# Original Research Article

# Assessing Climate Change Resilience in Central Indian Agriculture: A Regional Indicators-Based Approach and Agro-Climatic Zone Mapping


## ABSTRACT

Climate change has adversely hampered the agricultural economy of India, especially central India. To get insight into the present level of climate change resilience in Central India (Madhya Pradesh, Maharashtra, Chhattisgarh, Southern UP) a composite climate change resilience capacity index (CCRCI) was developed for selected 102 districts using 50 climatic, soil, crop, livestock and socio-economic indicators in agriculture. Mann- Kendall non-parametric trend analysis was employed to evaluate long-term climatic trends (*kharif* 1981- summer 2023) for key climatic indicators like daily average temperature, precipitation, relative humidity and root zone soil wetness. Standard methodologies of index development like normalisation and principal component analysis (PCA) for weight assignment were executed. After developing CCRCI, agro-climatic zone-wise mapping was done for all the selected districts. Results revealed that Maharashtra had the largest number of high climate-resilience districts, followed by Madhya Pradesh with a mix of resilience levels in Chhattisgarh and Southern UP showing significant gaps in climate preparedness. The findings underscore the need for targeted interventions in low-resilience districts, particularly in agro-climatic Zones VII (Eastern Plateau and Hills Region) and IX (Western Plateau and Hills Region), where climate exposure and limited adaptability pose significant risks to agriculture. This mapping highlights the diversity of challenges and opportunities in central India, offering a framework for region-specific climate change resilience planning.



*Keywords: Assessment, agro-climatic zones, composite climate change resilience capacity index, CCRCI, resilience*

## 1. INTRODUCTION

Climate resilience is the ability to anticipate, prepare for, and respond to hazardous events, trends, or disturbances related to climate (Center for Climate and Energy Solutions, 2023). Climate change refers to long-term shifts in temperatures and weather patterns (United Nations Framework Convention on Climate Change, 2023). Such shifts can be natural, due to changes in the sun's activity or large volcanic eruptions. But since the 1800s, human activities have been the main driver of climate change, primarily due to the burning of fossil fuels like coal, oil and gas. The phenomenon of climate change is a pressing global issue that poses significant challenges to various sectors, particularly agriculture. In regions like central India, where agriculture plays a crucial role in the economy and livelihoods of millions of people, understanding the economics of climate change resilience capacity and developing effective coping strategies is of paramount importance. Central India, encompassing states such as Madhya Pradesh, Chhattisgarh, and parts of Maharashtra and Southern Uttar Pradesh faces diverse climate patterns and weather extremes, including erratic rainfall, prolonged droughts, and increased frequency of extreme events such as floods and heatwaves. These climatic shifts have far-reaching consequences on agricultural production, farmer incomes, food security, and overall rural development (Balasundram et al., 2023). The monsoon plays a vital role in shaping the agro-climatic zones and agricultural crop production in India. It is the primary source of water for nearly 60% of India's rainfed agriculture which influences sowing patterns, crop growth, and overall yields. The onset, distribution, and withdrawal of the monsoon vary across regions, creating diverse agro-climatic zones suited for specific crops. For instance, paddy thrives in the eastern and southern regions due to abundant monsoon rains, while pulses and oilseeds dominate the drier zones of western and central India. However, erratic rainfall patterns, delayed monsoons, or excessive rains can disrupt farming activities, increase crop losses, and affect farmers' livelihoods, making monsoon predictability and climate-resilient agricultural practices vital for sustaining India's agrarian economy. For this purpose, much care has been taken to incorporate climatic variables like daily average precipitation. The resilience capacity of farming systems in Central India is a key determinant of their ability to withstand and recover from climate-related shocks (Tofu et al., 2023). It involves a range of factors, including access to resources, knowledge, technology, financial support, and institutional frameworks. Evaluating the economics of resilience capacity is essential to understand the costs and benefits associated with building climate resilience in the agricultural sector. Assessing the economic implications of these strategies can help identify the most effective and cost-efficient approaches for farmers in Central India. Through an interdisciplinary analysis that combines economic principles, agricultural sciences and climate studies, this study strives to contribute to the growing body of knowledge on climate change resilience in agriculture (Okolie et al., 2023). By quantifying the economic implications of resilience-building and identifying sustainable coping strategies, it aims to pave the way for evidence-based policies and interventions that promote climate-resilient agriculture and support the livelihoods of farmers in Central India. This research aims to shed light on What is the present level of resilience capacity of farmers to climate change vulnerability in the selected districts of Central India? In pursuit of this research question, a new composite climate change resilience capacity index (CCRCI) was developed, which included climate, crop productivity system, livestock, social and economic indicators for selected 102 districts in Central India, followed by district-level mapping of climate exposure, agricultural productivity, climate adaptability and climate change resilience capacity in the study region.

## 2. MATERIALS AND METHODS

For the development of district-level CCRCI, secondary data were collected on various climatic, socio-economic and farming-related variables for the selected 102 districts of Central India. All the variables were selected based on extensive literature enquiry and data availability. District level daily average precipitation corrected (mm/day), temperature at 2 meters (Degree Celsius), relative humidity (percentage) at 2 meters and root zone soil wetness (from the surface 0 cm to 100 cm below grade) data were obtained for a period of 43 years (*kharif* 1981 to summer 2023) from the National Aeronautics and Space Administration (NASA) Langley Research Center (LaRC) Prediction of Worldwide Energy Resource (POWER) Project funded through the NASA Earth Science/Applied Science Program for selected districts. District-level crop production statistics data, land utilization statistics, the area under cultivation, and average size of operational holdings of small and marginal farmers were collected across Central India, as were per cent sown area, per cent cropped area, total irrigated area and other farming-related data for the previous three agricultural years on an average (2022-23 to 2023-24) from various state government reports and state statistical and economic surveys. District-level data on livestock indicators like total bovine population and total milk production for the same period were obtained from the advanced estimates and district-wise livestock census data published by the Department of Animal Husbandry, State governments, livestock census and other official reports.

## 2.1 Climate Change Resilience Capacity Estimation

Climate Resilience is defined as the capacity of social, economic and ecosystems to cope with a hazardous event or trend or disturbance, responding or reorganising in ways that maintain their essential function, identity and structure as well as biodiversity in the case of ecosystems while also maintaining the capacity for adaptation, learning and transformation (IPCC Sixth Assessment Report, 2022). Vulnerability is the degree to which a system is susceptible to and unable to cope with the adverse effects of climate change, including climate variability and extremes. Exposure is the nature and degree to which a system is exposed to climate change. Climate adaptability is the capability of a production system or region to better adjust to climate change (IPCC, 2007). Climate change resilience capacity estimation is a risk management tool applied to reduce the vulnerability and exposure of agroecosystems to climate change and to enhance system resilience. Therefore, improving climate resilience is essential to enhance the climate adaptability of agroecosystems (Zong et al., 2022).

$$\boldsymbol{Composite\ Climate\ Change\ Resilience\ Capacity\ Index}\ (\boldsymbol{CCRCI}) = \boldsymbol{Climate\ Exposure\ Index} - (\boldsymbol{Agricultural\ Productivity\ Index} + \boldsymbol{Climate\ adaptability\ Index}) \quad (1)$$

In Eq. (1), the effect of the system's climate exposure is called 'potential impact', which is very much destructive in nature, if the region or production system (agricultural productivity) has a high magnitude of the index. (Rannow et al., 2010; Gitz et al., 2012; Coulibaly et al., 2015; Nguyen et al., 2016).

$$\boldsymbol{Climate\ Resilience} = \boldsymbol{Potential\ Impact} - (\boldsymbol{Agricultural\ Productivity} + \boldsymbol{Climate\ Adpatibility}) \quad (2)$$

where,

$$\boldsymbol{Potential\ Impact} = \boldsymbol{Exposure} \quad (3)$$

**Note:** The 'sensitivity' component of vulnerability estimation is not considered for the present analysis to avoid indicator overlapping and double counting. Instead, much care has been taken to introduce 'agricultural productivity' as an important component in the assessment of climate change resilience capacity (Zong et al., 2022).

## 2.2 Steps in Resilience Capacity Assessment

The following steps have been used to construct the district-level climate change resilience capacity index.

