributing factors of the LVI-IPCC for Chhindwara and Dhar

Socioeconomic indicators such as reduced financial stability, lower livelihood diversification, and restricted access to social security networks further aggravate vulnerability by reducing the capacity of tribal communities to endure and recover from the adverse impact of CC. Phuong et al. (2023) concurred that CC irregularly affects households' livelihoods depending on various sensitivities. The comparatively lower LVI-IPCC (-0.072) signifies a somewhat lower vulnerability among tribal communities in Chhindwara. It may be attributed to several factors, including better infrastructure, relatively higher levels of adaptive capacity, and more excellent socioeconomic stability than Dhar. The finding aligns with previous studies that enhanced infrastructure facilities and higher levels of adaptive capacity reduce the vulnerability to CC impacts (Filho et al., 2019; McMartin et al., 2018; Piya et al., 2019). The availability of more robust social networks, along with higher levels of awareness and access to resources, could augment the resilience of tribal communities in Chhindwara, enabling them to better cope with CC. The higher LVI-IPCC value in the Dhar district underlines the urgent need for targeted interventions and adaptive strategies to improve resilience and promote livelihood security among vulnerable tribal communities. Policymakers should prioritise investments in climate-resilient infrastructure, sustainable agriculture practices, and social security systems to mitigate risks and enhance adaptive capacity. Fostering community-based adaptation initiatives, integrating indigenous knowledge systems, and promoting participatory decision-making processes are essential for empowering tribal communities to cope with CC impacts and achieve sustainable development goals. By addressing the underlying drivers of vulnerability and promoting inclusive development pathways, stakeholders can effectively reduce disparities and promote the well-being and resilience of tribal populations in Chhindwara, Dhar, and other similar contexts.

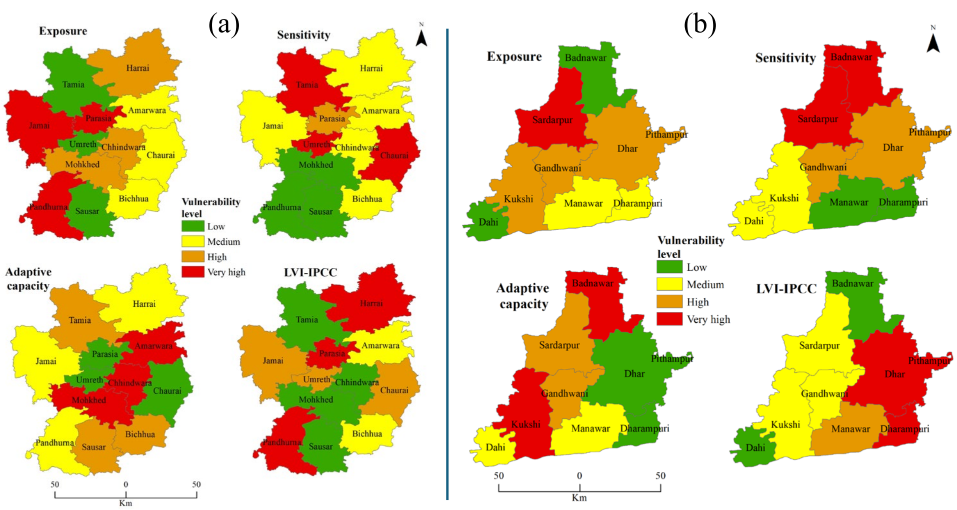


Fig. 5.6: Geographical variation of contributing factors and LVI-IPCC of (a) Chhindwara and (b) Dhar districts

5.3.5 Determinants of LVI-IPCC

The MLR results present indicators affecting the livelihood vulnerability of tribal households (Table 5.3). The relation between LVI-IPCC and contributing factors is shown in Fig. 5.7 for both districts. Based on the overall sample size (n= 535) from both districts, the analysis reveals that 10 out of 18 indicators significantly impact the livelihood vulnerability to CC among tribal households ($p < 0.05$). Significant factors include the household head not attending school (β= -0.018), agriculture as the primary source of income (β= 0.022), number of extreme weather events (β= 0.008), lack of access to safe drinking water (β= -0.014), number of livelihood strategies (β= 0.005), lack of access to sanitary latrines (β= -0.014), not benefiting from the Public Distribution System (PDS) (β= -0.020), lack of access to communication or social media platforms (β= -0.032), familiarity with early warning systems for natural disasters (β= 0.013), and economic status (β= -0.018). The findings indicate that active and wealthy households significantly reduce the vulnerability of tribal households compared to inactive and low-income families. Households which use weather forecasts for making farming decisions, are familiar with the early warning system for natural disasters, participate in training or skill development programs to enhance their ability to generate income, have better access to communication and social media, and are beneficiaries of the government schemes (such as Ladli Bahna Yojna and Kisan Samman Nidhi) exhibit lower vulnerability. These findings align with previous research, highlighting the importance of social networks and access to information in enhancing tribal communities' capacity for CC adaptation, thereby reducing their vulnerability (Nguyen & Leisz, 2021; Phuong et al., 2023; Son & Kingsbury, 2020). Belay & Fekadu (2021) highlight that participation in training programs and establishing broad social networks raise tribal communities' climate awareness, which is also a primary factor of CC vulnerability among tribal households in this study.

The educational status of the household head significantly influences vulnerability. Specifically, the head of the household who has not attended school shows greater vulnerability (β= -0.012 for Chhindwara and -0.022 for Dhar). It aligns with previous literature that underlines the role of education in enhancing adaptive capacity and resilience. Educated household heads are likelier to access information, adopt modern agricultural practices, and make updated decisions during extreme weather events (Lu et al., 2021). Enhancing educational opportunities and quality, especially through adult education and occupational training, can

Table 5.3: Results of linear regression of vulnerability determinants and LVI-IPCC for the Chhindwara and Dhar tribal households

