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IPEDClim: a high-resolution dataset of bioclimatic variables for ecohydrological applications in India

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Abstract

High-resolution gridded climate datasets are essential for ecological, agricultural, and environmental research. Species distribution models, which link species-occurrence records with environmental predictors, critically depend on bioclimatic variables (BCVs). In India, most studies rely on global BCVs such as WorldClim, CHELSA-bioclim and MERRAClim, which do not adequately represent local climate heterogeneity or integrate the national weather station network. To address this gap, we present IPEDClim, a 0.10° (~10 km) resolution dataset comprising of 19 precipitation and temperature-based BCVs derived from the observation-based Indian Precipitation Ensemble Dataset (IPED) and the EM-Earth. The dataset includes precipitation variables developed from 1991 to 2023, while temperature and combined variables were developed from 1991 to 2019. The variables capture key climatic attributes, including mean annual temperature, diurnal temperature range, seasonality, and precipitation extremes. The ensemble-mean construction enhances reliability in a region with a sparse observational network and improves fidelity relative to existing global products. In addition, we conducted a grid-based trend assessment (1991–2019/2023) using the non-parametric Mann–Kendall test and Sen’s slope at 0.10° resolution to quantify monotonic changes in each BCV. The results showed widespread warming across most of India, with annual mean temperature (BIO1) recording positive Sen’s slope values (+0.02 to +0.04°C yr^{−1}). Precipitation variables showed marked regional variability, including declining wettest-month precipitation (BIO13) of 10–20 mm yr^{−1} across the Western Ghats, central India and Northeast India, localized increases in driest-month precipitation (BIO14), and declining cold-season precipitation (BIO19) of 12.5–25 mm yr^{−1} across the Himalayan region and Northeast India. The dataset provides a robust foundation for ecological modeling, biodiversity conservation, agricultural planning, and climate impact assessments in India. Through the integration of high-resolution, observation-based ensembles, IPEDClim enables more detailed climate characterization and supports evidence-based decision-making in ecosystem management, water resource planning, and disaster risk reduction.

1. Introduction

Climatic data in ecological and biogeographical research play a crucial role in identifying species distributions, and, consequently, plant and animal species (Amiri *et al* 2020). The accuracy and completeness of these datasets are therefore vital. Species distribution models (SDMs), potential distribution models (PDMs), and ecological niche models (ENMs) all depend on climate data to predict species ranges and ecological tolerances (Bede-Fazekas and Somodi 2020). Amongst the most valuable inputs for these models are bioclimatic variables (BCVs), which transform raw climate data, such as temperature and precipitation, into ecologically meaningful metrics that capture seasonal trends and extreme conditions

influencing species distributions. BCVs were first introduced by Booth, (1985) and have since been continually expanded and refined in global ecological studies. Global BCVs are widely used and derived from global temperature and precipitation datasets. However, for the Indian region, precipitation products based on global datasets often suffer from significant uncertainties, often underestimating or overestimating precipitation (Magotra *et al* 2024). Moreover, in countries like India, where station observation dataset is not publicly available, it is important to use a region-specific sources in order to reduce such uncertainties. Recently, a high-resolution 0.1° Indian Precipitation Ensemble Dataset (IPED) has been published, which utilizes observational data to address these uncertainties (Peringiyil *et al* 2025). Hence, there is a need and opportunity to develop a high resolution BCV dataset for India.

One of the most commonly used indicators for detecting extreme events is defined by the World Meteorological Organization's 'Expert Team in Climate Change Detection and Indices (ETCCDI)' (Solomon *et al* 2007, Zhang *et al* 2011, Eini *et al* 2022). The ETCCDI is explicitly used to estimate trends and changes in climate extremes, and the list includes indices such as TXx, TNx, R95p, R99p, etc which have been widely used to characterize temperature and precipitation extreme events (Zhang *et al* 2011). Worldwide-accepted indices derived from daily temperature and precipitation datasets enable consistent comparison across different global or regional datasets (Bhattacharyya *et al* 2022, Eini *et al* 2022). In contrast, all the 19 BCVs, such as mean annual temperature, precipitation of the wettest month, mean temperature of the warmest quarter, etc were developed primarily for SDM (Fick and Hijmans 2017, Karger *et al* 2017, Vega *et al* 2017). A crucial step in the modeling pipeline is selecting biologically meaningful variables that determine habitat suitability. BCVs fit this role well, since many are directly linked to ecological processes relevant to species distribution (Title and Bemmels 2018). These variables are computed from monthly climatological normals rather than daily series, giving them comparatively lower data demands, and they combine precipitation and temperature seasonality directly. From these primary fields, they help characterize the bioclimatic 'envelope' representing favorable environmental conditions for a given species, a concept also referred to as habitat 'suitability' (Noce *et al* 2020). Variables including the mean temperature of the driest quarter or the precipitation of the warmest quarter capture combined seasonal stress in a single number, whereas ETCCDI indices do not. Furthermore, 30-year BCVs are usually computed as fixed climatological normals rather than as continuous time series data, in contrast to ETCCDI indices, which are explicitly designed as annual/seasonal series for monitoring change over time. In summary, BCVs are thus a descriptive characterization of the climate (Fick and Hijmans 2017, Vega *et al* 2017, Title and Bemmels 2018), whereas ETCCDI indices are constructed specifically to monitor changes in climate extremes over time (Zhang *et al* 2011, Bhattacharyya *et al* 2022).