### 2.2.1 Identification of suitable indicators

The selection of indicators is largely based on the researcher's judgement and is of utmost importance for any study on climate resilience assessment. Hence, much care has been taken into consideration to finalize the indicator variables under each component by a thorough review of published literature and discussion with experts to give the *apriori* functional relationship (see Table 1). The functional relationship of all selected indicators in the three components of climate change resilience (climate exposure, agricultural productivity and climate adaptability) is given in Table 1.

**Table 1. Indicators considered in the computation of CCRCI**

| S.No. | Indicator | Relationship with component |
|---|---|---|
| | **Climate Exposure** | |
| 1 | Trend in *kharif* precipitation (Coefficient of trend) | + |
| 2 | Trend in *rabi* precipitation (Coefficient of trend) | + |
| 3 | Trend in *summer* precipitation (Coefficient of trend) | + |
| 4 | Trend in *kharif* temperature (Coefficient of trend) | + |
| 5 | Trend in *rabi* temperature (Coefficient of trend) | + |

| | | |
|---|---|---|
| 6 | Trend in *summer* temperature (Coefficient of trend) | + |
| 7 | Trend in *kharif* relative humidity (Coefficient of trend) | + |
| 8 | Trend in *rabi* relative humidity (Coefficient of trend) | + |
| 9 | Trend in *summer* relative humidity (Coefficient of trend) | + |
| 10 | Trend in *kharif* root zone soil wetness (Coefficient of trend) | + |
| 11 | Trend in *rabi* root zone soil wetness (Coefficient of trend) | + |
| 12 | Trend in *summer* root zone soil wetness (Coefficient of trend) | + |
| 13 | Return period of moderate meteorological drought (No. of years) | - |
| 14 | Return period of severe meteorological drought (No. of years) | - |
| 15 | Return period of extreme meteorological drought (No. of years) | - |
| 16 | No. of consecutive two or more drought years (No. of years) | + |
| 17 | Return period of two years or more persistent droughts (No. of years) | - |
| 18 | No. of consecutive three or more drought years (No. of years) | + |
| 19 | Return period of three years or more persistent drought (No. of years) | - |
| 20 | No. of consecutive four or more drought years (No. of years) | + |
| 21 | Return period of four years or more persistent drought (No. of years) | - |
| | **Agricultural Productivity** | |
| 22 | Average size of operational holdings for marginal farmers (ha) | + |
| 23 | Average size of operational holdings for small farmers (ha) | + |
| 24 | Share of cropped area to the total cropped area of state (%) | + |
| 25 | Share of net sown area to the total geographic area of district (%) | + |
| 26 | Cropping intensity (%) | + |
| 27 | Gross irrigated area (ha) | + |
| 28 | Share of area under non-agricultural use the total geographic area of district (%) | - |
| 29 | Share of barren and uncultivable area to the total geographic area of district (%) | - |
| 30 | Density of Population (per Sq.km.) | + |
| 31 | Share of fallow land the total geographic area of district (%) | + |
| 32 | Total Annual Ground Water Recharge (Ham) (cubic hectare meters) | + |
| 33 | Current annual groundwater extraction for irrigation (Ham) (cubic hectare meters) | - |
| 34 | Net ground water availability (Ham) (cubic hectare meters) | + |
| 35 | Stage of groundwater extraction (%) | - |
| 36 | Total natural discharges (Ham) (cubic hectare meters) | + |
| | **Climate Adaptability** | |
| 37 | Multi-dimensional poverty index (0-1) | - |
| 38 | Total Bovine population (No.) | + |
| 39 | No. of fair price shops (No.) | + |
| 40 | Literacy Rate (%) | + |
| 41 | Nearest ICAR-KVK (0 if 'no' 1 if 'yes') | + |
| 42 | SICD (0-1) | + |
| 43 | Total milk production ('000 Metric Tonnes) | + |
| 44 | Percent area under forest to the total geographic area of district (%) | + |
| 45 | Share of permanent Pasture and grazing land to the total geographic area of district (%) | + |
| 46 | Area covered under PMFBY in *kharif* Season (thousand hectares) | + |
| 47 | Area covered under PMFBY in *rabi* Season (thousand hectares) | + |
| 48 | Area covered under WBCIS in *kharif* Season (thousand hectare) | + |
| 49 | Area covered under WBCIS in *rabi* Season (thousand hectares) | + |
| 50 | LDI (0-1) | + |

**Note:** Respective units of indicators are given in parentheses. Detailed secondary data sources are given in the references section.

### 2.2.2 Trend analysis for climatic variables

For climate variables, the non-parametric Mann-Kendall's test (Mann, 1945; Kendall, 1976) was performed. As a robust statistical tool, this test has mostly been utilised to investigate the regional variation and temporal trends of climatic time series (Arora et al., 2017; Mersin et al., 2022). The coefficient of trend (Sen's slope values) in daily average temperature, relative humidity, precipitation and ground root soil wetness of *kharif* (July to October), *rabi* (November to February) and summer (March to June) seasons have been calculated for the 43 years period ranging from *kharif* 1981 to summer 2023. The climate indicators show a positive functional relationship with the exposure (Gong et al., 2022; Jayadas and Ambujam, 2022). If the coefficients of selected indicator variables increase, the exposure of the region to vulnerability increases and simultaneously reduces the resilience capacity and *vice-versa* (Tripathi, 2017; Jiang et al., 2018).

**2.2.3 Drought return periods for a certain precipitation deficit (compared to a normal situation)**

Drought is a prolonged absence or marked deficiency of precipitation or a period of abnormally dry weather sufficiently prolonged for the lack of precipitation to cause a serious hydrological imbalance (World Meteorological Organization, 1992). The IMD defines drought as a period of year or season when the deficiency of rainfall is more than 25 per cent of the corresponding mean (IMD, 2022). Based on the percentage departure from the mean, the seasonal drought can be classified as moderate, severe and extreme (Meshram et al., 2014).

**Table 2. Classification of drought based on the percentage departure of rainfall from mean**

| Rainfall departure from mean (%) | Category of drought |
|---|---|
| < - 25 to - 45 | Moderate |
| < - 45 to - 60 | Severe |
| < - 60 or less | Extreme |

**Source:** Amrit et al. (2018)

The average return period of drought is calculated by the following equation (Amrit et al., 2018),

$$R = \frac{N}{n} \quad (4)$$

Where,
R is the average return period of drought.
N is the total number of years incorporated for data analysis.
n is the total number of years with a rainfall deficit of more than 25 per cent.
Mathematically, the return period (R) is the reciprocal of frequency (F),

$$\textit{i.e.}, F = \frac{1}{R} \quad (5)$$

Similarly, the return period of severe and extreme drought events has been calculated as the total number of years of rainfall record analysed divided by number of severe and extreme drought events respectively in each district (Amrit et al., 2018). For example, if the return period is of 10 years for a precipitation deficit of 20 per cent, it means that there is a precipitation deficit (expected) of 20 per cent for every ten years.

**2.2.4 Cropping intensity**

Cropping intensity shows the number of crops being cultivated from the same part of land in an agricultural year (Waha et al., 2020). Cropping intensity is calculated by computing the ratio between gross cropped area and net sown area, expressed in percentage. This indicator has a positive functional relationship with agricultural productivity (Maiti et al., 2017). The formula for cropping intensity is as follows:

$$Cropping\ intenisty = \frac{Gross\ cropped\ area}{Net\ sown\ area} \times 100 \quad (6)$$

**2.2.5 Stage of ground water extraction**

District level data on stage of ground water extraction was obtained from Central Ground Water Board for the period 2022-23. The stage of ground water (GW) extraction is defined by,

$$Stage\ of\ ground\ water\ extraction = \frac{Existing\ Gross\ GW Extraction\ for\ all\ Uses}{Annual\ Extractable\ GW\ Resources} * 100 \quad (7)$$

The existing gross ground water extraction for all uses refers to the total of existing gross ground water extraction for irrigation and all other purposes. The classification based on status of ground water quantity is defined by stage of ground water extraction as given below:

**Table 3. Stage of ground water extraction**

| Stage of Ground Water Extraction | Category |
|---|---|
| ≤ 70 % | Safe |
| > 70 % and ≤ 90 % | Semi-critical |
| > 90 % and ≤ 100 % | Critical |
| > 100 % | Over Exploited |

**Source:** National Compilation on Dynamic Ground Water Resources of India, 2023

### 2.2.6 Simpson index of crop diversification and livestock diversification index

Simpson Index of Crop Diversification (SICD) and Livestock Diversification Index (LDI) have been used for calculating the district-level crop and livestock diversification in Central India (Hoque et al., 2023; Kumar, 2023).