Items	**Explanation**	**Measurement**	**Chhindwara**		**Dhar**		**Overall**	
Explanatory variables			***β***	***S.E.***	***β***	***S.E.***	***β***	***S.E.***
Socio-demographic	Gender	Dummy (0 = men, 1 = women)	0.001	0.005	-0.005	0.006	-0.002	0.004
	Head of the household not attended school	Dummy (0 = No, 1 = Yes)	-0.012	0.006	-0.022**	0.005	-0.018**	0.004
	Age	Continuous (Years)	0.000	0.000	0.000	0.000	0.000	0.000
	Agriculture as a primary source of income	Dummy (0 = No, 1 = Yes)	-0.019**	0.006	-0.020**	0.005	-0.022**	0.004
Hazards	No. of extreme weather events	Continuous (Numeric)	0.008**	0.001	0.009**	0.001	0.008**	0.001
Land and Infrastructure	Don't have access to electricity	Dummy (0 = No, 1 = Yes)	0.009	0.016	-0.011	0.015	0.005	0.018
	Housing structure	Dummy (0 = Others, 1 = Kutcha)	0.003	0.003	0.000	0.003	-0.001	0.002
	Land holdings	Continuous (Hectare)	-0.001	0.001	-0.001	0.001	-0.001	0.001
Water	Don't have access to safe drinking water sources	Dummy (0 = No, 1 = Yes)	0.001	0.006	-0.029**	0.005	-0.014**	0.004
Food	Doesn't family have adequate food for the whole year	Dummy (0 = No, 1 = Yes)	-0.007	0.005	-0.004	0.005	-0.004	0.004
Livelihood strategy	No. of livelihood strategies	Continuous (Numeric)	0.004	0.003	0.008*	0.004	0.005*	0.003
	Have not any members of your household undergone training or skill development programs to enhance their ability to generate income	Dummy (0 = No, 1 = Yes)	-0.020	0.017	0.000	0.014	-0.006	0.010
Health	Don't have access to sanitary latrine	Dummy (0 = No, 1 = Yes)	-0.004	0.005	-0.021**	0.005	-0.014**	0.004
Social security	Not benefitting from the public distribution system (PDS)	Dummy (0 = No, 1 = Yes)	-0.036**	0.008	-0.014	0.009	-0.020**	0.007
Social network	Don't have access to communication media or social media platforms	Dummy (0 = No, 1 = Yes)	-0.025**	0.006	-0.035**	0.006	-0.032**	0.004
Awareness	Use a weather forecast for making farming decisions	Dummy (0 = No, 1 = Yes)	-0.023**	0.006	0.011	0.008	0.000	0.004
	Familiar with the early warning system for natural disasters	Dummy (0 = No, 1 = Yes)	-0.019**	0.008	0.034**	0.007	0.013*	0.006

Financial stability	Economic status	Dummy (0 = Others, 1 = Below Poverty line)	-0.013*	0.005	-0.020**	0.005	-0.018**	0.004
Model properties								
Observations			261		274		535	
R^2			0.495		0.653		0.427	
F			15.58		24.10		19.40	

** p<0.01, * p<0.05

significantly influence household heads' knowledge and skills (Deribew et al., 2012). Agriculture as the primary source of income is associated with decreased vulnerability (*β*= -0.019 for Chhindwara and -0.020 for Dhar). It proposes that assistance for agricultural activities, including access to high-yielding seeds, irrigation facilities, and market connections, can reinforce resilience. Agricultural assistance through subsidies, access to financial support, and extension services can enrich productivity and income stability (Malimi, 2023). Sustainable agricultural practices and diversification into high-value crops could further augment household income stability (Mustafa et al., 2019).

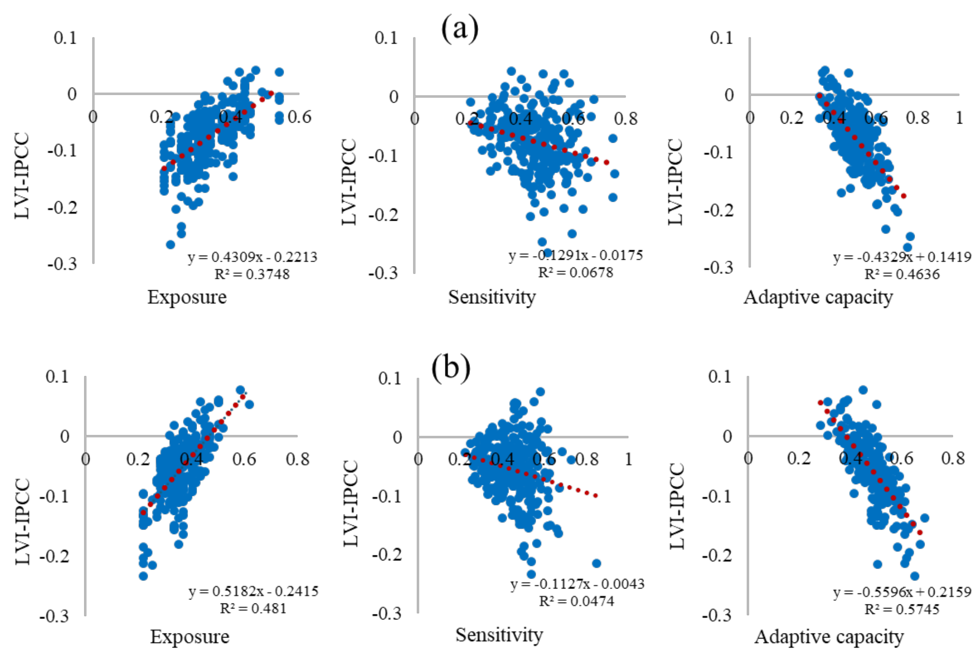


Fig. 5.7: Relationship among contributing factors and LVI-IPCC of (a) Chhindwara and (b) Dhar districts

From the environmental hazard perspective, the regression analysis illustrates that the frequency of natural hazards significantly increases vulnerability (*β*= 0.008 and 0.009 for Dhar). It emphasises the critical need for effective disaster risk management and climate adaptation strategies. Investment in early warning systems, community-based hazard preparation programs, and robust infrastructure can mitigate the detrimental effects of such events (Velazquez et al., 2020). The findings show that people residing in Kutcha houses are more susceptible than those in Pucca. Living in Kutcha houses increases their vulnerability to property loss during natural hazards (Ghosh & Ghosal, 2020; Phuong et al., 2023). Lack of access to safe drinking water is an essential element of vulnerability in Dhar (β= -0.029) and overall (β= -0.014). Access to safe drinking water is essential for health, agricultural output, and overall prosperity. Investments in water infrastructure, such as rainwater harvesting, borewells, and cooperation water cleansing systems, are crucial for enhancing resilience improve access to safe drinking water, particularly in Dhar (Pamidimukkala et al., 2021). The lack of adequate food for the year did not significantly influence vulnerability; guaranteeing food security remains essential. Food security measures should concentrate on raising agricultural productivity, varying crops, and expanding storage facilities to reduce post-harvest damages (Rahut et al., 2022).