Spatially interpolated gridded climate data, known as 'climate surfaces', are utilized across various fields, particularly in the environmental, agricultural, and biological sciences over India (Hijmans *et al* 2005, Fick and Hijmans 2017). For many applications, high spatial resolution data are preferred to accurately capture environmental variations that may be overlooked at lower resolutions, especially in mountainous regions and areas with steep climate gradients (Hijmans *et al* 2005). Additionally, India's diversity of climatic zones introduces both challenge and opportunities in the development of BCVs (Behera *et al* 2019). Currently, global databases, such as WorldClim, MERRAclim, and Climatologies at High Resolution for the Earth's Land Surface Areas (CHELSA) provide BCVs at multiple spatial resolutions (Fick and Hijmans 2017, Karger *et al* 2017, Vega *et al* 2017, 2018). These are generally free and widely utilized by researchers around the world (Hijmans *et al* 2005, Fick and Hijmans 2017, Karger *et al* 2017, Bede-Fazekas and Somodi 2020). WorldClim offers 19 BCVs at a high spatial resolution (up to 30 arc-seconds, or 0.9 km at the equator) for contemporary climate data (1970–2000). The spatial resolution of the CHELSA dataset is the same as the WorldClim dataset (Noce *et al* 2020), but they differ in the methodology of the derivation of BCVs. The MERRAclim dataset provides data at three distinct spatial resolutions - 2.5 arc-minutes, 5 arc-minutes, and 10 arc-minutes for three decades (1980 s, 1990 s and 2000 s) (Vega *et al* 2017). Although several SDM studies have been conducted over India, most of them use global BCVs (Khadka and James 2017, Deomurari *et al* 2023). There is a need to enhance estimates for areas with low station density, as well as for regions with unusual gradients, such as the North Western Himalayan regions, and for sharp gradients like rain shadows or abrupt temperature changes due to ocean-land transitions. Using datasets developed with in-situ observations from India may capture more detailed climatic information thus allowing agricultural applications, or conservation models to reflect the true climatic variety that prevails in this region. This is crucial because climate change, like almost everything else, can only be addressed at the local level: changes in weather patterns, increased droughts, changes in monsoon behavior-these have severe repercussions on India's ecosystems as well as

on human population (Wilbanks and Kates 1999). The current high-resolution temperature and precipitation datasets for India by the Indian Meteorological Department are of 1° and 0.25° resolution respectively, which restricts their applicability for finer analyses and more accurate applications and does not account for uncertainty (Srivastava *et al* 2009, Pai *et al* 2014).

Providing high-resolution BCVs for India is essential for numerous SDM studies across the country. The dataset from the Indian Meteorological Department (IMD) has underestimated precipitation over the decades (Khouider *et al* 2020, Goteti and Famiglietti 2024). A new high-resolution observation-based ensemble precipitation dataset (IPED) has recently become available for India. This dataset, developed with a resolution of 0.10° and 30 ensemble members daily, uses observation gauge data to improve accuracy (Peringiyl and Saharia 2024, Peringiyl *et al* 2025). It has shown better performance compared to the 0.25° -degree IMD gridded dataset detecting extreme events especially over Northwestern Himalayas (Peringiyl and Saharia 2026). However, an ensemble temperature dataset using regional observation networks is still unavailable over India. Global datasets, such as EM-Earth, provide ensemble temperature data at a resolution of 0.10° with 25 ensembles per day, developed from the SC Earth observation network (Tang *et al* 2021, 2022b). Ensemble datasets are characterized by accounting for uncertainty within the data. The development of BCVs from this ensemble dataset is still unexplored in the field.

