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Exploring Adaptive Capacity of Indian Agriculture to Climate Change: An Agroclimatic Zone Level Analysis

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ABSTRACT

Climate is changing, and farmers across the globe are at the centre of this crisis. Therefore, adaptive capacity is crucial for addressing it. This study aimed to capture the adaptive capacity of farmers in mainstream agroclimatic zones in India. To develop a robust adaptive capacity index for mainstream agroclimatic zones in India, this study utilises large-scale data collected from the NSSO's 77th round, the 2011 Census, and the 2015-16 Agricultural Census, along with an indicator approach. Furthermore, a total of 29 indicators covering six dimensions — physical resources capacity, financial resources capacity, human resources capacity, social resources capacity, livelihood diversity capacity, and information accessibility capacity —to capture the regional dimensions of climate adaptation in Indian agriculture. The grass-root robust results show that the Gujarat Plains and Hills zone has the highest adaptive capacity, while the East Coast Plains and Hills zone has the lowest adaptive capacity to deal with climate change. This paper emphasised the need for more investigation into the possibilities for successful involvement in local and regional methods of vulnerability assessment and the improvement of adaptive capacity. This study's empirical findings indicate that female-headed households should be prioritised in both ongoing and new intervention projects concerning climate change and agriculture.

Keywords: Climate change adaptation, adaptive capacity, agroclimatic zones, regional vulnerability, sustainable agriculture

JEL codes: Q01, Q15, Q18, Q54, R11

I

INTRODUCTION

Human activities on climate change are the leading cause of the observed temperature increase during the mid-20th century. During the period from 1880 to 2012, the global average surface temperature increased by 0.8^0C (IPCC, 2013). According to the Intergovernmental Panel on Climate Change (IPCC, 2013), several locations worldwide have already seen significant warming at a regional level. Approximately 20–40 per cent of the global population has experienced a temperature increase above 1.5^0C. The current increase in temperature has already led to significant changes in both human and ecological systems, including an increase in droughts, floods, and other forms of severe weather. It led to rising sea levels and a loss of biodiversity. The alterations are giving rise to unparalleled hazards for susceptible groups, such as farmers (Mysiak et al., 2016). Most vulnerable individuals residing in low- and middle-income nations, such as India, depend on agriculture and face periodic food insecurity, which is partially associated with increasing migration and poverty (IPCC, 2012b). Globally, numerous ecosystems face significant threats (IPCC, 2014a). The global economy's expansion has led to longer life expectancy and higher income levels in many parts of the world. However, despite these positive developments, some zones continue to suffer from widespread poverty and extreme income inequality, as well as limited access to resources. These conditions further exacerbate the vulnerability of these zones to the impacts of climate change, in addition to the existing problems of environmental degradation and pollution (Dryzek, 2016).

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In a 1.5°C warmer world, adaptation to climate change will be crucial, as major consequences will manifest in every area (IPCC, 2014a). Climate adaptation choices include several types of responses, including structural, physical, institutional, and social measures. The efficacy of these alternatives primarily relies on factors such as governance, political determination, adaptable capabilities, and financial resources (Sovacool et al., 2015). The simulation findings indicate that limiting warming to 1.5°C will result in a decrease in the number of individuals affected by hunger, water stress, and sickness (Clements, 2009). The findings also suggest that implementing measures to adapt to climate change might reduce the vulnerability of impoverished populations to the risks of flooding and drought, particularly in African and Asian countries (Winsemius et al., 2018). In terms of regional benefits from climate change adaptations, we anticipate fewer obstacles for impoverished communities in terms of food and water security, clean energy availability, and environmental well-being at 1.5°C compared to 2°C (Byers et al., 2016).

Assessing the adaptive capability at the local level is a challenging task. The adaptability of farmers relies on their perceptiveness, the availability of resources, government support, and social networking. Three theories, including the protective motive theory, the theory of planned behaviour, and the integrated framework, are available to examine how farmers respond to a changing climate.

The protective motive hypothesis was initially developed to examine the relationship between fear appeals and attitude modification. It is a prominent theory in the field of research on health preventive behaviour. In addition to its use in health-risk studies, protection motivation theory has also been applied to analyse other protective behaviours, such as nuclear war preventive behaviour (World Bank, 2005) and water conservation behaviour (Birthal and Ali, 2005). This demonstrates that the theory can be used as a general decision-making model for various threats (Huang and Wang, 2014). The marketing communication field has conducted tests on several aspects of the theory (Newton et al., 2016). Nevertheless, the idea has not been extensively used in studies on natural hazards, environmental issues, or climate change. The protective motivation hypothesis consists of three stages: information perception, cognitive mediating processes, and coping behaviour. Initially, individuals receive two types of information: environmental information (such as fluctuations in precipitation and temperature) obtained from acquaintances, family members, neighbours, or through personal observation; and interpersonal information derived from personality traits and individual experiences. Regarding climate change adaptation, farmers can acquire knowledge about climate change and adaptation strategies from various sources, including public media, extension staff, agricultural cooperatives, fellow farmers, their families, or their own personal experiences. Furthermore, the primary evaluation of adaptation occurs within the cognitive mediating process. The stage captures the assessment of threats and the strategies used to cope with them. Individuals evaluate the advantages and disadvantages of adaptive and maladaptive reactions to form their assessments of potential danger and strategy for dealing with it. The chance of choosing an option is influenced by an increase in perceived advantages and a decrease in perceived costs. Maladaptive reaction is associated with both internal and extrinsic incentives, whereas the cost refers to how people perceive the intensity and vulnerability of the hazard. In the context of climate change adaptation, a maladaptive reaction refers to the failure to implement adaptive measures or engage in fatalism, denial, and wishful thinking. Thus, the incentives method is deemed inapplicable and is therefore disregarded for additional investigation. Fear is believed to have an indirect impact on behavioural modification due to the intensity of the perceived danger. Adaptive response refers to the advantages that may be characterised in terms of response efficacy and self-efficacy. Through a comparison of the advantages and disadvantages of adaptive reaction, people ultimately develop a coping evaluation, which leads to their desire to safeguard themselves from danger, also known as the protection motive (Asian Development Bank, 2014). Ultimately, coping behaviour is influenced by cognitive processes and reflects the actions people decide to take.

Moreover, the theory of planned behaviour (Ellis, 2000) is a well-recognised theory of decision-making that is often used to elucidate intentional adjustments. The idea enhances the protective motive theory by including psychological factors that influence people's desire to engage in behaviour, namely, farmers' adaptive behaviour against climate change. The theory addresses this constraint by including perceived behavioural control as a factor of intention. The three factors' contribution levels to intention are unequal and vary depending on behaviours and situation (Ellis, 2000).

As stated previously, both theories include both benefits and drawbacks. Therefore, this research employed a blended model that incorporates the favourable features of farmers' behaviour, their ability to respond to climate change, and their adaptation techniques, specifically through an integrated conceptual framework. The primary components of this framework include the evaluation of both the risk and perception of climate change, as well as the assessment of adaptation strategies. Risk perception refers to the way people evaluate the level of danger they face based on their impression of the likelihood and severity of the threat, without taking any action to modify their behaviour (Deressa et al., 2009). Perceived likelihood pertains to an individual's anticipation of encountering a potential danger. Farmers may anticipate the likelihood of their crops being able to withstand rising temperatures, impending droughts, heightened saline intrusion, or erratic rainfall patterns.

Adaptation assessment involves assessing and evaluating risks. The concept comprises three components: perceived self-efficacy, perceived adaptation efficacy, and perceived adaptation costs. Regarding climate change, farmers' perceived self-efficacy would be diminished if they lacked sufficient technical expertise in farming, making it challenging for them to adapt their planting practices effectively to cope with unfavourable climatic conditions. Their perceived adaptation effectiveness includes their assessment of how well crop and variety diversity or enhanced water conservation measures mitigate the impacts of rising average temperatures or the risk of drought. In addition, farmers' perceived adaptation costs include factors such as their evaluation of expenses related to heat-tolerant crop types or the implementation of water conservation methods, as well as the time and effort invested in these procedures.

After doing a risk and adaptation assessment, farmers decide whether to adapt or engage in maladaptation. Adaptive reactions aid in mitigating harm, while maladaptive responses, such as fatalism, denial, and wishful thinking, serve to shield individuals from experiencing unpleasant emotions associated with perceived danger, such as dread. For instance, if farmers have a strong perception of elevated climate change risk but possess little ability to respond, they may choose to abstain from using new crop types, refrain from investing in water conservation practices, or opt against altering their cropping schedule.

Furthermore, when farmers choose adaptive reactions, they initially have the desire to carry out adaptation procedures. However, the choice to implement adaptation measures is influenced by objective resources, which in turn may be shaped by the willingness to adapt. For example, farmers may aim to modify their crop management strategies, broaden the range of crops and varieties they grow, and adjust their planting methods and schedules in response to evaluating the risks posed by climate change and their ability to adapt. Nonetheless, their tangible actions are influenced by their degree of expertise, the adequacy of their financial resources, the amount of time and effort they can allocate, and the presence of social or institutional assistance to facilitate the implementation of these measures (Figure 1).

With this aim, the present study seeks to evaluate the adaptive capabilities of farmers residing in India's major agroclimatic zones. Previous research has either evaluated the adaptation ability of farmers in a single area or made comparisons between two zones (Gupta and Bandyopadhyay, 2014; Datta and Bhagirath, 2022; Dasgupta et al., 2022; Jatav et al., 2024). Furthermore, Jatav (2024) has investigated the adaptive capacity of mainstream agro-climatic zones; however, his study is limited to adaptive capacity indices and excludes climate dimensions such as rainfall and temperature trends. Additionally, his study covered only three dimensions of adaptive capacity, namely environmental, social, and economic, whereas adaptive capacity assessment requires a more robust estimation. This gap exists in the current study.