If SID or LID increases, climate adaptability increases, hence the climate change resilience capacity increases.

$$SID = 1 - \sum_j \left(\frac{a_j}{GCA}\right)^2 \quad (8)$$

where,

- $a_j$ represents the area under the $j^{th}$ crop
- GCA represents the gross cropped area

$$LID = 1 - \sum_l \left(\frac{N_L}{TL}\right)^2 \quad (9)$$

- No of animals of specific $l^{th}$ livestock species
- Total livestock

Standard procedures of normalization and weight assignment (PCA) were performed after finalizing indicators.

$$X_t = \wedge_t F_t + e_t \quad (10)$$

where,

- $X_t$ indicates the *N*-dimensional vector of variables influencing the resilience capacity.
- $\wedge_t$ represents the *r* × 1 common factor.
- $F_t$ represents the factor loading.
- $e_t$ represents the associated idiosyncratic error term of order N × 1.

The weights from the PCA were calculated using following equation.

$$W_i = \sum |L_{ij}| E_j \quad (11)$$

where, $W_i$ represents the weight of the $i^{th}$ variable, $E_j$ represents the eigen value of the $j^{th}$factor, and $L_{ij}$ represents the loading value of the $i^{th}$ variable on $j^{th}$ factor.

### 2.2.7 Composite Climate Change Resilience Capacity Index

Climate exposure, agricultural productivity and climate adaptability indices were calculated separately by using their respective indicators along with their respective calculated weights in the following equation (Engström et al., 2020).

$$Index\ Composite\ CCRCI_{District} = \frac{\sum_{i=1}^{n} X_i W_i}{\sum_{i=1}^{n} W_i} \quad (12)$$

where, $X_i$ represents the normalized value of the $i^{th}$ variable, and $W_i$ is the weight of the $i^{th}$ variable.

Finally, the composite climate change resilience capacity index was calculated as per the IPCC approach, using Eq. (1).

$$Composite\ Climate\ Change\ Resilience\ Capacity\ Index\ (CCRCI) = Climate\ Exposure\ Index - (Agricultural\ Productivity\ Index + Climate\ adaptability\ Index \quad (13)$$

### 2.2.8 Categorization of selected districts in central India

After computation of the CCRCI, selected 102 districts in Central India were categorized as high, moderate and low using the 'mean ± standard deviation' norm (Adhav et al., 2021). The categorization is as follows:

- High Resilience = CCRCI > (Mean + 0.5*SD)
- Moderate Resilience = (Mean – 0.5*SD) < CCRCI < (Mean + 0.5*SD)
- Low Resilience = CCRCI < (Mean – 0.5*SD)

## 3. RESULTS AND DISCUSSION

### 3.1 Climate Exposure

The climate exposure index for selected 102 districts of Central India was developed using climatic variables like daily average temperature, precipitation, relative humidity, drought return periods and root zone soil wetness. The detailed description of climate exposure index values for all 102 districts is given in Table 4. A total of 21 indicator variables were used in the construction of the exposure index (Table 1). The highest climate exposure index (0.6075) was recorded in Sheopur (Madhya Pradesh) and the lowest in Dharashiv (Maharashtra) with an index value of 0.4043. A mean climate exposure index value of 0.5051 was observed for all 102 districts with a lower standard deviation of 0.0368 with a least divergence (difference between the maximum and minimum index value) of 0.2032. Twenty-nine districts of central India were in the low climate exposure category, 42 in moderate and 31 districts showed a high climate exposure index. Districts like Khargone (East Nemar), Harda, Mandsaur, Sagar, Rajgarh, Jhabua, Nashik, Neemuch and Burhanpur are in the top ten districts having high exposure index values. Low level of climate exposure was observed in Nanded, Solapur, Latur, Parbhani, Ratnagiri, Bastar, Washim, Wardha and Yavatmal. Highest PCA weightage was observed for the indicator - trend in summer temperature (6.45) followed by trend in *kharif* temperature (6.19). Lowest weightage of PCA was given to the return period of severe drought (2.70). PCA weightage shows the relative importance of these indicators in the construction of climate exposure index. More anomalies could be observed in *kharif* and *rabi* season in precipitation and temperature compared to in summer season. Root zone soil wetness varied in *rabi* and summer season.

**Table 4. Climate exposure, agricultural productivity, climate adaptability and composite climate change resilience capacity index (CCRCI) for the selected districts of Central India**

| State (Region) | S.No. | District | Climate Exposure | Agricultural Productivity | Climate Adaptability | Composite CCRCI |
|---|---|---|---|---|---|---|
| Madhya Pradesh | 1 | Balaghat | $0.5129^{M}$ | $0.4564^{M}$ | $0.3572^{M}$ | $0.3006^{M}$ |
| | 2 | Barwani | $0.5284^{H}$ | $0.3888^{L}$ | $0.2497^{L}$ | $0.1102^{L}$ |
| | 3 | Betul | $0.4996^{M}$ | $0.4981^{H}$ | $0.3876^{M}$ | $0.3861^{H}$ |
| | 4 | Bhind | $0.5053^{M}$ | $0.5338^{H}$ | $0.2906^{L}$ | $0.3192^{M}$ |
| | 5 | Bhopal | $0.5207^{M}$ | $0.4199^{M}$ | $0.3183^{M}$ | $0.2174^{L}$ |
| | 6 | Chhatarpur | $0.5386^{H}$ | $0.4762^{H}$ | $0.3465^{M}$ | $0.2841^{M}$ |
| | 7 | Chhindwara | $0.5071^{M}$ | $0.4897^{H}$ | $0.3820^{M}$ | $0.3646^{H}$ |
| | 8 | Damoh | $0.5319^{H}$ | $0.4018^{L}$ | $0.3221^{M}$ | $0.1920^{L}$ |
| | 9 | Datia | $0.4815^{L}$ | $0.4696^{M}$ | $0.2914^{L}$ | $0.2794^{M}$ |
| | 10 | Dewas | $0.5446^{H}$ | $0.4368^{M}$ | $0.4141^{H}$ | $0.3063^{M}$ |
| | 11 | Dhar | $0.4842^{L}$ | $0.5082^{H}$ | $0.3908^{M}$ | $0.4148^{H}$ |
| | 12 | Dindori | $0.5076^{M}$ | $0.4213^{M}$ | $0.2248^{L}$ | $0.1385^{L}$ |
| | 13 | Guna | $0.5439^{H}$ | $0.4173^{M}$ | $0.3074^{L}$ | $0.1808^{L}$ |
| | 14 | Gwalior | $0.5099^{M}$ | $0.4858^{H}$ | $0.3134^{L}$ | $0.2894^{M}$ |
| | 15 | Harda | $0.5460^{H}$ | $0.4744^{H}$ | $0.3184^{M}$ | $0.2468^{M}$ |
| | 16 | Narmadapuram | $0.5356^{H}$ | $0.7014^{H}$ | $0.3544^{M}$ | $0.5201^{H}$ |
| | 17 | Indore | $0.5232^{M}$ | $0.4056^{L}$ | $0.3849^{M}$ | $0.2674^{M}$ |
| | 18 | Jabalpur | $0.4727^{L}$ | $0.4922^{H}$ | $0.3222^{M}$ | $0.3416^{M}$ |