In this study, we utilize the mean of the observation-based ensemble precipitation dataset IPED and global EM-Earth temperature dataset to develop a high-resolution region-specific BCV dataset for India. To the best of our knowledge, there are no existing BCV datasets developed for India that use ensemble precipitation and temperature datasets. The outcome of our study is a set of 19 BCVs which are developed at a resolution of 0.10° . Our dataset, created from ensemble-based high-resolution data, enhances the accuracy of various applications in fields like ecology and biogeographical research.

2. Study area

The dataset grids are defined on a spatial domain spanning 68°E 98°E and 5.5°N – 37.5°N , as shown in figure 1 over India, where monsoon variability and climatic extremes significantly impact socio-economic conditions. For example, the Himalayan region has extreme seasonal fluctuations in temperature and precipitation, whereas coastal regions are extremely humid and have definite wet and dry seasons because of the monsoon cycle (Bhutiya *et al* 2010, Singh and Ranade 2010). The regions of semi-arid and arid lands in the west, like the Thar Desert, face extreme heat and highly irregular rainfall, which could influence vegetation and biodiversity uniquely (Dhir and Singhvi 2012).

3. Data sources

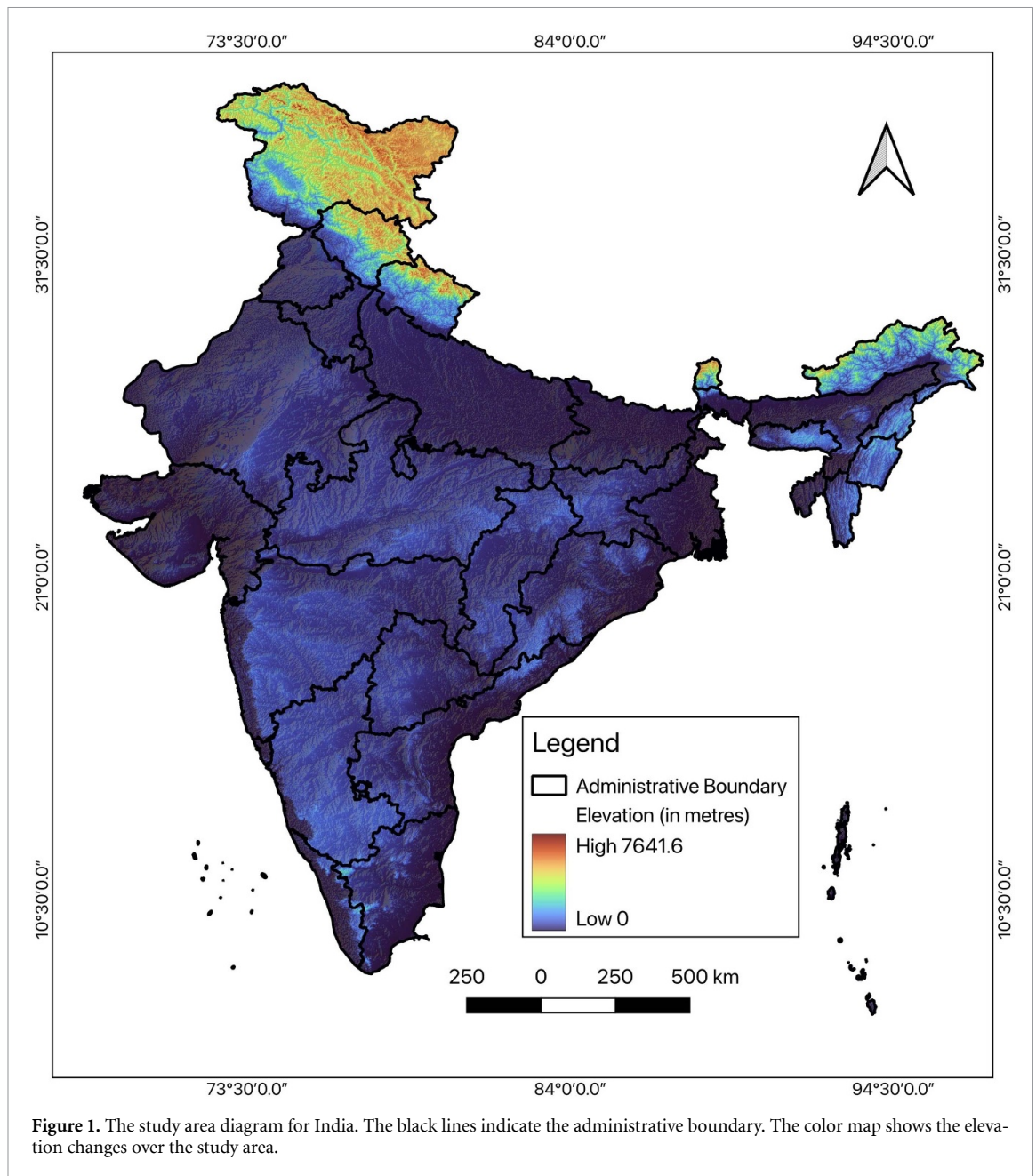
The following datasets are used for this study:

3.1. IPED

IPED is a recently developed observation-based ensemble precipitation dataset that builds upon the IMD gauge station network (Peringiyl and Saharia 2024, Peringiyl *et al* 2025). The dataset is available from 1991 to 2023 at a spatial resolution of 0.10° and daily timestep with 30 ensemble members per day. It is developed using Geospatial Probabilistic Estimation Package Tool, which uses a statistical based locally weighted linear regression and spatially correlated random field technique to develop the ensembles and (Tang *et al* 2024). We have used the daily mean of these 30 ensembles for our analysis.

3.2. EM-Earth dataset

The EM-Earth dataset (Tang *et al* 2022b) comprises high-resolution gridded estimates of multiple meteorological variables, including mean daily temperature (T_{mean}), daily temperature range (T_{range}), and dew-point temperature (T_{dew}) from 1950 to 2019 (Tang *et al* 2022a). The dataset is constructed by integrating station-based observations from the Serially Complete Earth (SC-Earth) dataset with reanalysis data from ERA5, a sophisticated global atmospheric reanalysis offered by the European Centre for Medium-Range Weather Forecasts (Hersbach *et al* 2020, Tang *et al* 2021). The SC-Earth dataset addresses temporal discontinuities in raw station observations by employing advanced gap-filling techniques, thereby offering a comprehensive and uninterrupted record of meteorological variables throughout the study period. EM-Earth provides temperature measurements with a spatial precision of 0.10° , surpassing that of many existing global datasets.



Since the EM-Earth dataset is currently available only up to 2019, the temperature-based and combined BCVs were generated for the period 1991–2019, whereas precipitation-based variables derived from IPED extend to 2023. This temporal difference reflects the availability of the source datasets rather than a methodological constraint. Future updates of IPEDClim will incorporate newer releases of EM-Earth or equivalent high-resolution temperature datasets, enabling a consistent temporal coverage for all BCVs.

3.3. CHELSA dataset

CHELSA is a high-resolution global climate dataset developed by downscaling the ERA-Interim reanalysis outputs to a 30 arc second (approximately 1 km) resolution (Karger *et al* 2017). The downscaling methodology incorporates statistical downscaling for the atmospheric temperature. In the case of precipitation, it incorporated orographic factors, valley shielding, and boundary-layer height, followed by a subsequent bias correction. CHELSA-monthly (www.chelsa-climate.org/datasets/chelsa_monthly) provides aggregated surface variables, summarized as monthly means, for the period 1979 to present. Because the pre-computed BCV product (CHELSA-BIOCLIM) is based on a fixed 1981–2010 climatological baseline

Table 1. A summary of all bioclimatic variables and their types and short forms.

Variable shortform	Variable description	Variable type
BIO1	Annual mean temperature	Temperature related
BIO2	Mean diurnal range temperature	Temperature related
BIO3	Isothermality	Temperature related
BIO4	Temperature seasonality	Temperature related
BIO5	Max temperature of warmest month	Temperature related
BIO6	Min temperature of coldest month	Temperature related
BIO7	Annual temperature range	Temperature related
BIO8	Mean temperature of most humid quarter	Combined
BIO9	Mean temperature of least humid quarter	Combined
BIO10	Mean temperature of warmest quarter	Temperature related
BIO11	Mean temperature of coldest quarter	Temperature related
BIO12	Annual precipitation	Precipitation related
BIO13	Mean precipitation of wettest month	Precipitation related
BIO14	Mean precipitation of driest month	Precipitation related
BIO15	Precipitation seasonality	Precipitation related
BIO16	Mean precipitation of wettest quarter	Precipitation related
BIO17	Mean precipitation of driest quarter	Precipitation related
BIO18	Mean precipitation of warmest quarter	Combined
BIO19	Mean precipitation of coldest quarter	Combined

that does not correspond to the 1991–2020 study period, BIO12 was computed directly from CHELSA-monthly precipitation data for the matching period, following the same monthly aggregation approach as used for IPEDClim-derived variables.