This research establishes connections between several areas of study in the current investigation. The research constructs an adaptive capability index by using 29 agroecological, socioeconomic and demographic indicators. These indicators have been allocated across six domains: physical resources capacity, financial resources capacity, human resources capacity, social resources capacity, livelihood diversity capacity, and information accessibility capacity, to comprehensively capture the adaptive capacity of Indian farmers to changing climates.

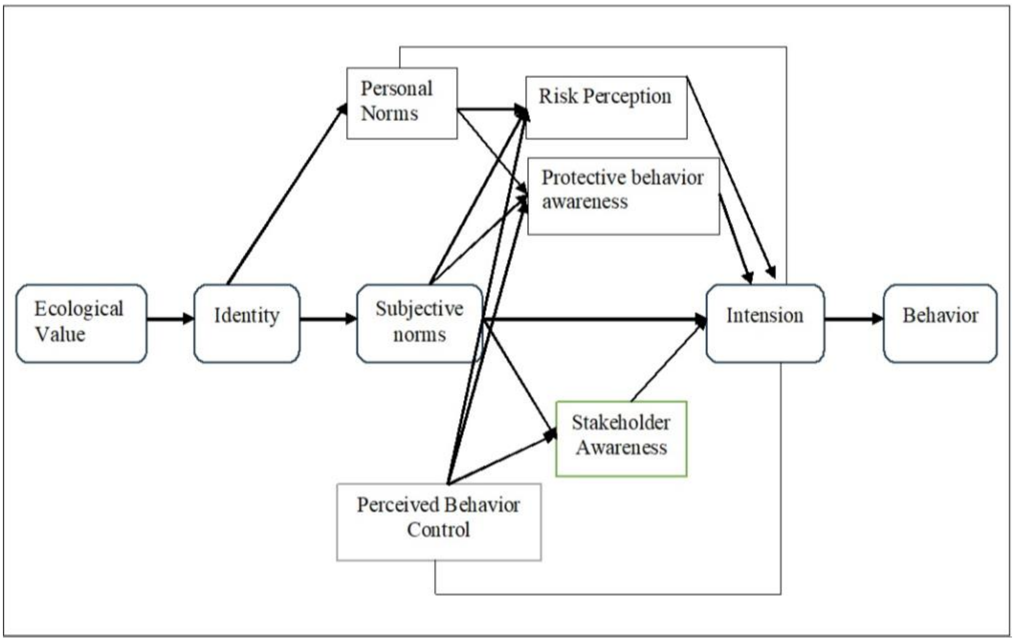

FIGURE 1. INTEGRATED FRAMEWORK
Source: Kim et al. 2024

II

MATERIALS AND METHODS

2.1 Study Area and Data Sources

The present study covers 14 mainstream agroclimatic zones, excluding the island zone. As far as spatial characteristics are concerned, the Himalayan zone is divided into two agroclimatic zones: the Western Himalayan Zone and the Eastern Himalayan Zone, which cover approximately 18.44 per cent of the geographical area. The Gangetic Plain Zone is divided into four agroclimatic zones: the Lower Gangetic Plain, the Middle Gangetic Plain, the Upper Gangetic Plain, and the Trans-Gangetic Plain. It covers approximately 15.89 per cent of the geographical area. The Plateau and Hills zone is divided into four agroclimatic zones: Eastern Plateau and Hills, Central Plateau and Hills, Western Plateau and Hills, and Southern Plateau and Hills. It covers 44.19 per cent of the geographical area. The Coastal Plains and Hill zone is divided into two zones, namely, East Coast Plains & Hills and West Coast Plains & Ghats, which cover 9.69 per cent of the geographical area. The Gujarat Plains, Hills, and Western Dry zones collectively cover approximately 11.53 per cent of the geographical area.

As far as the climatic conditions of all agroclimatic zones are concerned, they vary from cold and arid to humid in the Himalayan zone and humid to dry in the Gangetic Plains. Plateau zones remain semi-arid to dry, while coastal zones have semi-arid to dry, sub-humid climate conditions. The climatic conditions in the Gujarat plains vary from arid to dry sub-humid, while the climate in the Western Dry Zone ranges from arid to extremely arid.

To develop an adaptive capacity index for different agroclimatic zones of India, the present study used NSSO's 77th round (2019-20), the agriculture census (2015-16), census (2011), and the Ministry of Agriculture and Farmers Welfare, Government of India data.

2.2 Rationalisation of Adaptive Capacity Indicators

Adaptive capacity refers to a human system's ability to adjust to climate change, encompassing fluctuations and extreme occurrences, to mitigate potential damage, capitalise on opportunities, and address the ensuing consequences (Adger et al., 2003; Jatav and Singh, 2023). The system's adaptable capacity relies on the availability of financial resources, human resources, and adaptation options. This capacity fluctuates based on the particular hazards and sectors included. A region adept at flood management may regard a heat wave as unexpected (Fussel and Klein, 2006; Jatav and Sanatan, 2022; Jatav et al., 2022; Jatav and Kalu, 2023). This section examines the methodology for identifying appropriate and realistically viable indicators of adaptive capacity, taking into account the available information. This study classifies the indicators into six dimensions of adaptive capacity, namely (1) physical, (2) financial, (3) human, (4) social, (5) livelihood diversity, and (6) information accessibility.

The physical resources capacity index comprises eight indicators, including mean land size, cropped area under marginal farms, irrigation & cropping intensities, access to all seasonal roads, forest area, livestock ownership, and farmers with agricultural land (Table 1). It is evident that, post-green revolution, Indian agriculture is facing rapid land fragmentation, which results in higher cultivation costs (Chand et al., 2011). Sklenicka et al. (2014), based on grassroots evidence, found that land fragmentation leads to small land holdings that may be difficult to maintain economically without external support, especially from the government. Therefore, the role of livestock is vital in ensuring a regular income to sustain livelihoods, even during the off-cropping season (Birthal and Ali, 2005). Furthermore, assured irrigation resulted in higher productivity even in the dry regions (World Bank, 2005).

The financial resources denote the farmers' possession and availability of monetary assets, which are vital for adapting to climate change. Therefore, a total of five indicators —namely, membership in agricultural societies, crop insurance, remittances, credit from institutional sources, and access to tractors —are used to develop the financial resources capacity index for different agroclimatic zones (Table 1). As Chand et al. (2011) found that the cost of cultivation has increased manifold, both ex-ante and ex-post adaptation measures provide an additional safety net for farmers. Ex-ante adaptation measures, such as crop insurance, cover natural damages to crops at a minimal premium rate, often with an add-on feature of institutional credit in India. On the other hand, remittances from out-migrated family members and credit at minimal rates from agricultural credit societies have added adaptive capacity to the highly susceptible agricultural system to climate change (Huang and Wang, 2014).

Likewise, the human resources capacity index comprises four indicators: agricultural training, literacy rate, mean age, and working population. According to Deress et al. (2009), they found that a young, literate person with ultra-modern skills has a higher capability to cope with a changing climate than those who don't have them. Further, Ellis (2000) argued that educational background, age, talents, and overall attributes, which include training in agronomic methods to improve output.

Social resource capacity in highly climate-susceptible sectors in India, i.e., agriculture, plays a crucial role in helping the farming community cope with climate change (Deressa et al., 2008 & 2009; Singh, 2020a; Jatav, 2020). Therefore, to capture the social resources capacity of Indian farmers, this paper included four indicators, namely female-headed households, joint family structure, information sharing with fellow farmers, and out-migration, to develop a social resources capacity index for different mainstream agroclimatic zones of India. In their grassroots study of African farming families, Deressa et al. (2009) found that female-headed households are relatively more vulnerable than male-headed households. The reason behind this is that males have easy access to information about climate change. Singh (2020a) in the Bundelkhand region of Uttar Pradesh finds that marginalised socioeconomic groups, namely scheduled caste and scheduled tribes, have the least adaptive capacity to cope with a changing climate, and exhibit significant vulnerability to climate change. Consequently, the exchange of knowledge among farmers at the local level has improved their ability to adapt (Jatav, 2020).

The presence of a variety of livelihoods plays a crucial role in adapting to climate change (Pavola, 2008). Therefore, using household-level data collected primarily from the 77th round of the National Sample Survey Office, the livelihood diversity index was calculated for different agroclimatic zones of India, excluding the Island region. A total of four indicators — employment in MGNREGA, crop diversification, uncultivable area, and income from farming — were considered for the development of the livelihood diversity capacity index. In the modern Indian economy, MGNREGA provides employment guarantee to unskilled persons. Furthermore, diversifying crops is also crucial for livelihood diversification in response to climate change (Ziervogel et al., 2008). Therefore, these indicators are considered to contribute to the adaptive capacity of Indian farmers positively. On the other hand, uncultivable areas and a solely agricultural income source were considered negative indicators that restrict farmers' ability to cope with a changing climate.

Lastly, accessible information is a vital resource for effectively addressing climate change. Farmers can obtain information from various sources, including the Kisan Call Centre, Ratio, and television. They can then make informed decisions on selecting the most suitable and cost-effective adaptation measures. Additionally, minimum support prices provide farmers with the guarantee of receiving the highest possible price for their agricultural products.