| | | | | | | |
|---|---|---|---|---|---|---|
| | 19 | Jhabua | $0.5610^{H}$ | $0.3676^{L}$ | $0.1886^{L}$ | $0.0048^{L}$ |
| | 20 | Katni | $0.5079^{M}$ | $0.4249^{M}$ | $0.2774^{L}$ | $0.1944^{L}$ |
| | 21 | Khandwa (East Nemar) | $0.5179^{M}$ | $0.5105^{H}$ | $0.3963^{M}$ | $0.3890^{H}$ |
| | 22 | Khargone (West Nemar) | $0.5458^{H}$ | $0.5372^{H}$ | $0.4090^{H}$ | $0.4005^{H}$ |
| | 23 | Mandla | $0.4904^{M}$ | $0.4518^{M}$ | $0.3042^{L}$ | $0.2657^{M}$ |
| | 24 | Mandsaur | $0.5466^{H}$ | $0.3726^{L}$ | $0.3562^{M}$ | $0.1822^{L}$ |
| | 25 | Morena | $0.5238^{H}$ | $0.4418^{M}$ | $0.2840^{L}$ | $0.2019^{L}$ |
| | 26 | Narsinghpur | $0.4751^{L}$ | $0.5065^{H}$ | $0.3356^{M}$ | $0.3671^{H}$ |
| | 27 | Neemuch | $0.5689^{H}$ | $0.3195^{L}$ | $0.3310^{M}$ | $0.0817^{L}$ |
| | 28 | Panna | $0.5441^{H}$ | $0.4365^{M}$ | $0.2989^{L}$ | $0.1914^{L}$ |
| | 29 | Raisen | $0.5180^{M}$ | $0.5214^{H}$ | $0.3752^{M}$ | $0.3786^{H}$ |
| | 30 | Rajgarh | $0.5541^{H}$ | $0.4389^{M}$ | $0.3477^{M}$ | $0.2325^{L}$ |
| | 31 | Ratlam | $0.5151^{M}$ | $0.3591^{L}$ | $0.3454^{M}$ | $0.1894^{L}$ |
| | 32 | Rewa | $0.5214^{M}$ | $0.4600^{M}$ | $0.2953^{L}$ | $0.2338^{M}$ |
| | 33 | Sagar | $0.5470^{H}$ | $0.5225^{H}$ | $0.4266^{H}$ | $0.4021^{H}$ |
| | 34 | Satna | $0.4906^{M}$ | $0.4348^{M}$ | $0.3233^{M}$ | $0.2675^{M}$ |
| | 35 | Sehore | $0.5311^{H}$ | $0.4743^{H}$ | $0.4056^{M}$ | $0.3488^{M}$ |
| | 36 | Seoni | $0.4912^{M}$ | $0.4749^{H}$ | $0.3129^{L}$ | $0.2966^{M}$ |
| | 37 | Shahdol | $0.5095^{M}$ | $0.4702^{M}$ | $0.2542^{L}$ | $0.2149^{L}$ |
| | 38 | Shajapur | $0.5348^{H}$ | $0.4042^{L}$ | $0.3494^{M}$ | $0.2188^{L}$ |
| | 39 | Sheopur | $0.6075^{H}$ | $0.4025^{L}$ | $0.2607^{L}$ | $0.0558^{L}$ |
| | 40 | Shivpuri | $0.5380^{H}$ | $0.4557^{M}$ | $0.3345^{M}$ | $0.2521^{M}$ |
| | 41 | Sidhi | $0.5004^{M}$ | $0.3883^{L}$ | $0.2557^{L}$ | $0.1437^{L}$ |
| | 42 | Tikamgarh | $0.5367^{H}$ | $0.3838^{L}$ | $0.3153^{M}$ | $0.1624^{L}$ |
| | 43 | Ujjain | $0.5368^{H}$ | $0.4302^{M}$ | $0.4187^{H}$ | $0.3122^{M}$ |
| | 44 | Umaria | $0.4996^{M}$ | $0.4218^{M}$ | $0.2589^{L}$ | $0.1812^{L}$ |
| | 45 | Vidhisha | $0.5130^{M}$ | $0.4841^{H}$ | $0.3971^{M}$ | $0.3682^{H}$ |
| **Maharashtra** | 46 | Ahilya Nagar | $0.4699^{L}$ | $0.3926^{L}$ | $0.6669^{H}$ | $0.5897^{H}$ |
| | 47 | Akola | $0.4747^{L}$ | $0.4145^{M}$ | $0.4354^{H}$ | $0.3752^{H}$ |
| | 48 | Amrawati | $0.4973^{M}$ | $0.3930^{L}$ | $0.4757^{H}$ | $0.3713^{H}$ |
| | 49 | Chhatrapati Sambhajinagar | $0.5029^{M}$ | $0.3925^{L}$ | $0.5063^{H}$ | $0.3960^{H}$ |
| | 50 | Beed | $0.4674^{L}$ | $0.4622^{M}$ | $0.5541^{H}$ | $0.5489^{H}$ |
| | 51 | Buldhana | $0.5086^{M}$ | $0.4119^{L}$ | $0.5578^{H}$ | $0.4611^{H}$ |
| | 52 | Chandrapur | $0.5204^{M}$ | $0.4823^{H}$ | $0.4158^{H}$ | $0.3777^{H}$ |
| | 53 | Dhule | $0.4926^{M}$ | $0.3894^{L}$ | $0.3847^{M}$ | $0.2815^{M}$ |
| | 54 | Gadchiroli | $0.4870^{M}$ | $0.4755^{H}$ | $0.3150^{M}$ | $0.3035^{M}$ |
| | 55 | Gondia | $0.4747^{L}$ | $0.3678^{L}$ | $0.3810^{M}$ | $0.2741^{M}$ |
| | 56 | Jalgaon | $0.5050^{M}$ | $0.4379^{M}$ | $0.6205^{H}$ | $0.5534^{H}$ |
| | 57 | Jalna | $0.5104^{M}$ | $0.4364^{M}$ | $0.4922^{H}$ | $0.4182^{H}$ |
| | 58 | Kolhapur | $0.4631^{L}$ | $0.4710^{M}$ | $0.4423^{H}$ | $0.4502^{H}$ |
| | 59 | Latur | $0.4214^{L}$ | $0.4287^{M}$ | $0.4761^{H}$ | $0.4834^{H}$ |
| | 60 | Nagpur | $0.5271^{H}$ | $0.4494^{M}$ | $0.4792^{H}$ | $0.4015^{H}$ |
| | 61 | Nanded | $0.4083^{L}$ | $0.5213^{H}$ | $0.5462^{H}$ | $0.6592^{H}$ |
| | 62 | Nandurbar | $0.5355^{H}$ | $0.4040^{L}$ | $0.3298^{M}$ | $0.1983^{L}$ |
| | 63 | Nashik | $0.5614^{H}$ | $0.4946^{H}$ | $0.5279^{H}$ | $0.4610^{H}$ |
| | 64 | Dharashiv | $0.4043^{L}$ | $0.4485^{M}$ | $0.4850^{H}$ | $0.5293^{H}$ |
| | 65 | Parbhani | $0.4235^{L}$ | $0.4793^{H}$ | $0.4748^{H}$ | $0.5306^{H}$ |
| | 66 | Pune | $0.5429^{H}$ | $0.4812^{H}$ | $0.5134^{H}$ | $0.4517^{H}$ |
| | 67 | Sangli | $0.4577^{L}$ | $0.4715^{M}$ | $0.4612^{H}$ | $0.4750^{H}$ |
| | 68 | Satara | $0.5122^{M}$ | $0.3850^{L}$ | $0.4239^{H}$ | $0.2967^{M}$ |
| | 69 | Solapur | $0.4172^{L}$ | $0.4403^{M}$ | $0.5647^{H}$ | $0.5878^{H}$ |
| | 70 | Wardha | $0.4522^{L}$ | $0.4421^{M}$ | $0.4178^{H}$ | $0.4077^{H}$ |
| | 71 | Washim | $0.4456^{L}$ | $0.4276^{M}$ | $0.3996^{M}$ | $0.3815^{H}$ |
| | 72 | Yavatmal | $0.4567^{L}$ | $0.4770^{H}$ | $0.5153^{H}$ | $0.5356^{H}$ |
| | 73 | Thane | $0.5285^{H}$ | $0.3610^{L}$ | $0.3412^{M}$ | $0.1737^{L}$ |