Another outcome from the regression analysis illustrates that lack of access to communication or social media platforms significantly increases vulnerability (β= -0.025 for Chhindwara and -0.035 for Dhar). Media access is essential for raising awareness and preparing people for the hazards associated with CC. Improving digital literacy and increasing internet access can enhance communication and information broadcasting (Camargo et al., 2019). Familiarity with early warning systems for natural disasters shows a combined effect, lowering vulnerability in Chhindwara (β= -0.019) but raising it in Dhar (β= 0.034). It advises that while awareness is important, using these systems relies on their application and the community's trust in them. Active communication, regular training, and community involvement are necessary for the success of early warning systems (Zhang et al., 2021). Households below the poverty line reveal higher vulnerability (β= -0.013 for Chhindwara and -0.020 for Dhar). Economic stability is necessary for resilience. Poverty reduction policies, containing social protection schemes, income generation programs, and financial inclusion strategies, are essential for improving the resilience of tribal households (Korostelina & Barrett, 2023).

5.4 Conclusions

This study provides valuable insights into the vulnerability of tribal communities in the Chhindwara and Dhar districts to CC impacts. The vulnerability index highlights a moderate level of vulnerability, with Dhar exhibiting greater vulnerability than Chhindwara. Increased exposure to climate variability, socioeconomic disparities, and adaptive capacity significantly influence vulnerability. Limited access to education, infrastructure, safe drinking water, and social security further compounds vulnerability, underscoring the urgent need for targeted interventions. Chhindwara demonstrates relatively lower vulnerability, attributed to better infrastructure, higher adaptive capacity, and more excellent socioeconomic stability. More robust social networks, coupled with higher levels of awareness and access to resources, contribute to enhanced resilience among tribal communities in Chhindwara. Frequent natural hazards exacerbate vulnerability, emphasising the need for effective disaster risk management strategies. Addressing these vulnerabilities needs targeted interventions, including investments in climate-resilient infrastructure, promoting sustainable livelihoods, and enhancing social protection schemes. Integrating indigenous knowledge systems and fostering community-based adaptation initiatives are crucial for building resilience among tribal communities. The findings underscore the urgent need for holistic approaches considering the complex relationship of environmental and socioeconomic factors in reducing vulnerability and promoting sustainable development in tribal areas.

Chapter 6

Summary and Future Scope

The primary objective of this thesis is to assess the livelihood vulnerability to climate change (CC) and variability among tribal communities in Madhya Pradesh, India. The study is conducted at various scales to assess CC vulnerability. The first objective tried to explore the variations in rainfall and temperature patterns and their implications on tribal livelihoods. The second objective assessed district-wise climate vulnerability in Madhya Pradesh using environmental and socioeconomic indicators and found that tribal-dominated districts are more vulnerable to CC. Therefore, the further objectives taken in the tribal populous highly vulnerable districts, namely, Dhar and Chhindwara, to assess tribal people's perceptions on CC and its impacts and integrated assessment of livelihood vulnerability to climate variability among tribal communities in Dhar and Chhindwara districts, Madhya Pradesh, respectively. This chapter summarizes the major findings of all the objectives along with limitations associated with the present studies. This chapter also provides scope for future work as well as policy recommendations.

6.1 Exploring the Spatiotemporal Climatic Dynamics of Madhya Pradesh

The spatiotemporal analysis of rainfall and temperature trends across Madhya Pradesh reveals significant variations over 71 years (1951–2021), using descriptive analysis, temporal trends (Mann-Kendall and Sen's slope tests), and change points (Pettitt's test), spatial distribution. Moreover, spatial change analyses were conducted to understand the geographical distribution of climatic changes across the state. The following observations are presented below:

6.1.1 Descriptive Analysis

- The mean annual rainfall is 1041.36 mm, with high interannual variability ($\sigma = 179.18$). Monsoon rainfall contributes the majority (around 85%) of the annual rainfall, with relatively low variability (CV = 17.51%). Pre-monsoon, post-monsoon, and winter rainfall exhibit higher variability (CV > 79%), indicating unpredictable rainfall patterns. High rainfall variability disturbs crop yields and water availability, rising crop failures and food insecurity for tribal communities dependent on subsistence farming.
- Annual mean temperature (T_{mean}) is 25.52 °C, with low overall variability (CV = 1.42%). Seasonal temperature variability is more pronounced during post-monsoon seasons (CV = 3.47%) and winter (CV = 3.23%). Similarly, maximum temperature (T_{max}) shows a lower level of variability.
- Minimum temperature (T_{min}) shows the highest variability, particularly during winter (CV = 39.20%). The high CV value for T_{min} highlights significant variability, impacting agriculture, health, energy, and ecosystem stability essential to tribal livelihoods. Sudden temperature declines affect frost damage to crops and health issues like hypothermia.

6.1.2 Temporal Trend Analysis

- Annual ($Z = -1.023$) and monsoon rainfall ($Z = -0.933$) show non-significant declining trends, with a rate of -0.990 mm and -0.977 mm yearly. Declining rainfall patterns can negatively impact agriculture, water resources, and food security in Madhya Pradesh, leading to water shortages, especially for irrigation and drinking water.

- Post-monsoon ($Z = -0.764$) and winter ($Z = -0.735$) rainfall also show declining trends, potentially affecting groundwater recharge and water storage.
- Pre-monsoon rainfall shows an increasing trend ($Z = 0.288$). Increased pre-monsoon rainfall can benefit certain crops and water availability, but changes in distribution could disrupt agricultural planning.
- The annual T_{mean} shows a statistically significant increasing trend ($Z = 2.898$), with a warming rate of 0.006 °C/year. The post-monsoon T_{mean} also indicate a significant warming trend ($Z = 3.594$) at the rate of 0.018 °C/year. Rising T_{mean} can increase evapotranspiration, reduce soil moisture, and intensify water stress. It also impacts crop quality and reduces productivity.
- Similarly, annual T_{max} demonstrates an increasing trend ($Z = 1.772$) at 0.006 °C/year. Higher T_{max} can intensify heat stress, affecting human health, livestock, and crops, particularly during summer.
- T_{min} exhibits significant warming trends ($Z = 2.452$) annually, mainly during pre-monsoon ($Z = 2.422$), post-monsoon ($Z = 3.891$) and winter ($Z = 2.750$). Warmer nights can disrupt the growth cycles of crops and exacerbate pest infestations. Increased T_{min} can lead to higher energy demands for cooling during hotter nights.