TABLE 1. SELECTED RATIONAL ADAPTIVE CAPACITY INDICATORS

Sub-components	Indicators	Functional Relationship	Data Source	Source
Physical Resources Capacity Indicators (PRCI)	Average Farm Size (LS)	+	Agriculture Census, 2015-16	Chand *et al.,* 2011
	% of Area under Marginal Farms (MF)	-	Agriculture Census, 2015-16	Sklenicka *et al.,* 2014
	Irrigation Intensity (%) (II)	+	GoI, 2019	Birthal and Ali, 2005
	Cropping Intensity (%) (CI)	+	GoI, 2019	Birthal and Ali, 2005
	% of Accessibility of All Seasonal Roads (T)	+	Census, 2011	World Bank, 2005
	% of Forest Area (F)	+	GoI, 2019	World Bank, 2005
	% of Farmers owned any Livestock (L)	+	NSSO, 2019	Birthal and Ali, 2005
	% of Farmers own Land (LP)	+	NSSO, 2019	Birthal and Ali, 2005
Financial Resources Capacity Indicators (FRCI)	% of Farmers Member of Agricultural Societies (MAC)	+	Census, 2011	Newton *et al.,* 2016
	% of Farmers taken Crop Insurance (Insurance)	+	NSSO, 2019	Newton *et al.,* 2016
	% of Farmers receiving Remittances (Remittances)	+	NSSO, 2019	Newton *et al.,* 2016
	% of Farmers taken Loan from Institutional Sources (Credit)	+	NSSO, 2019	Huang and Wang, 2014
	% of Farmers access Tractors (Tractors)	+	NSSO, 2019	Newton *et al.,* 2016
Human Resources Capacity Indicators (HRCI)	% of Farmers taken Agricultural Training (Training)	+	NSSO, 2019	Ellis, 2000
	Literacy Rate (in %) (Literacy)	+	Census, 2011	Deressa et al., 2009
	Average Age of farmers (in years) (Age)	+	NSSO, 2019	Hassan and Nhemachena, 2008
	% of Working Population in the Households of farmers (Population)	+	NSSO, 2019	Hassan and Nhemachena, 2008
Social Resources Capacity Indicators (SRCI)	% of Female-headed Households (FHH)	-	NSSO, 2019	Deressa *et al.,* 2008
	% of HHs living in Joint Family (more than 6 people in HHs) (Family)	+	NSSO, 2019	Deressa *et al.,* 2009
	% of HHs taken Information to Fellow Farmers (Knowledge)	+	NSSO, 2019	Deressa *et al.,* 2008
	% of HH member stayed away from usual place of residence for 15 day or more for employment purpose (Migration)	+	NSSO, 2019	Singh, 2020a
Livelihood Diversity Capacity Indicators (LDI)	% of HHs working in MGNREGA (MGNREGA)	+	NSSO, 2019	Paavola, 2008; Singh, 2013
	% of Farmers growing more than one Crop (Crop diversification)	+	NSSO, 2019	Adger *et al.,* 2003; *Ziervogel et al.,* 2008
	% of Area not available for Cultivation (AAC)	-	GoI, 2019	Adger *et al.,* 2003
	% of Income from Farm Produce (NFI)	+	NSSO, 2019	Adger *et al.,* 2003
Information Accessibility Capacity Indicators (IAI)	% of HHs having access of Telephone (Telephone)	+	Census, 2011	Hahn *et al.,* 2009
	% of farmers aware about Minimum Support Price (MSP)	+	NSSO, 2019	Hahn *et al.,* 2009
	% of farmers taken Information to Radio and TV (Information)	+	NSSO, 2019	Hahn *et al.,* 2009
	% of Farmers perceived that Natural Calamities are cause Crop Loss (Perception)	+	NSSO, 2019	Hahn *et al.,* 2009

Source: Author's Calculation, 2025.

Farmers' ability and desire to adjust agricultural systems are contingent on their understanding of climate change and their assessment of the hazards associated with severe occurrences (Hahn et al., 2009).

2.3 Estimation Method

2.3.1Tracking Trends of Rainfall and Temperatures

The STATA version 13 software was employed to analyse the climate data, utilising statistical methods such as the Mann-Kendall and Sen's slope tests. Other researchers have widely adopted these methods to gain insights into the trends of temperature and precipitation phenomena (Bharath and Venkatesh 2022). Daily gridded data from 1951 to 2022 were collected from the Indian Meteorological Department. Furthermore, daily gridded data were converted into three periods: annual, rabi, and kharif, for different agroclimatic zones. In this study, the Mann-Kendall test was employed to detect potential progressive changes in the sequence of extreme variables. This nonparametric test, based on ranking, allows for the determination of the significance of the correlation between time and the research variable (i.e., rainfall and temperature), as established by Mann and Kendall. For a random variable x, which requires assessment for stationarity, a simple independent value (let x_1…., x_n represent) was needed. The following is a definition of the Mann-Kendall statistics (Equation 1).

$$S = \sum_{i=1}^{Y=1} \sum_{t=i+1}^{Y} sgn(x_1 - x_2) \dots\dots\dots\dots (1)$$

Where, Y is the sample size, and x_i and x_t are the consecutive data values. The test statistic is computed by tallying the number of cases in which the second value is greater than the first for all pairings (x_i, x_t), as well as the number of cases where it is smaller. The difference between these two counts is then calculated by equation (Equation 2), and the resulting value of Z is utilised to ascertain the presence of a statistically significant trend:

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var\,(S)'}}, \\ 0, \\ \frac{S-1}{\sqrt{Var\,(S)'}} \end{cases} \dots\dots\dots(2)$$

If S > 0; if S = 0, and if S<0

In the presence of identical values in the series, the variance S can be defined as follows (Equation 3).

$$Var(S) = \frac{1}{18} Y(Y-1)(2Y+5) - \sum_{p=1}^{q} t_p(t_p-1)(2t_p+5) \ldots\ldots (3)$$

Where t_p represents the count of ties that involve k values. A positive (or negative) value of Z signifies an upward (or downward) trend, and its significance is evaluated by comparing it to the critical value or significance level of the test.

2.3.2 Application of the Indicator Approach

This paper uses an indicator approach to normalise and calculate the adaptive capacity index for various agroclimatic zones in India, due to the differing measurements of the data utilised. Further, theoretically, there are two approaches, theory-driven and data-driven (Below et al., 2012). This paper has adopted a data-driven approach (Singh and Singh, 2019), as the data-driven (i.e., indicator approach) has merit in analysing data across gender, caste, class, and dimensions (Halsnas and Trarup, 2009). Following a comprehensive review of the literature, a total of 29 indicators were identified for the development of the adaptive capacity index. Further, as data and differential values, the data were normalised to the indicators to create a single scale based on their functional relationship with adaptive capacity, using equation (4) for a positive relationship and equation (5) for a negative relationship (Pandeyy and Jha, 2012; Jatav and Kalu, 2023).

$$Index_{sv} = \frac{S_v - S_{min}}{S_{max} - S_{min}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (4)$$

$$Index_{sv} = \frac{S_{max} - S_v}{S_{max} - S_{min}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (5)$$

Where, S_v is the actual value of the indicator at the agroclimatic zone level, and S_{min} and S_{max} are the minimum and maximum values of the indicator agroclimatic zone (Hahn *et al.,* 2009; Jatav, 2024). In this way, the indicators were normalised on a scale of 0 to 1.

2.3.3 Assigning Weight

Given that assigning appropriate weights to different components is an important issue in constructing an index, this study adopted the statistical weight method suggested by Iyengar and Sudarshan (1982).

$$W_i = \frac{1}{\sum_{i=1}^{n} \frac{1}{\sqrt{var(Index_{sv})}} * \sqrt{Var(Index_{sv})}} \ldots\ldots\ldots\ldots\ldots. (6)$$

Where, W_i is the weight of ith indicator, and Var(〖Index〗 _sv) is the variance of the standardised value of the ith indicator in the jth agroclimatic zone. The calculated weights were used to construct the component index P_i for the jth agroclimatic zone, as shown in equation (4).

$$P_i = \frac{\sum_{i=1}^{n} Index_{sv} * W_i}{\sum_{i=1}^{n} W_i}\left(0 < W_i < 1, \sum_{i=1}^{n} W_i = 1\right) \dots\dots\dots..(7)$$

Finally, the adaptive capacity index for each agroclimatic zone is calculated as an average of size components, i.e., PRCI, FRCI, HRCI, SRCI, LDI, and IAI. Based on the index score, this study ranked the agroclimatic zones in descending order. An agroclimatic zone with a higher index score indicates that it has higher adaptive capacity. Further, using the quartile estimation technique, the least and most adaptive capacity districts are also identified. Moreover, Figure 2 illustrates how adaptive capacity indicators were selected and how adaptive capacity indices for various agroclimatic zones were calculated.

III

RESULTS AND DISCUSSION

3.1 Changes in Rainfall and Temperatures

Table 2 depicts changes in rainfall patterns in India over 1951–2020. The Indian agricultural system caters to seasonal variations by dividing changes in minimum temperature, maximum temperature, and rainfall into three phases: annual (January to December), kharif season (June to September), and Rabi season (October to March). The long-term annual rainfall recorded 1192.32 millimetres, while the kharif and rabi seasons recorded 226.02 and 28.84 millimetres, respectively. From 1951–80 to 1981–2020, there was a decline in all phases, including annual, kharif, and rabi. The decline was 27.46 millimetres in annual rainfall, 7.33 millimetres in kharif season rainfall, and 0.79 millimetres in rabi season. Our results are based on the findings of Dash et al. (2009), who reported a decreasing trend in monsoon rainfall. For the period 1871–2011, there was a decrease in annual rainfall (-0.04 millimetres per year).