| | | | | | | |
|---|---|---|---|---|---|---|
| | 74 | Ratnagiri | 0.4434$^{L}$ | 0.3192$^{L}$ | 0.2918$^{L}$ | 0.1675$^{L}$ |
| | 75 | Raigad | 0.5085$^{M}$ | 0.3423$^{L}$ | 0.3048$^{L}$ | 0.1387$^{L}$ |
| | 76 | Sindhudurg | 0.4716$^{L}$ | 0.2417$^{L}$ | 0.2744$^{L}$ | 0.0445$^{L}$ |
| **Chhattisgarh** | 77 | Bastar | 0.4437$^{L}$ | 0.4180$^{M}$ | 0.2114$^{L}$ | 0.1858$^{L}$ |
| | 78 | Bilaspur | 0.4943$^{M}$ | 0.4262$^{M}$ | 0.3167$^{M}$ | 0.2485$^{M}$ |
| | 79 | Dantewada | 0.4824$^{L}$ | 0.4301$^{M}$ | 0.1663$^{L}$ | 0.1141$^{L}$ |
| | 80 | Dhamtari | 0.5176$^{M}$ | 0.3987$^{L}$ | 0.3153$^{M}$ | 0.1964$^{L}$ |
| | 81 | Durg | 0.5131$^{M}$ | 0.4140$^{M}$ | 0.3158$^{M}$ | 0.2167$^{L}$ |
| | 82 | Janjgir-Champa | 0.5195$^{M}$ | 0.4240$^{M}$ | 0.2575$^{L}$ | 0.1620$^{L}$ |
| | 83 | Jashpur | 0.4700$^{L}$ | 0.4269$^{M}$ | 0.3046$^{L}$ | 0.2615$^{M}$ |
| | 84 | Kanker | 0.5304$^{H}$ | 0.4688$^{M}$ | 0.2824$^{L}$ | 0.2209$^{L}$ |
| | 85 | Korba | 0.4861$^{L}$ | 0.3992$^{L}$ | 0.3041$^{L}$ | 0.2172$^{L}$ |
| | 86 | Korea | 0.5039$^{M}$ | 0.3732$^{L}$ | 0.3186$^{M}$ | 0.1878$^{L}$ |
| | 87 | Kabirdham | 0.4827$^{L}$ | 0.4298$^{M}$ | 0.3599$^{M}$ | 0.3070$^{M}$ |
| | 88 | Mahasamund | 0.5105$^{M}$ | 0.4475$^{M}$ | 0.2846$^{L}$ | 0.2216$^{L}$ |
| | 89 | Raigarh | 0.4789$^{L}$ | 0.4437$^{M}$ | 0.3106$^{L}$ | 0.2754$^{M}$ |
| | 90 | Raipur | 0.5193$^{M}$ | 0.4386$^{M}$ | 0.2757$^{L}$ | 0.1949$^{L}$ |
| | 91 | Rajnandgaon | 0.5014$^{M}$ | 0.3968$^{L}$ | 0.2893$^{L}$ | 0.1847$^{L}$ |
| | 92 | Surguja | 0.4916$^{M}$ | 0.4172$^{M}$ | 0.3422$^{M}$ | 0.2678$^{M}$ |
| **Southern UP** | 93 | Banda | 0.4754$^{L}$ | 0.4965$^{H}$ | 0.2892$^{L}$ | 0.3103$^{M}$ |
| | 94 | Hamirpur | 0.4783$^{L}$ | 0.4540$^{M}$ | 0.3214$^{M}$ | 0.2971$^{M}$ |
| | 95 | Jalaun | 0.5263$^{H}$ | 0.4863$^{H}$ | 0.3441$^{M}$ | 0.3042$^{M}$ |
| | 96 | Jhansi | 0.5145$^{M}$ | 0.4668$^{M}$ | 0.3736$^{M}$ | 0.3258$^{M}$ |
| | 97 | Lalitpur | 0.5188$^{M}$ | 0.4484$^{M}$ | 0.3232$^{M}$ | 0.2528$^{M}$ |
| | 98 | Mahoba | 0.4953$^{M}$ | 0.4786$^{H}$ | 0.2993$^{L}$ | 0.2825$^{M}$ |
| | 99 | Chitrakut | 0.5342$^{H}$ | 0.3735$^{L}$ | 0.2871$^{L}$ | 0.1264$^{L}$ |
| **Madhya Pradesh** | 100 | Anuppur | 0.4849$^{L}$ | 0.5300$^{H}$ | 0.3051$^{L}$ | 0.3502$^{M}$ |
| | 101 | Ashok Nagar | 0.5323$^{H}$ | 0.5269$^{H}$ | 0.3074$^{L}$ | 0.3019$^{M}$ |
| | 102 | Burhanpur | 0.6058$^{H}$ | 0.6249$^{H}$ | 0.3225$^{M}$ | 0.3415$^{M}$ |

**Note:** Letters in superscript: H=High, M=Moderate, L=Low category of respective index.

### 3.2 Agricultural Productivity

The Agricultural Productivity Index (Table 4) was computed for selected 102 districts in central India using fifteen selective indicators. The highest agricultural productivity index was observed for Narmadapuram (Madhya Pradesh) (0.7014) and the lowest in Sindhudurg (Maharashtra) (0.2417) with a mean index value of 0.4426 and standard deviation of 0.0598. A higher divergence of 0.4597 in the agricultural productivity index was observed across central India. Out of total 102 districts in central India, thirty districts were in the high productivity category, 44 were in the moderate and 28 were in the low agricultural productivity category. Districts like Khandwa, Nanded, Raisen, Sagar, Ashok Nagar, Anuppur, Bhind, Khargone (East Nemar) and Burhanpur had the highest agricultural productivity compared to other districts. Also, the gap filler districts between high and low productivity were – Shivpuri, Balaghat, Tewa, Beed, Jhansi, Kanker, Datia, Shahdol, Kolhapur, Sangli. Low productivity was observed in the districts with low observed ground water availability, a low share of cropped area. The highest PCA weightage was observed to total annual ground water recharge (5.11) and the lowest to cropping intensity (2.52). The key results explain the importance of regenerative water resources for strengthening agricultural productivity in the region in order to establish climate resilience.

### 3.3 Climate Adaptability

Climate adaptability is a highly important component of climate-resilient agriculture. A comprehensive climate adaptability index (Table 4) was developed for selected districts in Central India using a total of 14 indicators (Table 1). The highest climate adaptability was observed in Ahilya Nagar (Maharashtra) with an index value of 0.6669 and the lowest in Dantewada (Chhattisgarh) with an index magnitude of 0.1663. In central India, the mean climate adaptability index value was 0.3601 with a standard deviation of 0.0920. A bit high divergence of 0.5005 in index range suggested the regional differences in crop insurance coverage and other indicator variables. Almost one-third of districts in central India (35) were in the low climate adaptability category. This exerts a key policy pressure in the region to effectively sensitize the mechanism and key contributors in order to build stronger climate resilience in central India. In the moderate category of climate adaptability, 41 districts were present indicating indifference in the adoption of effective climate management practices. Only 26 districts out of 120 showed a higher level of climate adaptability in central India. Districts like Pune, Nashik, Nanded, Beed, Buldhana, Solapur and Jalgaon were amongst the top districts having high climate adaptability. All these districts are from state of Maharashtra indicating a leading role of state policies in establishing resilience. Jhabua, Bastar, Dindori, Barwani, Shahdol, Sidhi, Janjgir, Umaria and Sheopur showed the lowest climate adaptability compared to other districts, which emphasizes need for re-evaluation of climate policies in Chhattisgarh and Madhya Pradesh. The PCA analysis results break the folklore in contemporary research as the highest PCA weights were given to the total bovine population (4.29) as key indicator in diversifying farming systems to reduce climate risk. Also, multi-dimensional poverty index got PCA weightage of 4.25 signifying the need in reduction of overall poverty in the region in order to establish higher climate resilience. Area covered under PMFBY in *kharif* season (4.14), area covered under PMFBY in *rabi* season and literacy rate (4.14) also showed high relative weights compared to other indicators. This ultimately gives a green signal to effective crop insurance schemes reducing climate risk and increasing climate adaptability.

### 3.4 Distribution of important indicators over different CCRCI categories in Central India

After developing composite CCRCI (Table 4) an indicator distribution analysis was performed to check how these indicators contributed to high, moderate and low resilience to climate change. Table 5 gives an in-depth idea about how indicators vary over classification range and magnitude and how they contribute towards high, moderate and low climate change resilience.