6.1.3 Change Point Analysis

- Abrupt changes were detected in annual rainfall (1998), monsoon (1998), pre-monsoon (1955), post-monsoon (1987), and winter (1986). Sudden changes in monsoon rainfall interrupt crop cycles and reduce productivity, while pre-monsoon and post-monsoon shifts affect soil preparation and agricultural timing. Shifting rainfall patterns also disrupt biodiversity, habitats, and ecosystems.

- Sudden shifts in annual T_{mean} (2004) and seasonal patterns (monsoon = 2007, pre-monsoon = 2000, post-monsoon = 1998, winter = 1959) augment water stress, reduce soil moisture, and impact crop productivity.
- Change points in T_{max} were observed annually (2010) and seasonally (monsoon = 1990, pre-monsoon = 2008, post-monsoon = 1963, winter = 1966), intensifying heat stress on crops, livestock, and human health, especially during summer.
- Abrupt changes in T_{min} occurred annually (1999) and seasonally (monsoon = 1960, pre-monsoon = 2003, post-monsoon = 2008, winter = 1995), leading to warmer nights, disrupting crop growth cycles and increasing pest infestations.

6.1.4 Spatial Change Analysis

- After 1998, the pre-monsoon season saw more areas receiving <25 mm rainfall in the northern and northwest regions of Madhya Pradesh. Monsoon rainfall decreased significantly, with areas above 1000 mm decreasing and the maximum monsoonal rainfall reducing from 1623 mm to 1311 mm. During post-monsoon, areas with <25 mm rainfall expanded, while winter saw a reduction in regions receiving >50 mm. Overall, annual rainfall distribution shifted toward regions with <1000 mm, with the maximum annual rainfall decreasing from 1769 mm to 1401 mm.
- T_{mean} ranged from 29-30 °C, shifting to 30-31 °C post-2004, with higher temperatures across most regions during pre-monsoon and monsoon. After the monsoon, temperatures increased above 24 °C and reduced <23 °C area, while winter temperatures increased >19 °C areas and decreased below 18 °C. Annual T_{mean} increased >25.5 °C areas after 2004.

- The T_{max} increased, with regions reaching 41-43 °C during the pre-monsoon and areas above 34 °C expanding post-monsoon after 2010. Areas below 32 °C decreased during the post-monsoon season, and the annual T_{max} saw a shift, with more areas exceeding 32 °C. Minor shifts were observed in winter T_{max}.
- The pre-monsoon T_{min} declined below 16 °C areas, while those above 17 °C increased after 1999. During the monsoon season, T_{min} above 24 °C emerged in the northern regions. Post-monsoon T_{min} dropped below 13 °C but increased above 14 °C. Winter T_{min} increased above 9 °C and decreased below 9 °C. Annual T_{min}, areas below 18.5 °C sharply decreased, with most of the state covering above 18.5 °C after 1999.

Rainfall patterns show a decline in monsoon, post-monsoon, and winter seasons, while pre-monsoon rainfall shows an increasing trend. Temperature indicates warming trends are observed across all regions, with higher increases in minimum temperatures in the northern and central districts, suggesting widespread impacts on agriculture, water resources, and livelihoods. Abrupt changes in rainfall and temperature patterns disrupt agricultural cycles and increase water stress, heat stress, and pest infestations. These shifts, especially post-1998, emphasize the urgent need for adaptive strategies to mitigate CC impacts, especially for agriculture and tribal communities.

6.2 Assessing District-Level Climate Vulnerability in Madhya Pradesh Using Environmental and Socioeconomic Factors

The climate vulnerability of Madhya Pradesh varies significantly across its districts due to differing environmental conditions (like rainfall, forest cover, and agricultural land) and socioeconomic factors (such as HDI and population density). The major findings have been highlighted below:

6.2.1 Evolution of Composite Vulnerability Index

The vulnerability index divides districts into 4 categories: low, medium, high, and very high vulnerability, based on their index quantile values.

6.2.1.1 Environmental Vulnerability Index (EVI)

- ❖ Districts such as Anuppur, Tikamgarh, and Shajapur show low environmental vulnerability (0.214 – 0.364) due to lower T_{min}, dense forest coverage, forest fires, and drought-affected areas. These factors contribute to improved preparedness for environmental changes and vulnerability.
- ❖ Districts such as Indore, Panna, Sagar, and Alirajpur demonstrate moderate vulnerability (0.365 – 0.425) due to challenges like rainfall variations, moderate forest density, droughts and forest fires.
- ❖ Districts such as Chhatarpur, Dewas, Hoshangabad, and Dhar reveal higher vulnerability (0.426 – 0.487), influenced by increased rainfall, higher T_{max}, large agricultural areas, and frequent floods and drought incidents.
- ❖ Damoh, Raisen, Sidhi, Rajgarh, Chhindwara, Jhabua, Balaghat, Barwani, Satna, Mandla, and Dindori are the most environmentally vulnerable districts (0.488 – 0.593). These districts face extreme environmental challenges such as heavy precipitation, extreme temperatures, expansive dense forests, large agricultural areas, frequent floods, droughts, and forest fires.

6.2.1.2 Socioeconomic Vulnerability Index (SVI)

- ❖ Districts such as Gwalior, Sagar, and Damoh were identified as having low SVI (0.309-0.372). These districts demonstrate lower population densities and socially deprived populations, indicating higher socioeconomic resilience to CC impacts.
- ❖ Districts like Indore, Ujjain, Katni, and Satna come under the medium SVI category (0.373-0.401). These districts are

characterized by higher Human Development Index (HDI) values, population densities, and relatively lower socially deprived populations. Their infrastructure and human resources keep them in a better position to address climate challenges.

- ❖ Districts such as Rajgarh and Narsimhapur show a high SVI (0.405-0.432), with higher dependency on agricultural labour and a lower HDI.
- ❖ Districts like Dhar, Jhabua, East Nimar and Dindori face the highest socioeconomic vulnerability (0.441-0.552) due to a higher percentage of socially deprived populations, agricultural labourers, and cultivators. The low HDI in some districts emphasizes the need for targeted interventions to address these challenges.