Conversely, all phases experienced increases in both minimum and maximum temperatures. The annual minimum temperature increased by 0.19 °C in the same period, with further increases of 0.20 °C in the kharif season and 0.22 °C in the rabi season. Furthermore, across all phases, the maximum temperature was relatively higher than the minimum temperature.

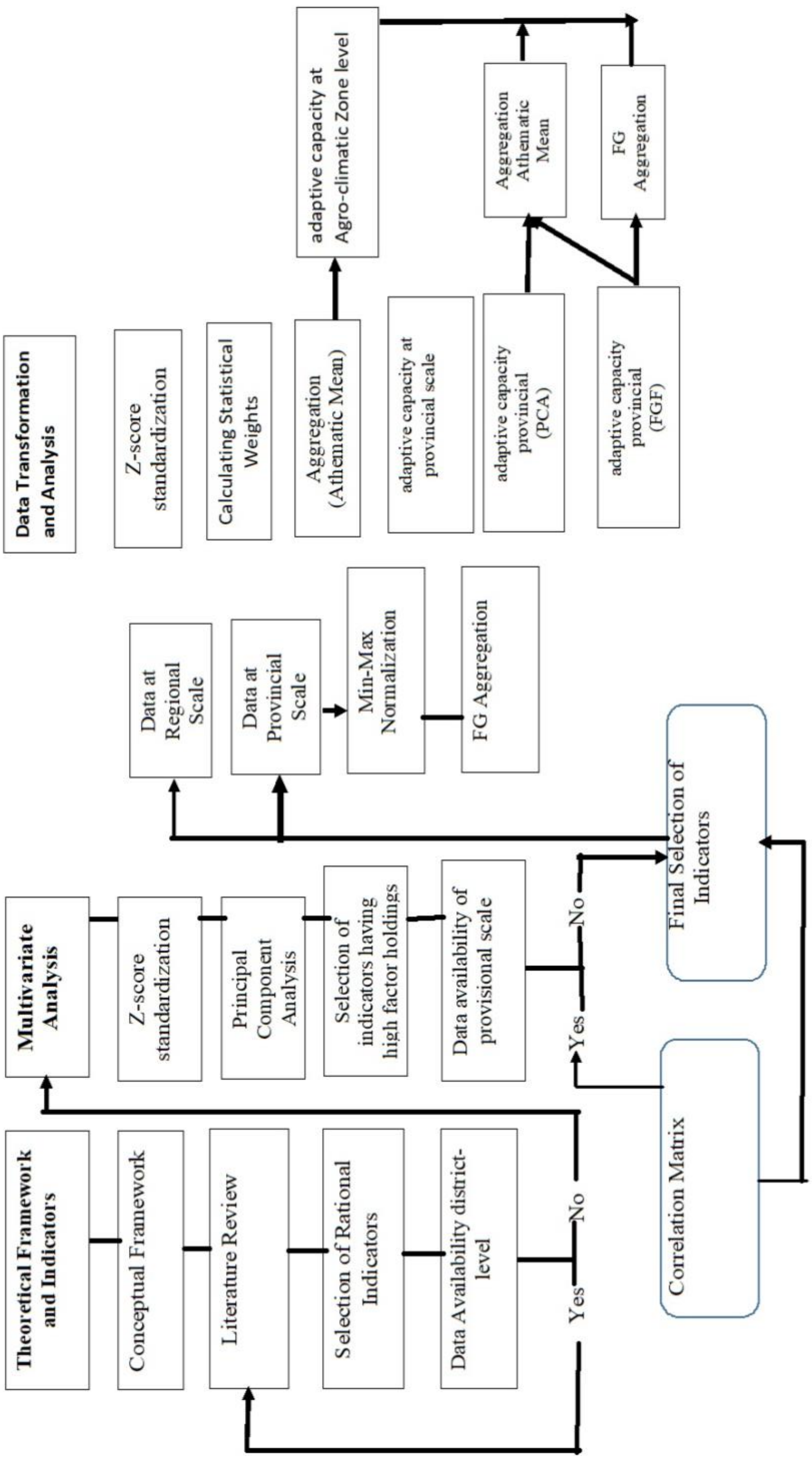

FIGURE 2. FLOW CHART FOR ADAPTIVE CAPACITY ASSESSMENT

TABLE 2. CHANGES IN RAINFALL AND TEMPERATURES

Variables	1951-80	1981-2020	1951-2020	Change 1951-80 to 1981-2020
		Rainfall (mm)		
Annual	1208.01	1180.55	1192.32	-27.46
Kharif Season	230.21	222.88	226.02	-7.33
Rabi Season	29.29	28.50	28.84	-0.79
		Minimum Temperature (°C)		
Annual	18.91	19.10	19.01	0.19
Kharif Season	23.72	23.92	23.83	0.20
Rabi Season	14.80	15.02	14.93	0.22
		Maximum Temperature (°C)		
Annual	30.87	31.14	31.02	0.27
Kharif Season	32.21	32.64	32.45	0.43
Rabi Season	28.16	28.38	28.28	0.22

Source: Author's estimation, 2025.

Moreover, the linear trends of rainfall and temperature also confirm that rainfall has declined annually, particularly during the kharif and rabi seasons, while temperature has been increasing over the period 1951–2020 (Figure 3–11).