4. Methodology

The study incorporates nineteen BCVs (BIO1–BIO19) encompassing temperature, precipitation, and combined climate indicators, each representing distinct aspects of thermal and hydrological regimes relevant to ecological and climatic assessments (table 1). Figure 2 describes the overall framework of the study. The framework included temperature-based metrics, such as mean annual temperature, diurnal range, and isothermality, as well as precipitation-based metrics, such as total annual precipitation and seasonal rainfall patterns. It converts raw climate data into targeted variables that are very crucial for the ecological modeling and biodiversity research in the region. The following steps were followed:

Step 1: After accessing the IPED and EM-Earth datasets, using the xarray package to clip the EM-Earth dataset to the latitude-longitude coordinates of India using the India shapefile and subsequently re-grid the coordinates to align with the IPED dataset using cdo package.

Step 2: The EM-Earth dataset is provided in the form of mean daily temperature (t_{mean}) and diurnal range of daily temperature (t_{range}). We derive the datasets for maximum and minimum daily temperatures (t_{max} and t_{min}) using the following formulas equations (1) and (2):

$$t_{\text{max}} = t_{\text{mean}} + t_{\text{range}}/2 \quad (1)$$

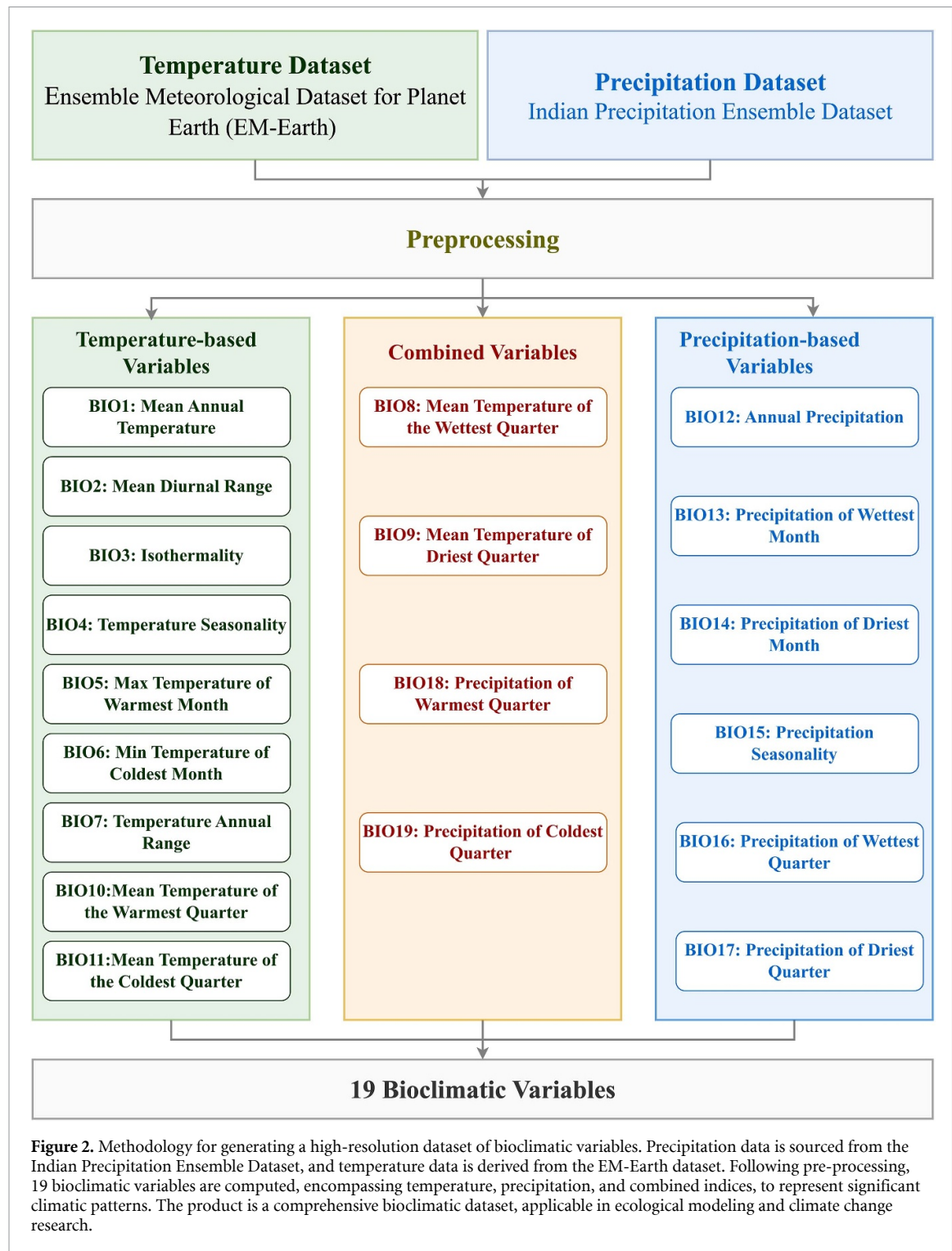
$$t_{\text{min}} = t_{\text{mean}} - t_{\text{range}}/2. \quad (2)$$