6.2.1.3 Composite Vulnerability Index (CVI)

- ❖ Districts like Gwalior, Jabalpur, Sagar, and Bhopal indicate lower vulnerability (0.321-0.378) to CC impacts due to lower levels of social deprivation, better HDI, reduced dense forest cover, and lower incidence of drought.
- ❖ Districts such as Damoh, Sehore, and Indore exhibit moderate vulnerability (0.381-0.407) because of reduced EVI and SVI, attributed to factors like extensive forest coverage, lower population density (except in Indore), and a smaller proportion of marginalized populations. Higher HDI further supports resilience in these districts.
- ❖ Districts including Narsimhapur, Shajapur, and Singrauli experience higher vulnerability (0.409-0.442), linked to greater exposure to climatic extremes and higher dependency on agricultural labour. Increased vulnerability is calling for targeted climate adaptation and mitigation strategies. Agricultural resilience is essential, focusing on

improving water management, crop diversification, and flood and drought mitigation.

- ❖ Districts like Betul, Balaghat, and Barwani display the highest vulnerability (0.448-0.540) due to frequent floods, droughts, and larger agricultural areas. These regions also experience high dependency on agricultural labour, a higher proportion of marginalized populations and lower HDI, contributing to greater socioeconomic vulnerability.

6.2.2 Validation of the Composite Vulnerability Index

- ❖ The hierarchical cluster analysis was used to validate the CVI results, which revealed latent patterns in the data. The dendrogram map visually represented these patterns, showing the hierarchical relationships among districts based on their vulnerability characteristics. It helps to understand the degree of similarity and dissimilarity in vulnerability profiles across the study area.
- ❖ The hierarchical cluster analysis classified the districts into 25 clusters. This classification identified complex variations in vulnerability across the study area, demonstrating that vulnerability is not uniform and can vary depending on environmental and socioeconomic factors. It also revealed that some districts share similar vulnerability profiles due to common environmental conditions, socioeconomic challenges, or both.

The district-wise climate vulnerability assessment reveals regional disparities in Madhya Pradesh, with districts categorized into varying levels of vulnerability based on environmental and socioeconomic factors. Districts like Gwalior and Bhopal show lower vulnerability, benefiting from better resilience factors, while districts such as Betul and Dindori face high vulnerability due to a combination of environmental and socioeconomic challenges. Based on CVI values, Gwalior is the least vulnerable district, and Barwani is the most vulnerable. The hierarchical cluster analysis confirms these findings, identifying 25 distinct clusters with varying vulnerability profiles. The study highlights the need for targeted, region-specific interventions to address the diverse climatic challenges across the state.

6.3 Tribal People's Perceptions on Climate Change and its Impacts in Dhar and Chhindwara District

Based on the results of CVI, Dhar and Chhindwara districts were selected for tribal people's perception on CC and its impacts on their livelihoods. The major findings from the observed and perceived CC and its impacts, including the determinants affecting these perceptions, have been noted down from the study.

6.3.1 Observed Climate Change and Impacts

- ❖ Both the districts experienced a negative rainfall trend (ITA = -0.193 for Dhar and -0.072 for Chhindwara). T_{mean} and T_{max} are increasing in both districts. T_{min} shows a variance, with Dhar experiencing an increasing trend (ITA = 0.805), while Chhindwara exhibits a decreasing trend (ITA = -0.253). The SPI-3 analysis shows dry and wet conditions in these regions, with negative values indicating dry conditions.
- ❖ The observed shifts in rainfall and temperature contribute to increased crop heat stress, water scarcity, and reduced agricultural productivity. Tribal communities dependent on agriculture, livestock, and NTFPs observed challenges due to shifting climatic patterns, affecting food security and economic stability. The variation in climatic conditions also affects the timing of seasonal activities, including the collection of NTFPs, further impacting the socioeconomic conditions of tribal populations.

6.3.2 Perceived Climate Change

6.3.2.1 Perception on Climate Change

- The majority of the respondents observed rainfall variations and increasing temperatures in Dhar and Chhindwara. Similarly, almost 97% of respondents in both districts agreed that summer days are becoming hotter.

- The most noted consequences of CC were shifts in rainfall patterns, temperature fluctuations, and a decline in agricultural productivity. These findings suggest tribal communities are vulnerable due to their reliance on natural resources and rainfed farming practices.

6.3.2.2 Determinants of Perception on Climate Change

- In Dhar, male respondents were more likely to perceive CC ($OR=0.42$, $p<0.05$), whereas gender did not play an important role in Chhindwara.

- Higher education was a major determinant of CC perception in both districts, with families possessing more education being much more likely to perceive CC ($OR=2.48$ in Dhar and $OR=6.09$ in Chhindwara).

- In Chhindwara, wealthier families were less likely to perceive CC ($OR=0.32$, $p<0.01$), possibly due to their lower dependence on natural resources. However, in Dhar, income did not significantly affect CC perception.

- Primary occupation was a key determinant in Chhindwara ($OR=2.45$, $p<0.05$), with those engaged in agriculture as a primary source of income more likely to perceive CC.

- Access to infrastructure revealed regional variations. In Chhindwara, access to electricity increased the likelihood of perceiving CC ($OR=5.62$, $p<0.01$), while in Dhar, improved access to drinking water sources was a more important determinant ($OR=2.69$, $p<0.01$).

- ❖ Similarly, access to communication media increased the likelihood of perceiving CC in both districts. The odds of perceiving CC were 4.12 times higher in Dhar and 5.50 times higher in Chhindwara for those with media access.

6.3.3 Perceived Climate Change Impacts

6.3.3.1 Perception of climate change impacts

- ❖ In Dhar, 50.7% of respondents perceive increased drought occurrences, with 36.9% expressing concern about water scarcity. Similarly, in Chhindwara, 39.5% strongly agree that drought incidents are increasing.
- ❖ Water levels are perceived to be declining, with 85.1% of respondents in Chhindwara strongly agreeing with this statement. Both districts reported a severe worsening of water shortages.
- ❖ In Dhar, 41.2% agree that agricultural productivity is decreasing, and 46% express concern over crop failure and economic loss. The respondents from both districts stated that crop damage was increasing due to pests and environmental factors such as heatwaves, untimely rainfall, and hailstorms, with over 39% agreeing that such factors have worsened in recent years.
- ❖ Health-related issues, such as water-borne diseases, are increasingly concerning in Chhindwara, with 54.8% of respondents strongly agreeing that health risks related to water scarcity are rising. This includes diarrhoea, dysentery, malaria, and skin-related conditions.
- ❖ There is a growing trend of rural-urban migration in both districts, attributed to the socioeconomic impacts of environmental challenges, such as water shortages and agricultural failure.