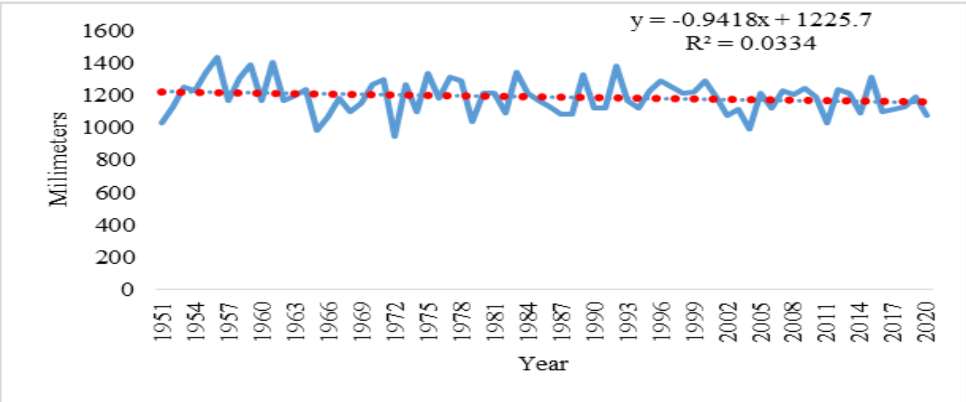

FIGURE 3. TRENDS OF ANNUAL RAINFALL IN INDIA

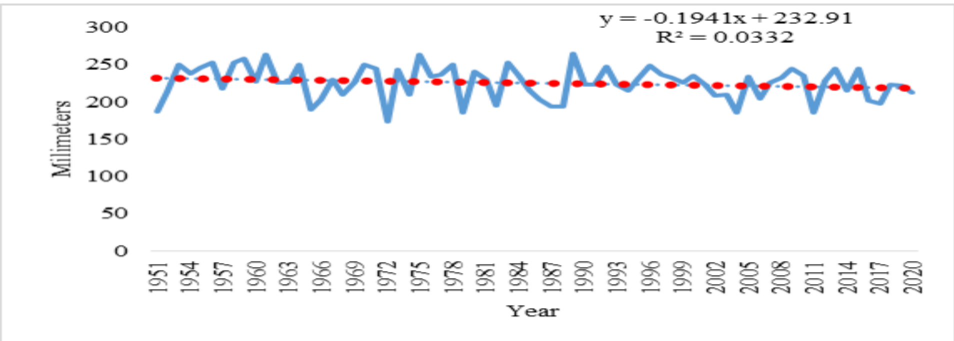

FIGURE 4. TRENDS OF KHARIF SEASON RAINFALL

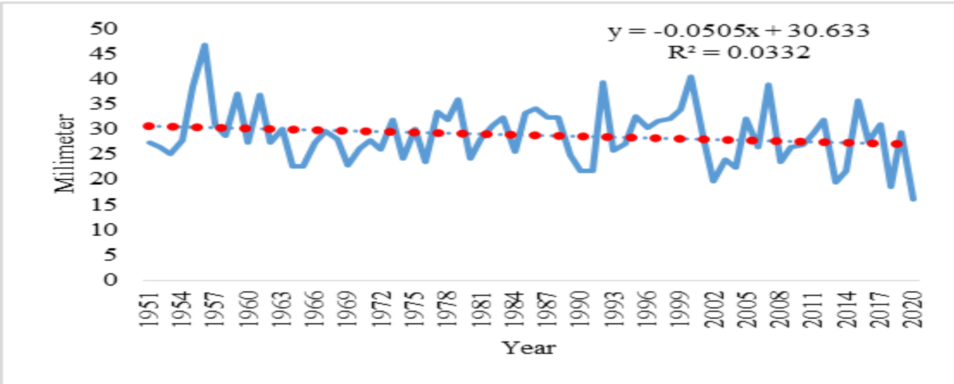

FIGURE 5. TRENDS OF RABI SEASON RAINFALL

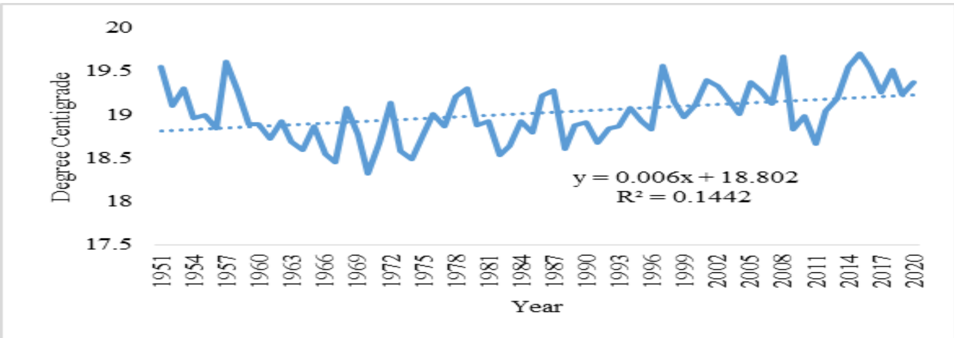

FIGURE 6. TRENDS OF ANNUAL MINIMUM TEMPERATURE IN INDIA

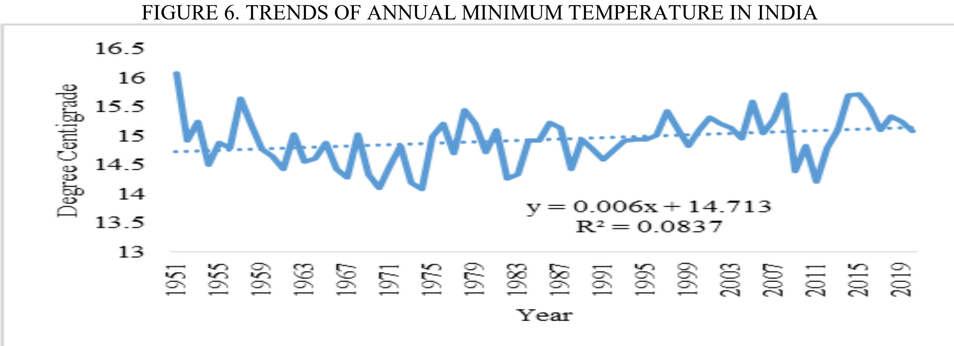

FIGURE 7. TRENDS OF KHARIF SEASON MINIMUM TEMPERATURE IN INDIA

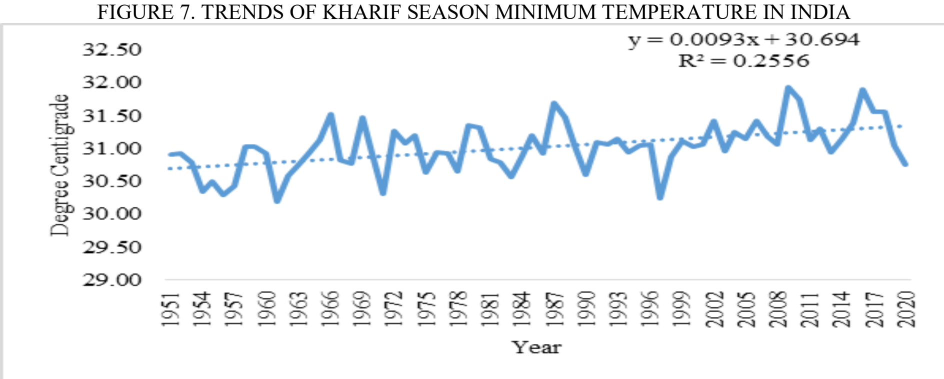

FIGURE 8. TRENDS OF RABI SEASON MINIMUM TEMPERATURE IN INDIA

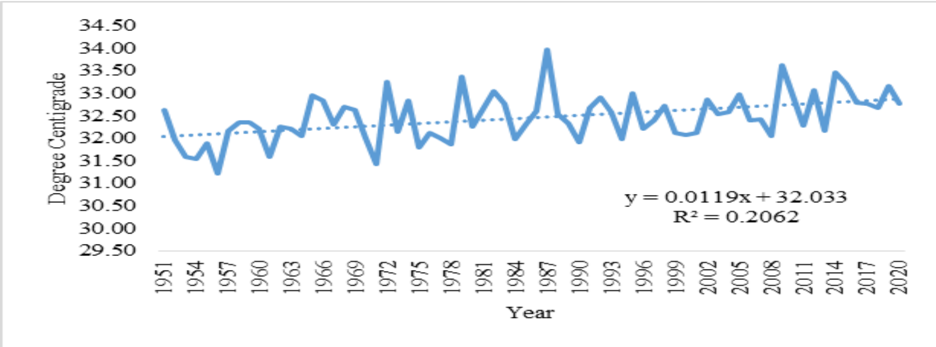

FIGURE 9. TRENDS OF ANNUAL MAXIMUM TEMPERATURE IN INDIA

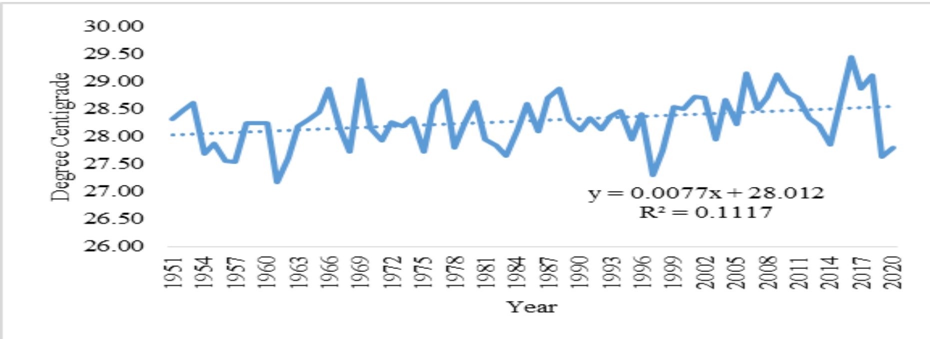

FIGURE 10. TRENDS OF KHARIF SEASON MAXIMUM TEMPERATURE IN INDIA

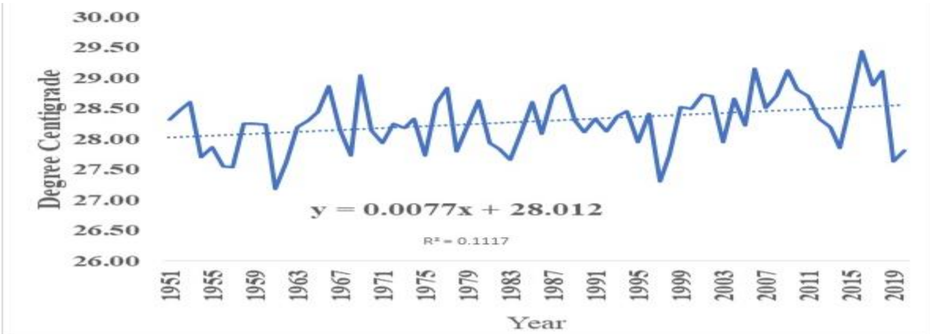

FIGURE 11. TRENDS OF RABI SEASON MAXIMUM TEMPERATURE IN INDIA

3.2 Detecting trends of rainfall: Evidence from the Mann-Kendall Test

This section tracks the long-term trends of rainfall using the Mann-Kendall test. As rainfall in India is non-linear, Hence, it's better to use a non-linear test to detect trends instead of a linear test. This paper utilised data from 1951 to 2020 for various agroclimatic zones to identify annual rainfall trends, followed by the kharif and rabi seasons. This paper used STATA version 13 to calculate the Mann-Kendall tau trends. The results show that annual rainfall has declined over the period 1951–2020 across all agroclimatic zones, except for the east coast plains and hills zone, followed by the Gujarat plains and hills zone, and the western dry zone (Table 3). However, reports indicated a shift in rainfall during the kharif season. Agroclimatic zones, such as the eastern Himalayan region, the Gujarat plains and hills, and the western dry zones, reported an increase in rainfall. In contrast, other zones showed a significant decline in kharif season rainfall distribution. Additionally, rainfall during the rabi season is crucial for the growth of fruits and vegetables. The rabi season saw a significant decline in rainfall across all agroclimatic zones, resulting in a higher artificial water requirement for wheat and other crops grown during the rabi season.

TABLE 3: DETECTING TRENDS OF RAINFALL IN INDIA

Agroclimatic Zone	Rainfall		
	Annual	Kharif	Rabi
Western Himalayan Zone (WHR)	-0.041*	-0.060*	-0.073*
Eastern Himalayan Zone (EHR)	-0.001*	0.009*	-0.065*
Lower Gangetic Plain Zone (LGPR)	-0.021	-0.028*	-0.045*
Middle Gangetic Plain Zone (MGPR)	-0.151**	-0.152**	-0.087*
Upper Gangetic Plain Zone (UGPR)	-0.275*	-0.241*	-0.211*
Trans Gangetic Plain Zone (TGPR)	-0.209**	-0.157**	-0.135**
Eastern Plateau and Hills Zone (EPHR)	-0.062*	-0.062*	-0.131**
Central Plateau and Hills Zone (CPHR)	-0.128*	-0.109*	-0.116*
Western Plateau and Hills Zone (WPHR)	-0.082*	-0.039*	-0.058*
Southern Plateau and Hills Zone (SPHR)	-0.057*	-0.090*	-0.054*
East Coast Plains and Hills Zone (ECPHR)	0.041*	-0.026*	0.024*
West Coast Plains and Hills Zone (WCPHR)	-0.094*	-0.059*	-0.049*
Gujarat Plains and Hills Zone (GPHR)	0.030*	0.028*	-0.045*
Western Dry Zone (WDR)	0.039*	0.034*	-0.034*

** Significant at 1%
* Significant at 5%
Source Author's estimation, 2025

3.3 Detecting Trends in Minimum and Maximum Temperatures: Evidence from the Mann-Kendall Test

The non-parametric test (i.e., the Mann-Kendall test) results show that the annual minimum temperature has increased in all the agro-climatic zones except EPHR (Table 4). Further, the kharif season is vital for the Indian agricultural system. The increase in nighttime temperatures is critical for vegetation. The Mann-Kendall trend analysis revealed that minimum temperatures have increased in all agro-climatic zones except LGPR, MGPR, UGPR, and TGPR. Furthermore, the Rabi season's night temperatures pose a potential threat to food security, as the Indian wheat crop primarily grows during this season, and the plains are home to the leading cereal crop. The Mann-Kendall test results indicate that nighttime temperatures are rising in all agro-climatic zones.