**Table 5. Distribution of important indicators over different climate change resilience capacity categories in Central India**

| Categories | Low | Moderate | High |
|---|---|---|---|
| Average CCRCI (0-1) | 0.17 | 0.29 | 0.45 |
| Share of cropped area (%) | 27.35 | 43.93 | 28.71 |
| Share of net sown area (%) | 29.80 | 35.40 | 34.79 |
| Gross irrigated area (ha) | 5623443<br>(24.00) | 9420879<br>(40.22) | 8379049<br>(35.77) |
| Net ground water availability (Ham) | 706369.46<br>(21.82) | 989627.26<br>(30.57) | 1541000.32<br>(47.60) |
| Multi-dimensional poverty index (0-1) | 0.09 | 0.08 | 0.05 |
| Total Bovine population (No.) | 22687862<br>(26.39) | 28099906<br>(32.69) | 35162797<br>(40.91) |
| Total milk production ('000 Metric Tonnes) | 7410.10<br>(21.74) | 10764.34<br>(31.59) | 15899.68<br>(46.66) |
| Percent area under forest (%) | 37.53 | 35.31 | 27.15 |
| Area covered under PMFBY in *kharif* Season (thousand hectare) | 2415.74<br>(14.36) | 2899.07<br>(17.24) | 11497.61<br>(68.38) |

| | | | |
|---|---|---|---|
| Area covered under PMFBY in *rabi* Season (thousand hectare) | 834.80 (11.86) | 1379.67 (19.60) | 4821.30 (68.52) |
| Area covered under WBCIS in *kharif* Season (thousand hectare) | 2.45 (2.63) | 43.67 (46.93) | 46.92 (50.42) |
| Area covered under WBCIS in *rabi* Season (thousand hectare) | 48.17 (30.85) | 6.57 (4.20) | 101.37 (64.93) |
| No. of districts under semi critical, critical and over exploited stage of ground water extraction (%) | 10 | 5 | 6 |

**Note:** Figures in the parentheses indicate percentage to the respective total.

The table 5 shows the average composite CCRCI index across different categories. Higher values indicate better resilience to climate change. Also, indicators like share of cropped area (%) indicate the proportion of land under cultivation relative to the total area. The moderate CCRCI category has the largest share (43.93 %) and low CCRCI showed coverage up to 28.71 percent. Share of net sown area in moderate and low categories of CCRCI have almost similar values – 35.40 percent and high 34.79 percent. Gross irrigated area of 8,379,049 ha contributed to higher climate resilience. Regions with high net ground water availability (47.60 %) showed higher resilience and stability to cope with the climate change. Lower average value of multi-dimensional poverty index (0.05) suggested better living standards and less poverty in high-climate resilience regions. Total milk production of 15,899.68 thousand Mt (46.66 %) and total bovine population of 35,162,797 (40.91 percent) were major contributors for developing higher resilience in Central India. Surprisingly in lower resilience areas, highest forest cover was observed (37.53 %) this may be due to improper utilization forest resources. Area covered under PMFBY in *kharif* season (68.38 %) and area covered under PMFBY in *rabi* season (68.52 %) significantly showed that higher climate resilience could be developed with the larger crop insurance coverage reducing the climatic risk of farming community. The same risk reduction contributors were area covered under WBCIS in *kharif* and *rabi* season. Ten districts of central India were above the safe level of (>70%) showing significant extraction of ground water resources which contributed to the lower CCRCI. The high resilience capacity regions generally showed better agricultural performance (e.g., milk production, irrigation, groundwater availability) but had lower forest cover and higher adoption of crop insurance schemes. Low resilience areas, though lagging in several indicators, had a significant proportion of forest cover. The moderate category often bridged the gap between the two extremes.

### 3.5 Inter-index comparison of climate exposure, agricultural productivity and climate adaptability

The comparative analysis (Table 4 and Fig. 1) of the climate exposure, agricultural productivity, and Climate Adaptability indices across 120 districts in Central India revealed a complex landscape of vulnerabilities and resilience that necessitate a nuanced understanding of regional dynamics. This comprehensive assessment highlighted significant disparities among districts in central India, which can inform targeted interventions and policy development. For instance, districts such as Jhabua (H-L-L) and Sheopur (H-L-L) emerge as critical areas of concern. These regions were marked by high levels of climate exposure, which referred to their susceptibility to adverse climate events and conditions. Coupled with low agricultural productivity and limited climate adaptability, these districts faced heightened risks that could exacerbate food insecurity and economic instability. The findings suggest that immediate and focused interventions are essential in these areas to mitigate the impacts of climate change and enhance local resilience. Conversely, districts like Sagar (H-H-H) and Nashik (H-H-H) stood out for their robust performance across all three indices. The strong correlation observed in these regions indicated a higher level of resilience, suggesting that they were better equipped to withstand climate-related challenges while maintaining agricultural productivity. This resilience can be attributed to a combination of favourable climatic conditions, effective agricultural practices and proactive adaptation strategies that have been implemented in these districts.

Moreover, the analysis revealed that certain districts, including Barwani (H-L-L) and Dantewada ((L-M-L), exhibited significant discrepancies between their levels of climate exposure and adaptability. While these areas may face considerable climate risks, their adaptability measures are not commensurate, indicating a gap that needs to be addressed. This highlighted the necessity for targeted policies that focus on enhancing resilience, particularly in districts where exposure levels were high but adaptability remained low. The evaluation also underscored regional differences within Central India. Madhya Pradesh and Chhattisgarh were characterized by numerous districts that experience high climate exposure alongside moderate to low adaptability. This situation poses a significant challenge for these states, as they must navigate the dual pressures of climate vulnerability and agricultural productivity. In contrast, Maharashtra demonstrated a more favourable adaptability profile across various districts, even in the face of moderate exposure levels. This suggested that Maharashtra may have implemented more effective adaptation strategies or possesses inherent advantages that bolster its climate resilience.

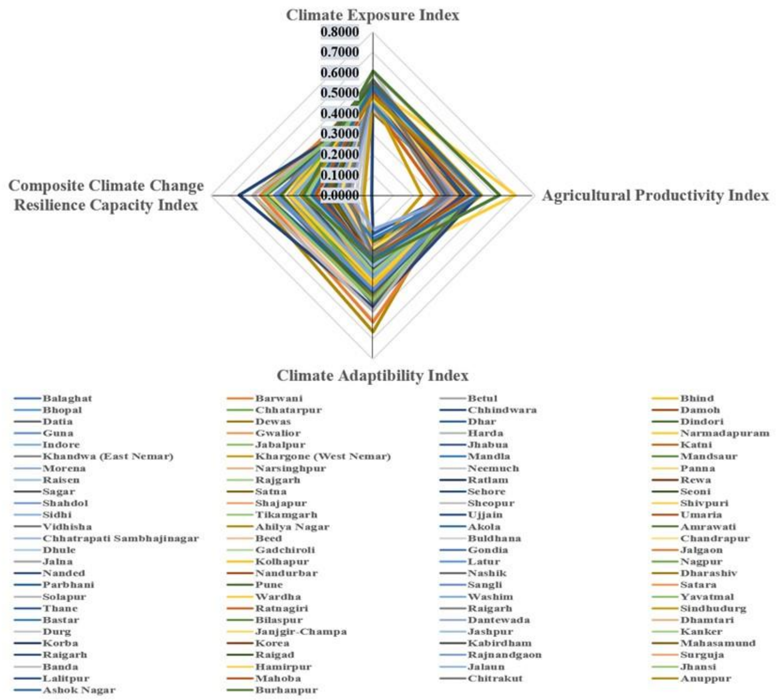


**Fig. 1. Radar pictorial of Climate Exposure, Agricultural Productivity, Climate Adaptability and Composite CCRCI**

The fig. 1. presents a radar chart depicting the values of four indices - climate exposure index, agricultural productivity index, climate adaptability index and CCRCI for multiple districts in Central India. Each axis of the radar chart corresponds to one of these indices, with values ranging from 0.0 to 0.8, as indicated by concentric rings. The climate exposure index indicates the degree to which districts are exposed to adverse climatic conditions. Districts with higher values (closer to 0.8) are more vulnerable to climate-related risks. Certain districts, such as Barwani and Sheopur, likely exhibited higher values on this axis, showing significant exposure. The agricultural productivity index reflects the overall agricultural input productivity of districts. Higher values indicate better productivity. Districts like Indore and Narmadapuram, with higher agricultural productivity showed longer stretches on this axis. The climate adaptability index represents the capacity of districts to adapt to changing climatic conditions. Higher values suggest better adaptation strategies and resilience. Regions like Nashik and Pune were expected to score well in this category. This visualization allows for identifying certain patterns such as

**Highly exposed but poorly climate adaptive districts**: Districts such as Jhabua or Dantewada, with high exposure but low adaptability, would appear skewed toward the Climate Exposure axis.

**High climate resilient districts**: Balanced performance in indices, as seen in districts like Nashik or Sagar, results in well-distributed and larger polygons.