6.3.3.2 Determinants of Perception on Climate Change Impacts

- ❖ Gender was a key factor in Dhar, affecting perceptions of natural resources and health, but not in Chhindwara. Age and education had limited influence on perceptions, though education was negatively correlated with perceptions of climatic extremes in Dhar. This suggests that education could affect awareness or concern about the impacts of CC.

- ❖ Family size is negatively associated with livelihood perceptions in Chhindwara, indicating that larger families could perceive higher vulnerability to climate impacts on their livelihoods.
- ❖ Household income had a positive association with perceptions of natural resource depletion and agricultural challenges in Dhar. However, it negatively affected perceptions of water scarcity, livelihood, and health issues in Chhindwara. This highlights the relationship between economic status and vulnerability to CC.
- ❖ The occupation of respondents was strongly associated with perceptions of agricultural changes in both districts. This reflects the high dependence of tribal communities on agriculture for their livelihoods, making them vulnerable to changes in climate conditions affecting crop yields.
- ❖ Access to safe drinking water and healthcare services related to perceptions of water scarcity and health risks in Dhar. The negative relationships suggest poor access to water and healthcare services exacerbate perceptions of vulnerability to climate-related water and health challenges.

Tribal communities in Dhar and Chhindwara perceived changes in climatic conditions, such as reduced rainfall and increasing temperatures, severely affecting their livelihoods. Water scarcity, crop failures, and health risks related to CC are significant concerns. Determinants such as education, occupation, and access to infrastructure affect perceptions of CC, with differences observed in these districts. To strengthen resilience, addressing these regional disparities by improving infrastructure, enhancing educational opportunities, and developing adaptive strategies to mitigate the effects of climate variability is essential.

6.4 Integrated Assessment of Livelihood Vulnerability to Climate Variability among Tribal Communities in Dhar and Chhindwara District, Madhya Pradesh

Tribal communities in the districts of Dhar and Chhindwara, Madhya Pradesh, are vulnerable to the impacts of climate variability. These communities primarily depend on rain-fed agriculture, making them vulnerable to changes in rainfall patterns, temperature extremes, and frequent natural hazards like floods and droughts. Furthermore, infrastructure challenges like poor housing, limited access to electricity, water scarcity, and inadequate healthcare increase their vulnerability. Disparities in adaptive capacity, influenced by factors such as education, livelihood diversification, and access to resources, create differences in vulnerability across these two districts. The major findings of tribal livelihood vulnerability to climate variability from this study are as follows:

6.4.1 Exposure

- ❖ The average exposure index is 0.348, with Dhar (0.360) being more vulnerable than Chhindwara (0.336). It indicates that the tribal populations in both districts face significant environmental challenges.
- ❖ Both districts experience similar levels of climatic variability, particularly in rainfall and temperature patterns. This variability is crucial as it affects rain-fed agriculture, a livelihood for tribal communities. The standard deviation of average monthly rainfall is almost the same in both districts, but temperature extremes (maximum and minimum) are more visible in Dhar, with a higher variation than in Chhindwara. Dhar experiences higher temperature fluctuations (T_{max} = 0.459 °C, T_{min} = 0.557 °C) compared to Chhindwara (T_{max} = 0.376 °C, T_{min} = 0.576 °C), which could

severely impact crop yields and water availability, increasing vulnerability for tribal communities.

- ❖ The respondents from Dhar observed higher occurrences of floods (0.094) and droughts (0.350) in the last 10 years compared to Chhindwara (0.051 and 0.314, respectively), while both districts experienced the same frequency of hailstorms (0.405). This refers to the fact that Dhar is more prone to disruptive climatic events, which can affect agricultural cycles and food security for tribal households.

6.4.2 Sensitivity

- ❖ The average sensitivity index (0.446) highlights the vulnerability of tribal communities in Chhindwara (0.452) and Dhar (0.440) to climatic challenges. It reveals a gap in basic infrastructure that Chhindwara had a higher percentage of households without electricity and those living in kutcha houses than Dhar. Inadequate housing and essential services compound vulnerability, reducing people's ability to cope with CC.
- ❖ The higher food sensitivity index in Dhar (0.583) compared to Chhindwara (0.457) and the prevalence of food insecurity (65.7% in Dhar and 54% in Chhindwara) underline the unstable food situation.
- ❖ Groundwater depletion affects 97.7% of households in Chhindwara and 79.2% in Dhar, with increasing water shortages impacting 92% of Chhindwara households and 78.8% in Dhar. Dependence on rain-fed agriculture (75.9% in Chhindwara and 37.6% in Dhar) augments water insecurity, which affects crops, health, and livelihoods.
- ❖ Poor access to health facilities (8.64 km average distance in Chhindwara and 3.32 km in Dhar) and inadequate sanitation and preventive health practices create health vulnerabilities. These health challenges are intensified by other factors, such as poor infrastructure, food insecurity, and water scarcity, undermining the community's resilience.

- ❖ Limited access to social welfare schemes like MGNREGA (99.6% of households in Dhar and 44.4% in Chhindwara are not benefiting) exhibits a gap in economic security. Heavy reliance on traditional cooking fuels (93.9% in Chhindwara and 87.2% in Dhar) exposes energy poverty, which limits efficiency and poses health risks. This reliance, coupled with broader deficits in infrastructure, social welfare, and health, further imbedding the vulnerabilities of these tribal communities.

6.4.3 Adaptive Capacity

- ❖ The lower percentage of uneducated household heads in Chhindwara (36.4%) than in Dhar (47.4%) highlights better educational status among its tribal communities. This educational advantage is linked to higher CC awareness (52.0% in Chhindwara and 35.6% in Dhar), emphasizing the role of education in improving adaptive capacity. Increased education levels facilitate better access to climate information and informed decision-making.
- ❖ Greater reliance on agriculture in Dhar (46.7%) compared to Chhindwara (36.8%) reflects increased vulnerability to climate variability. Dhar also shows higher livelihood diversification and household reliance on migration for income, which can bolster resilience but can reduce social cohesion. The lack of training opportunities in both districts (98.1% in Chhindwara and 96.7% in Dhar) restricts livelihood diversification and long-term adaptability.
- ❖ The respondents from Chhindwara reported higher use of weather forecasting and early warning systems, which suggests better integration of climate tools into agricultural practices.
- ❖ Both districts face significant financial instability, with a high dependence on borrowing and a higher proportion of households below the poverty line (65.1% in Chhindwara and 70.4% in Dhar). The absence of permanent employment (93.1%) highlights the unstable nature of livelihoods, limiting adaptive capacity.