Additionally, the annual day temperature (maximum temperature) has been rising in all zones except the Gangetic Plains zone, while the maximum temperature increased in the kharif and rabi seasons in all agro-climatic zones.

3.4 Socioeconomic Status of Indian Farmers

The socioeconomic characteristics reveal that farming families consist of young individuals with a high level of education, living in nuclear family arrangements (Table 5). Most farmers own marginal and tiny plots of land, often less than 2 hectares in size. Regarding technical proficiency, a mere 1.12 per cent of farmers have received formal agricultural training.

TABLE 4. TRACKING THE TRENDS OF MINIMUM TEMPERATURE IN DIFFERENT AGROCLIMATIC ZONES

Agroclimatic zone	Minimum Temperature			Maximum Temperature		
	Annual	Kharif	Rabi	Annual	Kharif	Rabi
WHR	0.473*	0.388*	0.296*	0.338*	0.460*	0.429*
EHR	0.249*	0.441*	0.506*	0.448*	0.369*	0.159**
LGPR	0.214*	-0.008^{NS}	0.294*	-0.087^{NS}	0.279*	0.183**
MGPR	0.031^{NS}	-0.018^{NS}	0.191**	-0.089^{NS}	0.012^{NS}	0.114^{NS}
UGPR	0.181**	-0.058^{NS}	0.109**	-0.086^{NS}	0.087^{NS}	0.256*
TGPR	0.298*	-0.046^{NS}	0.034^{NS}	-0.065^{NS}	0.197**	0.337*
EPHR	-0.061^{NS}	0.209**	0.142**	0.194**	-0.074^{NS}	0.066^{NS}
CPHR	0.293*	0.174**	0.141**	0.102^{NS}	0.144**	0.297*
WPHR	0.173^{NS}	0.317*	0.146**	0.232*	0.135**	0.154**
SPHR	0.211**	0.616*	0.371*	0.656*	0.342*	0.146**
ECPHR	0.174**	0.544*	0.315*	0.539*	0.184**	0.205**
WCPHR	0.255*	0.599*	0.431*	0.621*	0.399*	0.179**
GPHR	0.383^{NS}	0.218*	0.183**	0.106^{NS}	0.357*	0.301*
WDR	0.362^{NS}	0.187**	0.181**	0.076^{NS}	0.251*	0.342*

** Significant at 1%
* Significant at 5%
Source: Author's estimation, 2025

In contrast, around 18.98 per cent and 16.53 per cent of farmers have sought guidance from other farmers and self-help organisations (SHGs), respectively. MGNREGA served as the primary source of hope during the off-cropping season, with approximately 45.07 per cent of farmers participating in MGNREGA to ensure their livelihood stability. As a result of connections in the institutional credit system, around 60 per cent of farmers have obtained loans from institutions, whereas farmers have a 52 per cent rate of indebtedness. The situation extends beyond loans, including a lack of information about the Minimum Support Price (MSP). Furthermore, a mere 19.72 per cent of farmers possess knowledge about the MSP. Consequently, due to limited access to advanced technology and market trends, approximately 12.87 per cent of farmers have not diversified their cropping patterns as an adaptation strategy to mitigate the adverse effects of climate change and cope with market disruptions. There was just one encouraging aspect: farmers had a reasonable level of awareness about natural disasters. Approximately 63.89 per cent of farmers acknowledged that natural disasters were the primary cause of crop losses.

TABLE 5. SOCIOECONOMIC CHARACTERISTICS OF INDIAN FARMERS

Indicators	India
Average Family Size (Nos.)	5.27
Literacy Rate (%)	74.04
Average Age (Years)	29.89
Farmers taken Professional Training (%)	1.12
Seasonal Migration for Employment (%)	1.47
Average Annual Farm Income (Rs.)	52, 272
Average Land Size (Hec.)	1.15
Indebtedness Rate (%)	52.00
Farmers have taken Credit from Institutional sources (%)	60.00
Irrigation Intensity (%)	123.10
Cropping Intensity (%)	142.13
Area not available for Cultivation (%)	16.11
Farmers are members of SHG (%)	16.53
Farmers having Livestock (%)	74.34
Farmers working under MGNREGA	45.07
Female-headed household (%)	12.97
Farmers are aware of the Minimum Support Price (%)	19.72
Farmers sharing Knowledge to Fellow Farmers (%)	18.98
Farmers receiving Remittances (%)	10.17
Farmers living in Joint Family (%)	40.45
Farmers growing more than one Crop in a Season (%)	12.87
Farmers perceived that Natural Calamities were the main reason for Crop Loss(%)	63.89

Source: Estimated from NSSO, 77^{th} round unit level data, 2019, Census, 2011, MoAFW, 2019

3.5 Physical Resources Capacity Index (PRCI)

Physical resources are tangible assets that serve as preventive measures against natural disasters. According to the physical resource capacity index, the Gujarat Plains and Hills Zone have the highest resource capacity (i.e., 0.584). In contrast, the Upper Gangetic Plain Zone has the lowest resource capacity (i.e., 0.449).

According to the cross-indicator analysis, improved transportation and land ownership were the main factors contributing to higher resource capacity in the Gujarat Plains and Hills Zone (Table 6). The minimal forest area, on the other hand, was the main factor influencing lower resource capacity in the Upper Gangetic Plain Zone. Globally interconnected economies need efficient transportation to allocate resources effectively to combat climate change (Dasgupta and Laplante, 2007). Additionally, forest ecosystems are robust and provide sustenance and energy to the nearby population. Throughout history, woods have functioned as reservoirs and played a role in maintaining the equilibrium of gases in the atmosphere (Seppälä et al., 2009).

TABLE 6. AGRO-CLIMATIC ZONE WISE STATUS OF PHYSICAL RESOURCES CAPACITY INDEX

Agro-climatic Zone	Land Size	Marginal Farmers	Irrigation Intensity	Cropping Intensity	Transportati on	Forest Area	Livestock	Farmers Poses Land	Physical Resources	Rank
GPHR	0.499	0.674	0.269	0.314	0.943	0.150	0.822	0.998	0.584	1
TGPR	0.473	0.324	0.582	0.429	0.882	0.036	0.936	1.000	0.583	2
WPHR	0.561	0.579	0.300	0.339	0.671	0.215	0.732	0.994	0.549	3
SPHR	0.628	0.461	0.257	0.296	0.855	0.166	0.710	1.000	0.547	4
WDR	0.507	0.704	0.272	0.450	0.490	0.002	0.893	1.000	0.540	5
WCPHR	0.424	0.257	0.393	0.495	0.911	0.216	0.586	1.000	0.535	6
WHR	0.380	0.337	0.549	0.267	0.567	0.241	0.865	0.996	0.525	7
EHR	0.515	0.553	0.647	0.220	0.362	0.308	0.574	1.000	0.522	8
MGPR	0.559	0.843	0.178	0.367	0.374	0.059	0.790	0.998	0.521	9
ECPHR	0.449	0.343	0.622	0.221	0.650	0.238	0.639	0.997	0.520	10
CPHR	0.523	0.599	0.078	0.475	0.386	0.179	0.876	0.998	0.514	11
EPHR	0.327	0.506	0.303	0.296	0.437	0.339	0.608	0.999	0.477	12
LGPR	0.642	0.205	0.000	0.515	0.356	0.147	0.725	1.000	0.449	13
UPGR	0.004	0.260	0.435	0.449	0.406	0.047	0.819	0.999	0.427	14

Source: Author's estimation, 2025

3.6 Financial Resources Capacity Index (FRCI)

According to the financial resource capacity index calculations, the West Coast Plains and Hills Zone have the highest financial resource capacity, while the Eastern Himalayan Zone has the lowest (Table 7). According to the cross-indicator study, farmers in the West Coast Plains and Hills area have the highest level of participation in agricultural societies. Additionally, they get the maximum amount of remittances among the Agroclimatic Zones. In contrast, farmers residing in the Eastern Himalayan area have the lowest rate of participation in agricultural societies and receive the smallest amount of remittances. Additionally, a small proportion of farmers have successfully protected their crops from natural disasters.