**Target areas for intervention**: Districts with large disparities between exposure and adaptability are priority zones for policy focus to enhance resilience.

## 3.6 Composite Climate Change Resilience Capacity Index (CCRCI)

The composite Climate Change Resilience Capacity Index (CCRCI) for all 102 districts of central, India (Table 4) provided a thorough evaluation of how well districts in Madhya Pradesh, Maharashtra, Chhattisgarh, and Southern Uttar Pradesh can adapt and mitigate the ill effects of climate change. Each district was categorised in High (H), Medium (M), or Low (L) climate change resilience based on their CCRCI index values ranging from 0 to 1, showing their ability to cope with climate change effects. Composite CCRCI as an integrated measure combining the three indices to evaluate overall climate resilience. A balanced score across the indices leads to higher composite values. Districts with balanced performance across climate exposure, agricultural productivity and climate adaptability, such as Sagar or Dewas, likely exhibit a more compact, larger shape on the radar chart (Fig. 1). The districts are colour-coded to differentiate between regions, and each district's performance forms an individual polygon on the radar chart. Regions with sharper or larger polygons indicate higher variability across indices, while smaller or more rounded polygons suggest balanced performance (Fig. 1).

In Madhya Pradesh, districts with high resilience included Narmadapuram (0.5201), Dhar (0.4148) and Narsinghpur (0.3671) indicating strong adaptation of coping strategies. Medium-resilience districts like Balaghat (0.3006), Rewa (0.2338) and Sehore (0.3488) showed average preparedness, while low-resilience areas such as Jhabua (0.0048), Neemuch (0.0817) and Panna (0.1914) were very vulnerable and required significant policy focus. In Maharashtra, many districts showed high resilience, including Nanded (0.6592), Jalgaon (0.5534), and Beed (0.5489), reflecting effective climate-resilient policies and infrastructure. Medium-resilience districts were Dhule (0.2815), Gadchiroli (0.3035) and Satara (0.2967), while low-resilience districts in coastal areas like Sindhudurg (0.0445), Ratnagiri (0.1675) and Thane (0.1737) indicated increased vulnerability. Chhattisgarh had no districts rated as high resilience, highlighting a lack of strong preparedness. Medium-resilience areas like Kabirdham (0.3070), Jashpur (0.2615) and Raigarh (0.2754) had moderate capacities, but most of the districts including Dantewada (0.1141), Rajnandgaon (0.1847) and Janjgir-Champa (0.1620) were in the low-resilience category, showing a critical need for focused interventions. In Southern Uttar Pradesh, there were no high-resilience districts. Medium-resilience areas like Banda (0.3103), Jhansi (0.3258) and Hamirpur (0.2971) showed moderate preparedness, while low-resilience districts, such as Chitrak (0.1264) were particularly vulnerable to climate change impacts. Overall, Maharashtra had the highest number of high-resilience districts, followed by Madhya Pradesh with a mix of resilience levels and Chhattisgarh and Southern UP showed significant gaps in climate preparedness. This analysis highlighted the critical need to prioritize low-resilience (highly vulnerable) districts, particularly those with low and moderate resilience through targeted policy interventions, resource allocation and capacity-building measures to strengthen climate adaptation across Central India.

## 3.7 Agro-climatic zone-wise mapping of districts in central India

The mapping of selected districts (Table 6) in Central India is based on varying levels of the

CCRCI (Fig. 3) and their respective cropped areas covered across agro-climatic zones which revealed critical insights into regional variations and agricultural challenges. Central India predominantly falls under the Tropical Wet and Dry (Aw) climate zone according to the Köppen climate classification. This zone is characterized by distinct wet and dry seasons with high temperatures throughout the year. However, variations occur in parts of Madhya Pradesh and Chhattisgarh, where some regions experience characteristics of a Humid Subtropical (Cwa) climate, marked by cooler winters and monsoonal rains. Understanding these classifications is essential for planning climate-resilient agricultural practices in Central India. For the present analysis, agro-climatic zones of Central India, as per the Planning Commission's classification, which include the Eastern Plateau and Hills Region (Zone VII), Central Plateau and Hills Region (Zone VIII), Western Plateau and Hills Region (Zone IX) and West Coast Plains and Ghat Region (Zone XII) were selected for more clarity. Each zone is characterized by unique climatic conditions, soil types, and cropping patterns.

**Eastern Plateau and Hills Region (Zone VII)** is represented by Chhattisgarh, Madhya Pradesh and parts of Maharashtra (Figure 2). Low climate resilience areas in this Zone include districts like Bilaspur, Jashpur and Kabirdham from Chhattisgarh, covering 64.16 % of the state's total cropped area. These areas are dominated by red and yellow soils and support crops such as rice, pulses, millets and oilseeds, mostly under rainfed conditions. Moderate climate resilience areas got Smaller coverage in Chhattisgarh (35.84 %) and Madhya Pradesh (e.g., Balaghat, Anuppur) with a focus on similar cropping systems. The limited presence of high climate resilience areas in this Zone, indicated a need for improved strategies in rice and millet-based cropping systems.

**Central Plateau and Hills Region (Zone VIII)** is represented by Madhya Pradesh and Uttar Pradesh (Figure 2). High climate resilience areas in this Zone covered districts like Betul, Chhindwara, Narmadapuram, and Narsinghpur (22.39 % of MP's cropped area). These districts grow diverse crops like coarse cereals, pulses, and oilseeds under rainfed and semi-arid conditions. Moderate climate resilience areas included 49.05 % of MP's cropped area and 63.75% of Southern UP's cropped area (e.g., Banda, Hamirpur), indicating average climate adaptability and agricultural productivity. Low resilience areas in the districts like Morena, Tikamgarh, and Sheopur in MP (13.07%) faced constraints such as semi-arid conditions and reliance on rainfed agriculture.

**Western Plateau and Hills Region (Zone IX)** covers Madhya Pradesh and Maharashtra (Figure 2). In this Zone, high resilience areas have limited presence with districts like Dhar and Khargone (8.56 % of MP's cropped area). Moderate climate resilience areas in this Zone included districts like Dewas and Indore (8.39 % of MP), along with 62.32 % of Maharashtra's cropped area, which are critical zones for semi-arid crops like cotton, oilseeds, and millets. Low resilience areas in this Zone covered Districts like Barwani and Jhabua (14.03 % of MP's cropped area) suffered from poor climate resilience, primarily due to semi-arid conditions and dependence on black soils.

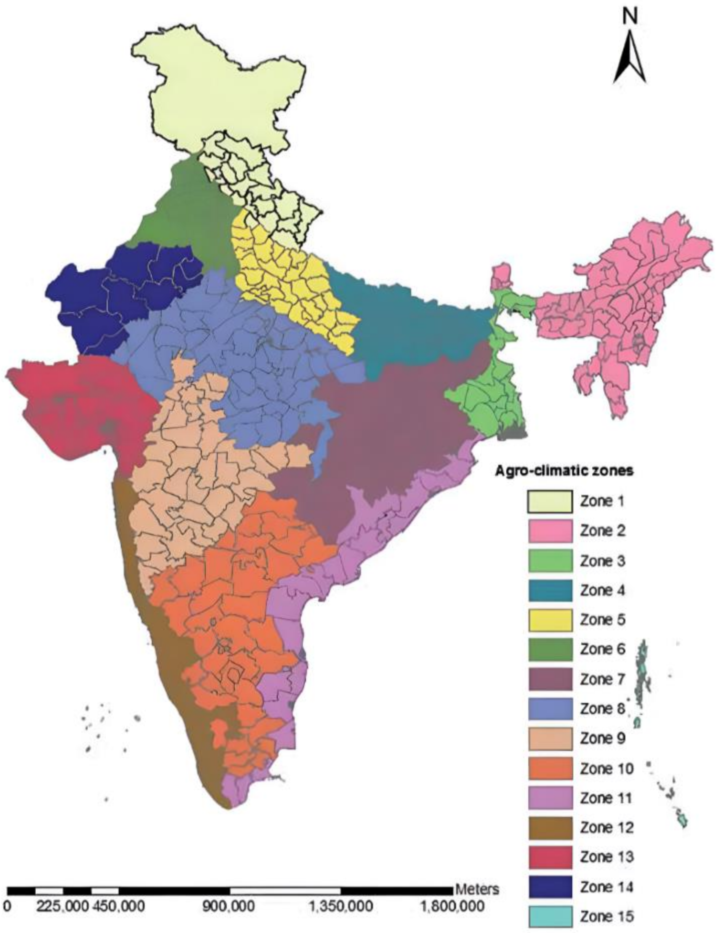


**Fig. 2. Fifteen agro-climatic regions/zones of Planning Commission (scaled map)**

**Source:** Planning Commission (Khanna, 1989)

**Table 6. Agroclimatic zone (Planning Commission) wise classification of climate change resilience capacity in Central India (n=120 overall CCRCI)**