- ❖ The social network index is higher in Chhindwara (0.525) than in Dhar (0.474), indicating stronger community ties, crucial for mutual support during crises. However, Dhar's better access to transportation, communication, and markets improves economic activity, illustrating a balance between social cohesion and infrastructural advantages.

6.4.4 LVI-IPCC

- ❖ Dhar district shows a higher LVI-IPCC value (-0.049) than Chhindwara (-0.072), indicating greater vulnerability to CC impacts. It is worsened by higher sensitivity to climate hazards, such as extreme temperature fluctuations, floods, and droughts, which disproportionately affect tribal households reliant on agriculture and natural resources. Chhindwara shows relatively lower vulnerability due to higher adaptive capacity, which is supported by better infrastructure, socioeconomic stability, and access to resources.
- ❖ Socioeconomic factors such as reduced financial stability, limited livelihood diversification, and access to social security networks heighten Dhar's vulnerability. This suggests that addressing socioeconomic inequalities is essential for enhancing the resilience of tribal communities.
- ❖ The presence of robust social networks, greater awareness, and access to resources in Chhindwara enriches resilience and reduces vulnerability. This underlines the importance of social cohesion and community empowerment in mitigating climate impacts.

6.4.5 Determinants of LVI-IPCC

- ❖ Households with uneducated heads experience higher vulnerability, as education enables access to information and the adoption of modern adaptive practices. The implication is that improving educational access, especially adult education, can enhance resilience to climate impacts.

- Agriculture as a primary income source emphasizes the stabilizing effect of agricultural support, high-yield inputs, and sustainable practices. Diversification of income sources within agricultural households could further enhance resilience.
- A higher frequency of natural hazards increases vulnerability, underscoring the importance of effective disaster preparedness and robust infrastructure. Enhanced early warning systems and hazard mitigation strategies could reduce this impact.
- Lack of safe drinking water is a key determinant of vulnerability, particularly in the Dhar district. Investments in water infrastructure and clean water access are essential for improving health and agricultural productivity, which are foundational to resilience.
- Living in Kutcha houses heightens vulnerability to property loss during natural hazards, revealing the need for housing improvements to mitigate climate impacts and ensure community safety.
- Limited access to communication platforms and social media increases vulnerability by restricting awareness and preparedness for climate impacts. Enhancing digital connectivity and media access can improve knowledge dissemination and engagement with early warning systems.
- Poverty is associated strongly with increased vulnerability, showing the major role of financial inclusion and income stability in enhancing resilience. Economic empowerment of tribal households is an essential strategy for reducing vulnerability.
- Awareness and familiarity with early warning systems lessen vulnerability in Chhindwara but show inconsistent effects in Dhar, emphasizing the importance of community trust, understanding, and localized application of these systems.
- Participation in skill development and training programs expands livelihood security and reduces vulnerability. These activities

enhance adaptive capacities, demonstrating the value of building social networks and community awareness.

The livelihoods of tribal communities in Dhar and Chhindwara are greatly influenced by their exposure to climate hazards, sensitivity to infrastructure gaps, and adaptive capacities. Dhar experiences higher vulnerability due to its greater incidence of extreme weather events and food insecurity. At the same time, Chhindwara benefits from relatively better infrastructure and higher education levels, which enhance its adaptive capacity. Key determinants of vulnerability comprise inadequate housing, limited access to water, and insufficient communication infrastructure. Reducing these vulnerabilities, enhancing educational opportunities, improving infrastructure, and strengthening social safety nets are essential for building resilience in these communities.

6.5 Limitations

While carrying out this empirical assessment of livelihood vulnerability to CC and variability among tribal communities in Madhya Pradesh, several limitations have been identified. Some of the major limitations are described below.

- ❖ The reliance on long-term gridded climate data from the India Meteorological Department (IMD) with spatial resolutions of $0.25° \times 0.25°$ for rainfall and $1° \times 1°$ for temperature is one of the major limitations of this study. Although these datasets offer comprehensive temporal insights (1951–2023), their spatial resolution may not capture localized microclimates or extreme weather events, especially in regions with diverse topographies, scarce meteorological stations, or local weather patterns. It can limit the study's ability to correctly represent climate variability at a small scale, which is essential for understanding climate impacts at the community level.

- ❖ The district-level CC vulnerability assessment primarily emphasizes historical data, such as Environmental factors from the Forest Survey of India 2021, the State Disaster Management Plan – Madhya Pradesh, FIRMS, MODIS, and socioeconomic data from the Census 2011, which could potentially result in the omission of emerging vulnerabilities. It is important to note that these sources may have certain limitations regarding accuracy and timeliness. These data may not show current conditions or the changing nature of vulnerability due to the rapid socioeconomic changes in Madhya Pradesh, especially in rural and tribal areas. Changes in infrastructure, economic development, and population dynamics, which could directly influence vulnerability, might not be captured by old data.
- ❖ District-level assessments may not effectively capture localized variations, and selecting indicators and their respective weightings can be subjective. Factors beyond environmental and socioeconomic factors, such as governance and infrastructure, are not comprehensively considered.
- ❖ Furthermore, the socio-demographic data collected from respondents can't cover all aspects of experiences, which could lead to biases in understanding the broader impacts on these communities. The emphasis on rainfall and temperature data does not explain other essential climatic factors, such as humidity and hailstorms, that can significantly influence the livelihoods of tribal communities in these regions.
- ❖ This study focuses on tribal communities in particular regions, which only applies to the same regions. It can't be generalized to other communities or regions.
- ❖ Lastly, the study employs robust statistical methods, including the Mann-Kendall test, the Pettitt test, and innovative trend analysis for

climate data analysis. Still, it didn't use future projections and their impacts on livelihood.

As discussed here, these limitations call for the scope of future research to enhance climate resilience in vulnerable regions like Madhya Pradesh.

6.6 Scope for Future Research

Future research focused on livelihood vulnerability to CC and variability in Madhya Pradesh can build upon the findings of this study by highlighting existing limitations and exploring possibilities to improve understanding.