TABLE 7. AGROCLIMATIC ZONE WISE STATUS OF FINANCIAL RESOURCES CAPACITY INDEX

Agro-climatic Zone	Micro-Finance	Insurance	Remittances	Institutional Credit	Tractors	Financial Resources Capacity Index	Rank
WCPHR	0.409	0.050	0.180	0.653	0.008	0.260	1
GPHR	0.356	0.166	0.028	0.606	0.026	0.237	2
WPHR	0.379	0.078	0.061	0.614	0.017	0.230	3
ECPHR	0.152	0.090	0.263	0.536	0.004	0.209	4
SPHR	0.210	0.060	0.086	0.666	0.008	0.206	5
WDR	0.174	0.226	0.105	0.470	0.039	0.203	6
TGPR	0.284	0.004	0.084	0.559	0.041	0.195	7
CPHR	0.115	0.147	0.081	0.543	0.034	0.184	8
UPGR	0.070	0.044	0.196	0.584	0.020	0.183	9
WHR	0.103	0.008	0.140	0.494	0.014	0.152	10
MGPR	0.159	0.013	0.090	0.435	0.022	0.144	11
EPHR	0.103	0.096	0.067	0.405	0.014	0.137	12
LGPR	0.103	0.051	0.152	0.306	0.002	0.123	13
EHR	0.029	0.004	0.020	0.357	0.002	0.082	14

Source: Author's Calculation, 2025

3.7 Human Resources Capacity Index (HRCI)

The human resource capacity index calculation reveals that the Trans-Gangetic Plain Zone has the highest human resource capacity index, with a score of 0.492, while the Eastern Plateau and Hills Zone has the lowest human resource capacity index, with a score of 0.330 (Table 8). According to the cross-indicator study, farmers in the Tran Gangetic Plain area have a high level of experience. Conversely, farmers from the Eastern Plateau and Hills zone have the least amount of experience.

TABLE 8. AGROCLIMATIC ZONE-WISE STATUS OF HUMAN RESOURCES CAPACITY INDEX

Agro Climatic Zone	Formal Training	Literacy Rate	Mean Age	Working Population	Human Resources Capacity Index	Rank
TGPR	0.011	0.713	0.910	0.334	0.492	1
LGPR	0.015	0.722	0.556	0.310	0.401	2
WCPHR	0.021	0.821	0.479	0.280	0.400	3
MGPR	0.009	0.623	0.499	0.456	0.397	4
WPHR	0.012	0.716	0.503	0.354	0.396	5
EHR	0.008	0.721	0.513	0.368	0.395	6
CPHR	0.007	0.641	0.500	0.434	0.395	7
WDR	0.002	0.596	0.426	0.442	0.367	8
ECPHR	0.016	0.687	0.414	0.322	0.360	9
SPHR	0.035	0.672	0.413	0.295	0.354	10
UPGR	0.003	0.660	0.275	0.435	0.343	11
WHR	0.009	0.711	0.307	0.339	0.341	12
GPHR	0.007	0.730	0.250	0.370	0.339	13
EPHR	0.011	0.658	0.295	0.355	0.330	14

Source: Author’s Calculation, 2025

3.8 Social Resources Capacity Index (SRCI)

The estimated social resource capacity index values indicate that the Gujarat Plains and Hills Zone have the highest social resource capacity (i.e., 0.451), while the Eastern Coast Plains and Hills Zone (Table 9) have the lowest social resource capacity (i.e., 0.168).

TABLE 9. AGROCLIMATIC ZONE-WISE STATUS OF SOCIAL RESOURCES CAPACITY INDEX

Agroclimatic Zone	Female Head of Household	Joint Family	Knowledge sharing	Seasonal Migration	Social Resources Capacity Index	Rank
GPHR	0.895	0.415	0.474	0.019	0.451	1
MGPR	0.909	0.550	0.217	0.014	0.422	2
CPHR	0.910	0.465	0.204	0.033	0.403	3
UPGR	0.876	0.543	0.130	0.009	0.389	4
TGPR	0.912	0.464	0.171	0.003	0.388	5
EPHR	0.868	0.353	0.281	0.008	0.377	6
LGPR	0.866	0.318	0.260	0.023	0.367	7
WPHR	0.883	0.335	0.220	0.027	0.365	8
WDR	0.871	0.449	0.089	0.035	0.361	9
EHR	0.876	0.430	0.083	0.019	0.352	10
WHR	0.861	0.400	0.105	0.010	0.344	11
SPHR	0.820	0.275	0.247	0.008	0.338	12
WCPHR	0.789	0.252	0.181	0.012	0.309	13
ECPHR	0.181	0.220	0.261	0.011	0.168	14

Source: Author’s Calculation, 2025

According to the cross-indicator analysis, farmers in the Gujarat Plains and Hills Zone are highly inclined to share their knowledge with other farmers and have sought guidance from agricultural professionals and scientists. Conversely, in the Eastern Coast Plains and Hills Zone, decision-making sensitivity, particularly among female-headed households, diminishes the social resource capacity of the farmers.

3.9 Livelihood Diversity Capacity Index (LDCI)

According to the livelihood diversity capacity index scores, farmers in the Western Dry Zone have the highest level of employment diversification (i.e., 0.539). In contrast, farmers in the Trans Gangetic Plains Zone have the lowest level of livelihood diversification (i.e., 0.174) and rely solely on agriculture (Table 10). According to the cross-indicator analysis, farmers in the Western Dry Zone have the highest proportion of work in MGNREGA, whereas farmers in the Trans Gangetic Plains Zone have the lowest proportion of work in MGNREGA. Additionally, farmers in the Trans Gangetic Plains Zone have the lowest level of crop diversification and the highest amount of uncultivable land.

TABLE 10. AGROCLIMATIC ZONE WISE STATUS OF LIVELIHOOD DIVERSITY CAPACITY INDEX

Agro-climatic Zone	MGNR EGA	Crop Diversif ication	Area not available for Cultivation	Non-farm Income	Livelihood Diversity Capacity index	Rank
WDR	0.846	0.149	0.873	0.287	0.539	1
CPHR	0.635	0.177	0.875	0.321	0.502	2
EPHR	0.677	0.045	0.893	0.325	0.485	3
WPHR	0.452	0.287	0.874	0.264	0.469	4
EHR	0.674	0.031	0.834	0.310	0.462	5
WHR	0.446	0.146	0.882	0.298	0.443	6
UPGR	0.261	0.200	0.850	0.326	0.409	7
SPHR	0.455	0.195	0.808	0.169	0.407	8
MGPR	0.162	0.192	0.807	0.383	0.386	9
WCPHR	0.307	0.144	0.860	0.129	0.360	10
GPHR	0.221	0.101	0.858	0.243	0.356	11
ECPHR	0.618	0.145	0.189	0.187	0.285	12
LGPR	0.589	0.003	0.229	0.244	0.266	13
TGPR	0.058	0.100	0.168	0.372	0.174	14

Source: Author’s Calculation, 2025

3.10 Information Accessibility Capacity Index (IAI)

The computed information accessibility capacity index scores indicate that farmers from the Southern Plateau and Hills zone have the highest level of access to information about climate change (0.578), whereas farmers from the Western Dry Zone have the lowest level of access (0.390). According to the cross-indicator analysis, the Southern Plateau and Hills Zone have the highest percentage of farmers who believe that climate change leads to crop loss. Conversely, the Western Dry Zone has the lowest level of awareness regarding the minimum support price, the lowest rate of seeking technical advice from experts, and the lowest perception of climate change (Table 11).

TABLE 11. AGROCLIMATIC ZONE WISE STATUS OF INFORMATION ACCESSIBILITY CAPACITY INDEX

Agro-climatic Zone	Telephone	Awareness of MSP	Information gathering	Farmer's perception	Information Accessibility Capacity Index	Rank
SPHR	0.980	0.156	0.373	0.803	0.578	1
WCPHR	0.970	0.150	0.437	0.689	0.561	2
GPHR	0.985	0.167	0.251	0.803	0.552	3
TGPR	0.981	0.387	0.339	0.476	0.546	4
LGPR	0.912	0.265	0.203	0.732	0.528	5
EPHR	0.733	0.382	0.126	0.709	0.487	6
ECPHR	0.933	0.152	0.220	0.632	0.484	7
WHR	0.925	0.130	0.290	0.572	0.479	8
UPGR	0.795	0.251	0.164	0.682	0.473	9
CPHR	0.839	0.135	0.152	0.761	0.472	10
WPHR	0.869	0.110	0.218	0.687	0.471	11
MGPR	0.665	0.294	0.192	0.562	0.428	12
EHR	0.723	0.051	0.178	0.658	0.403	13
WDR	0.989	0.102	0.051	0.419	0.390	14

Source: Author's Calculation, 2025

3.11 Adaptive Capacity Index (ACI)

The computed values for the relative adaptive capacity index indicate that the Gujarat Plains and Hills Zone have the highest adaptive capacity. At the same time, the East Coast Plains and Hills Zone exhibit the lowest adaptive capacity in addressing climate change (Table 12). The cross-indices research shows that the Gujarat Plains and Hills Zone have the highest capacity in terms of physical resources (0.584), financial resources (0.237), social resources (0.451), and information accessibility (0.552).

3.12 Identification of Low Adaptive Capacity Districts

By using quartile estimation, districts were classified into four categories: (i) low (0–25th percentile), (ii) medium (26–50th percentile), (iii) high (51–75th percentile), and (iv) very high (76–100th percentile). Thereafter, this paper identified low adaptive capacity districts within the sub-components of adaptive capacity indices. The results show that none of the 640 districts fall under the low adaptive capacity category (Table 13). Furthermore, out of 640 districts, 339 (53.44%) have a low financial resource capacity. Furthermore, out of 640 done (0.16%), it falls under low human resource capacity. As far as social resource capacity is concerned, out of 640 districts, 16 (2.56%) fall under the low-capacity category. Likewise, five districts (0.80%) have low livelihood diversity capacity. The results for information accessibility capacity show that out of 640 districts, only nine (1.44%) fall under the low information accessibility capacity category. The overall adaptive capacity index indicates that of the 640 districts, 386

(61.76%) have medium capacity, followed by 239 districts (38.24%) with high adaptive capacity, while none of the districts fall under the low or very high adaptive capacity categories.