| S.No. | Agro-climatic regions / zones | States represented | Climate change resilience capacity | | | | | | Characteristics |
|---|---|---|---|---|---|---|---|---|---|
| | | | High | % share of total cropped area of respective state | Moderate | % share of total cropped area of respective state | Low | % share of total cropped area of respective state | |
| VII | Eastern plateau and hills region | Chhattisgarh | - | - | Bilaspur, Jashpur, Kabirdham, Raigarh, Surguja | 35.84 | Bastar, Dantewada, Dhamtari, Durg, Janjgir-Champa, Kanker, Korba, Korea, Mahasamund, Raipur, Rajnandgaon, | 64.16 | Red and yellow soils, suitable for rice, pulses, millets, oilseeds; rainfed |
| | | Madhya Pradesh | - | - | Balaghat, Anuppur | 10.27 | Dindori, Katni, Shahdol, Umaria, | 4.54 | |
| | | Maharashtra | Chandrapur | 2.61 | Gadchiroli, Gondia | 2.16 | - | - | |
| VIII | Central plateau and hills region | Madhya Pradesh | Betul, Chhindwara, Narmadapuram, | 22.39 | Bhind, Chhatarpur, Datia, | 49.05 | Bhopal, Damoh, Guna, | 13.07 | Diverse crops; coarse cereals, pulses, oilseeds; |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | Narsinghpur, Raisen, Sagar, Vidhisha | | Gwalior, Harda, Jabalpur, Mandla, Rewa, Satna, Sehore, Seoni, Shivpuri, Ashok Nagar, Burhanpur | | Morena, Panna, Sheopur, Sidhi, Tikamgarh | | rainfed and semi-arid |
| | | **Uttar Pradesh** | **-** | **-** | Banda, Hamirpur, Jalaun, Jhansi, Lalitpur, Mahoba | 63.75 | Chitrakut, | 5.84 | |
| **IX** | **Western plateau and hills region** | **Madhya Pradesh** | Dhar, Khandwa (East Nemar), Khargone (West Nemar) | 8.56 | Dewas, Indore, Ujjain | 8.39 | Barwani, Jhabua, Mandsaur, Neemuch, Rajgarh, Ratlam, Shajapur | 14.03 | Semi-arid, black soils; ideal for cotton, millets, oilseeds |
| | | **Maharashtra** | Ahilya Nagar, Akola, | 62.32 | Dhule | 2.43 | **-** | **-** | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | Amrawati, Chhatrapati, Sambhajinagar, Beed, Buldhana, Jalgaon, Jalna, Latur, Nagpur, Nanded, Dharashiv, Parbhani, Solapur, Wardha, Washim, Yavatmal | | | | | | |
| **XII** | **West coast plains and ghat region** | **Maharashtra** | Kolhapur, Nashik, Pune, Sangli | 18.94 | Satara | 3.77 | Nandurbar, Thane, Ratnagiri, Raigad, Sindhudurg | 7.73 | High rainfall, lateritic soils; rice, coconut, spices, horticulture. |
| | | | **Total % Area (sum=400)** | **114.82** | | **175.66** | | **109.37** | |
| | | | **Adjusted % Area** | **28.71** | | **43.91** | | **27.39** | |

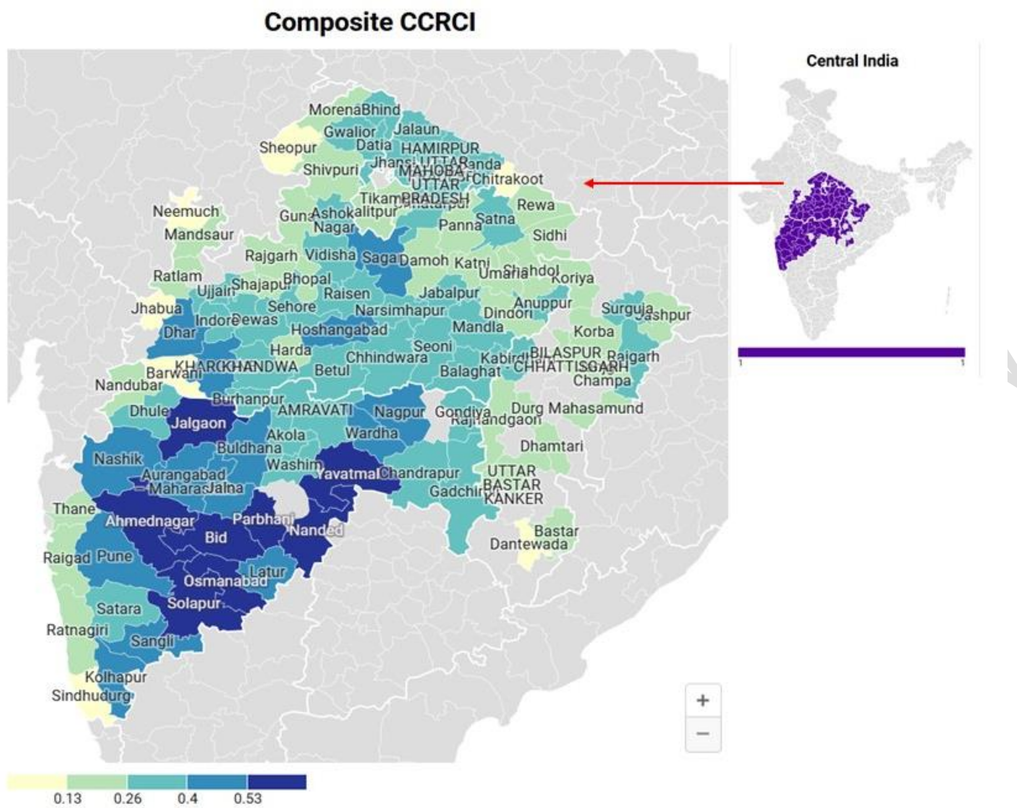


**Fig. 3. Mapping of Composite Climate Change Resilience Capacity Index (CCRCI)**

**West Coast Plains and Ghat Region (Zone XII)** covers specific coastal and hilly regions of Maharashtra (Figure 2). In this Zone high climate resilience was observed in the districts like Kolhapur, Nashik, Pune, and Sangli (18.94 % of Maharashtra's cropped area). These regions are largely benefited from high rainfall and fertile lateritic soils, supporting rice, coconut and horticultural crops. Moderate and low climate resilience areas in this zone had geographically smaller districts such as Ratnagiri and Sindhudurg (7.73 %) faced moderate challenges, while limited low-resilience areas indicated higher stability in this zone.

## 4. CONCLUSION

The findings underscore the need for targeted interventions in low-resilience districts, particularly in agro-climatic Zones VII and IX, where climate exposure and limited adaptability pose significant risks to agriculture. Enhancing irrigation infrastructure, promoting climate-resilient crop varieties and implementing adaptive agricultural practices are essential to improve resilience. Additionally, moderate-resilience areas, such as those in Zone VIII, require supportive measures to prevent regression into low-resilience categories. High-resilience districts, such as those in Zone XII, serve as benchmarks and can act as resource centres for climate adaptation strategies. This mapping highlights the diversity of challenges and opportunities in Central India's agro-climatic zones, offering a framework for region-specific climate resilience planning. Furthermore, the results of the present analysis are purely based on selected indicators and secondary data of these indicators used for the development of the CCRCI index. As indicators selection is purely subjective and based on authors' judgment and expert opinion, there could be potential biases and uncertainties. Still, much care has been taken while formulating methodologies and indicators selection based on recent climate research studies. There is much scope for exploring potential areas for future research in the climate change resilience assessment in agriculture, such as refining the resilience index with additional indicators, formulating the necessary framework, testing its applicability in other regions or exploring how climate resilience interacts with socio-economic factors.

## DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

## COMPETING INTERESTS

Authors have declared that no competing interests exist.

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