- ❖ Enhancing spatial and temporal resolution in climate data is necessary to provide a more accurate representation of climate impacts at the community level and improve the accuracy of vulnerability assessments. Furthermore, incorporating real-time data from weather stations could make climate information more reliable and timelier.
- ❖ Future research should include up-to-date socioeconomic data, which will provide a more holistic view of vulnerability and better predict how CC impacts may unfold.
- ❖ Exploring advanced methodologies for vulnerability assessment, such as Bayesian networks, machine learning algorithms, or system dynamics modelling, could allow for a more comprehensive understanding of the factors influencing vulnerability.
- ❖ A more sector-specific approach to vulnerability could be beneficial, focusing on areas like agriculture, water resources, health, and infrastructure. Interdisciplinary research involving climatologists, ecologists, social scientists, and policymakers would further enhance findings and provide valuable insights for adaptation and policy development.
- ❖ An essential future direction is to include Indigenous Knowledge Systems (IKS) in climate vulnerability studies. Understanding

traditional ecological knowledge, early warning practices, and community-based coping mechanisms will improve the scientific narrative and support more culturally grounded adaptation planning.

- Gender-specific climate vulnerability analysis, particularly among tribal women, is another important research scope. Future studies should explore how gender roles, access to resources, and adaptive capacities differ between male and female members of tribal communities to develop more inclusive adaptation strategies.

- Another essential scope for future research is to increase understanding of the relationship between local knowledge, climate perceptions, and livelihood strategies. Future studies can advance a more holistic view of how tribal communities perceive CC and adapt their livelihood strategies by employing qualitative methods such as in-depth interviews, participatory rural appraisals, or focus group discussions.

- Conducting cross-regional and comparative studies with other regions in India or internationally could provide a broader understanding of collective vulnerabilities and help identify best practices for CC adaptation.

6.7 Policy Recommendations

Understanding the connection between CC effects and tribal communities is necessary for developing future approaches to enhance resilience and reduce vulnerability. Based on the findings of this study, the policy recommendations outlined to address CC impacts in Madhya Pradesh focus on tribal communities (Fig 6.1), as described below:

- Integrating adaptive agricultural practices, such as climate-resilient crops, irrigation efficiency, and agroforestry, along with implementing policies like the National Mission for Sustainable Agriculture , the Farmers' Produce Trade and Commerce

(Promotion and Facilitation) Bill, 2020, the Farmers (Empowerment and Protection) Agreement of Price Assurance and Farm Services Bill, 2020, and the Essential Commodities (Amendment) Bill, 2020, is crucial for building resilience and reducing vulnerability to climate change.

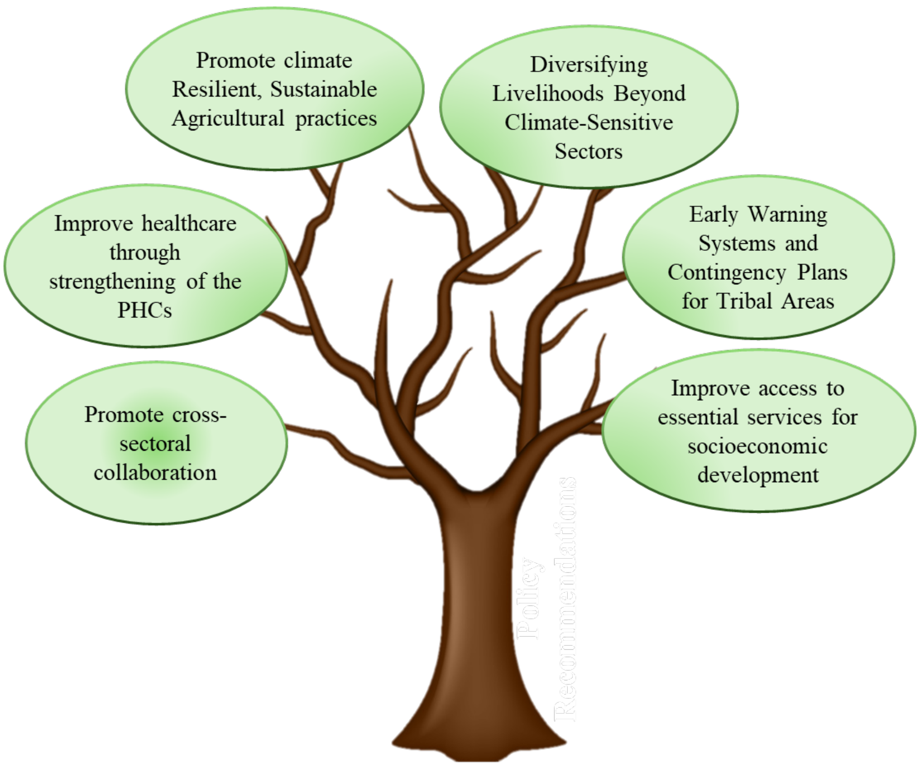


Fig. 6.1: Recommendations for future research and policy development

- Increasing climate vulnerability poses a high threat to their health. However, these poor people rely heavily on local medical practices that are highly accessible and cheap. Therefore, schemes that improve healthcare facilities in these areas are necessary to reduce climate-induced health risks such as heat stress and water-borne diseases. Expanding healthcare infrastructure through primary health centres (PHCs), integrating mobile health units, and awareness campaigns on hygiene and climate-related health impacts are essential to protect vulnerable populations (Saxena & Joshi, 2024).

- Moreover, diversifying livelihoods through skill development programs in sectors such as handicrafts, small enterprises, and ecotourism can reduce dependency on agriculture and forest resources, enhancing economic stability. Livelihood diversification and the provision of employment opportunities through policy measures have the potential to alleviate vulnerability. Enhancing programmes such as the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) and skill development initiatives will enhance employment opportunities (George et al., 2023).
- For socioeconomic development, augmenting access to essential services like potable water, sanitation facilities, reliable electricity, and clean energy is important for reducing climate vulnerability and improving human development indicators (du Plessis, 2023) (Arana, 2016). Improving the Targeted Public Distribution System and expanding educational and healthcare infrastructure can contribute to adaptive capacity (George et al., 2023).
- Effective early warning systems that provide timely weather predictions can improve preparation for severe weather incidents (Pulwarty & Sivakumar, 2014). This strategy is essential to the perceptions of increased frequency and intensity of climate hazards among the tribal communities.
- Cross-sectoral collaboration among government agencies, civil society organizations, and local communities is essential for implementing holistic strategies. Fostering partnerships between policymakers, researchers, and development practitioners as well as community people will ensure that climate adaptation solutions are region-specific, socially inclusive, and ecologically sustainable (Mallick et al., 2024).

These suggestions aim to create a resilient and adaptable framework that augments the capacity of tribal communities to cope with the challenges posed by CC while contributing to broader sustainable development goals, including SDG-13 on climate action.

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