3.13 Validation of Agroclimatic Zone-wise Adaptive Capacity Index

Validating the built index is crucial. The reason we may deem it "good" is that it exhibits a noteworthy association with its corresponding index. The Spearman's rank correlation coefficients indicate a positive association between the adaptive capacity index and all six sub-components, as shown in Figure 12. Furthermore, it may be inferred that having higher adaptive capacity is contingent upon the presence, consistency, and ease of dealing with a changing climate. Therefore, it has a strong correlation with its constituent parts (Shakeel et al., 2012).

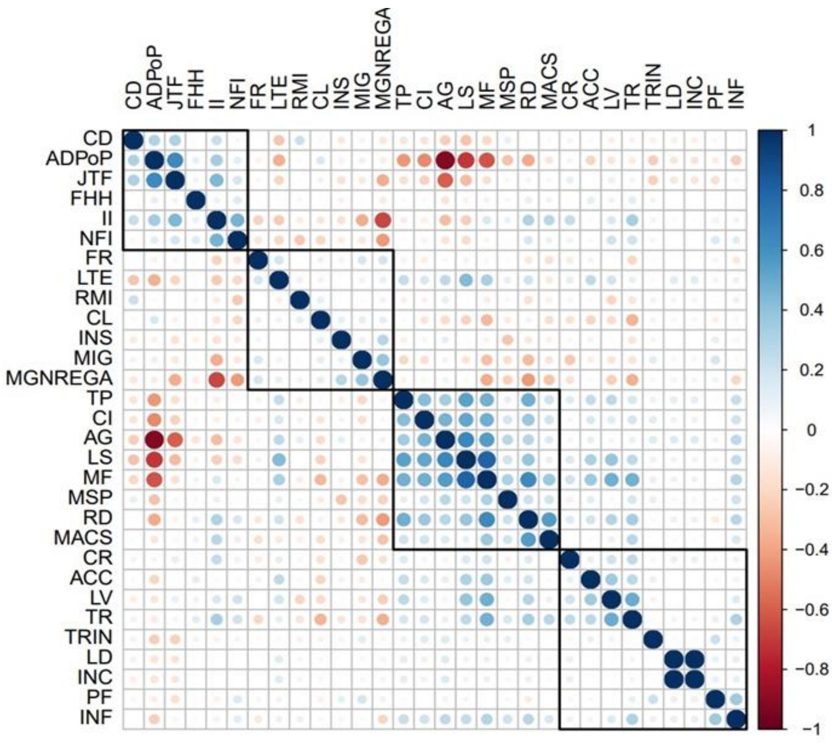

Figure 12. Validation of Agroclimatic Zone-wise Adaptive Capacity Index
Source: Author's estimation, 2024.

IV
DISCUSSION

Policies regarding climate change adaptation require meticulous formulation due to their complex context among impoverished and vulnerable cultures exposed to a diverse array of hazards. They should be an essential component of a development process that ensures the incorporation of climate adaptation into all relevant sectors of society, while also considering other significant factors such as social, economic

TABLE 12. AGROCLIMATIC ZONE WISE ADAPTIVE CAPACITY INDEX

Agroclimatic Zone	Physical Resources Capacity Index	Financial Resources Capacity Index	Human Resources Capacity Index	Social Resources Capacity Index	Livelihood Diversity Capacity Index	Information Accessibility Capacity Index	Adaptive Capacity Index	Rank
GPHR	0.584	0.237	0.339	0.451	0.356	0.552	0.420	1
WPHR	0.549	0.230	0.396	0.367	0.469	0.471	0.414	2
CPHR	0.514	0.184	0.395	0.403	0.502	0.472	0.412	3
SPHR	0.547	0.206	0.354	0.338	0.407	0.578	0.405	4
WCPHR	0.535	0.260	0.400	0.309	0.360	0.561	0.404	5
WDR	0.540	0.203	0.367	0.361	0.539	0.390	0.400	6
TGPR	0.583	0.195	0.492	0.388	0.174	0.546	0.396	7
MGPR	0.521	0.144	0.397	0.422	0.386	0.428	0.383	8
EPHR	0.477	0.137	0.330	0.377	0.485	0.487	0.382	9
WHR	0.525	0.152	0.341	0.344	0.443	0.479	0.381	10
UPGR	0.427	0.183	0.343	0.389	0.409	0.473	0.371	11
EHR	0.522	0.082	0.395	0.352	0.462	0.403	0.369	12
LGPR	0.449	0.123	0.401	0.367	0.266	0.528	0.356	13
ECPHR	0.520	0.209	0.360	0.168	0.285	0.484	0.338	14

Source: Author's Calculation, 2024

TABLE 13. DISTRICT WISE CATEGORISATION OF ADAPTIVE CAPACITY INDICES

Components	Low (0.000-0.204)	Medium (0.205-0.408)	High (0.409-0.612)	Very High (0.613-0.816)	Total
Physical Resources Capacity Index	0 (0.00)	39 (6.24)	520(83.20)	66 (10.56)	625 (100.00)
Financial Resources Capacity Index	339 (54.24)	282 (45.12)	4 (0.54)	0 (0.00)	625 (100.00)
Human Resources Capacity Index	1 (0.16)	553 (88.48)	71 (11.36)	0 (0.00)	601 (100.00)
Social Resources Capacity Index	16 (2.56)	378 (60.48)	226 (36.16)	5 (0.80)	625 (100.00)
Livelihood Diversity Index	5 (0.80)	202 (32.32)	355 (56.80)	63 (10.08)	625 (100.00)
Information Accessibility Index	9 (1.44)	158 (25.28)	378 (60.48)	80 (12.80)	625 (100.00)
Adaptive Capacity Index	0 (0.00)	386 (61.76)	239 (38.24)	0 (0.00)	625 (100.00)

Source: Author's Calculation, 2024

and environmental concerns. Mertz et al. (2009) proposed that national-level strategies should include targeted investments in physical and institutional assets. These investments should aim to decrease susceptibility to climate change and enhance the capacity to adapt while avoiding any unintended negative consequences. The present study results also align with those of Mertz et al. (2009). This study also observed that investment in environmental protection resources may offset the negative impact of climate change and enhance the adaptive capacity of Indian farmers living in diverse agro-climatic conditions. Further, Aggarwal (2008) projected that a temperature rise would lead to more frequent hot extremes, floods, droughts, cyclones, and gradual glacier recession, which in turn would result in greater instability in food production and adaptive capacity for Indian farmers. These results also align with the findings of the present study. Due to higher variability in rainfall and temperature, it resulted in lower environmental resource capacity and increased the degree of vulnerability. Furthermore, Hassan and Nhemachena's (2008) study highlights the critical role of improved market access, extension and credit services, technology, and farm assets such as labour, land, and capital in assisting farmers in adapting to climate change. These findings also coincide with the results of the current study. This study also reported that access to extension services, such as consultation with agricultural experts, insurance, credit, and awareness of remunerative prices, are key drivers responsible for adapting to a changing climate. Datta and Bhagirath's (2022) study highlights that variations in natural, physical, and financial capital primarily account for the varying adaptive capacities among farming households. These results also align with our study on a broader spectrum.

V

CONCLUSION AND POLICY RECOMMENDATIONS

This research first inquired about the mechanisms of adaptation and the entities involved in the agricultural sector that undergo adaptation to address the challenges posed by climate change. The empirical results show that the Gujarat Plains and Hills zone has the highest adaptive capacity, while the East Coast Plains and Hills zone has the lowest adaptive capacity to deal with climate change. This paper emphasised the need for more investigation into the possibilities for successful involvement in local and regional methods of vulnerability assessment and the improvement of adaptive capacity. This study's empirical findings indicate that female-headed households should be prioritised in both ongoing and new intervention projects concerning climate change and agriculture. Providing financial resources enables engagement in supplementary income-generating activities. This will contribute to diversifying their livelihood sources and improving their resilience to the impacts of climate change and variability. Possible adaptation options for the most vulnerable region include diversifying agricultural systems by cultivating crops that require less water, adopting advanced farming technologies, such as using different crop varieties, harvesters, and irrigation pumps, constructing dams and roads, and improving the mangrove forest plantation programme in the coastal area.

The findings provide an assessment of Indian farmers' adaptation ability at the grassroots level, including regional aspects. This study emphasised the need for more investigation into the possibilities for successful involvement in local and regional methods of vulnerability assessment and the improvement of adaptive capacity. Policies regarding climate change adaptation require meticulous formulation due to their complex context among impoverished and vulnerable cultures exposed to a diverse array of hazards. They should be an essential component of a development process that ensures the incorporation of climate adaptation into all relevant sectors of society, while also considering other significant factors such as social, economic, and environmental concerns. The present study proposes that national-level strategies should include targeted investments in physical and institutional assets. These investments should aim to decrease susceptibility to climate change and enhance the capacity to adapt, while avoiding any unintended negative consequences. Possible adaptation options for the most vulnerable zone include diversifying agricultural systems by cultivating crops that require less water, adopting advanced farming technologies such as different crop varieties, harvesters, and irrigation pumps, constructing dams and roads, and improving the mangrove forest plantation program in the coastal area.

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