Step 3: The precipitation and temperature dataset is grouped by year and the BCVs are calculated as per the mentioned procedure in the following sections.

4.1. Temperature based BCVs

The following are the BCVs developed from the temperature, combined, and precipitation datasets. For more information, please refer to (O'Donnell and Ignizio 2012), <https://pubs.usgs.gov/ds/691/ds691.pdf>

- Mean annual temperature (BIO1): To calculate it, we averaged the monthly temperatures and then averaged the results over 12 months. This serves as an indicator of the total thermal energy available to an ecosystem, influencing species distribution, vegetation growth, and ecological processes.



- Mean diurnal range (BIO2): Each monthly diurnal range is the difference between the highest and lowest temperatures in that month. Using monthly averages like this is the same as finding the temperature difference each day in a month and then averaging those differences for the month. This difference is then averaged over the twelve months of the year. This index can help provide information for characterizing short-term thermal variability that influences species distributions and physiological responses.
- Isothermality (BIO3): It measures the magnitude of diurnal temperature fluctuations in comparison to the amplitude of seasonal (summer-to-winter) temperature variations. This is computed as: $\text{BIO2 (Mean Diurnal Range)} / \text{BIO7 (annual temperature range)}$, which is the difference between the highest

monthly temperature (warmest month) and the lowest monthly temperature (coldest month) multiplied by 100. It is generally useful for identifying tropical, insular, and maritime environments. A BIO3 of 100 means the daily temperature range is the same as the yearly temperature range, while a value below 100 means seasonal temperature variability exceeds the average day-to-night temperature variation.

- Temperature seasonality (BIO4): This is determined from the standard deviation of the 12 monthly mean temperatures. It is the magnitude of the seasonal temperature variability throughout the year. It distinguishes regions or climates with strong thermal seasonality (for example, the north Indian region where summers and winters differ strongly) from those with thermally stable annual temperature regimes. The higher BIO4 indicate greater seasonal temperature variability.
- Maximum temperature of warmest month (BIO5): It is calculated as the highest maximum temperature among the twelve monthly maximum temperatures in a year. This variable provides an estimate of upper thermal conditions experienced by a species or a crop that it would face in its hottest month in that region. This variable is widely used to measure heat stress, how well organisms handle heat, and the possible effects of very high temperatures on where species live and how well crops grow.
- Minimum temperature of coldest month (BIO6): The minimum temperature for each year is determined by identifying the lowest monthly temperature value within that year. This variable identifies the lowest minimum temperature for that region. BIO6 provides an estimate of the minimum temperatures that species and crops are likely to encounter during the coldest month of the year. This variable is widely used to assess cold stress, frost tolerance, and the potential impacts of low-temperature extremes on species distributions, ecosystem functioning, and agricultural productivity.
- Temperature annual range (BIO7): A quantitative measure of the annual variation in temperature. It is calculated as the difference between BIO5 (Max Temperature of Warmest Month) and BIO6 (Min Temperature of Coldest Month). BIO7 is valuable for assessing the influence of extreme temperature conditions on species distributions, ecosystem functioning, and agricultural productivity.
- Mean temperature of most humid quarter (BIO8): It is calculated by first identifying the most humid quarter, defined as the consecutive three-month period with the highest total precipitation, and then computing the mean temperature over the same three-month period. This variable represents the mean temperatures for the wettest three months of the year, helpful in the analysis of how these environmental factors influence species' seasonal distributions.
- Mean temperature of driest quarter (BIO9): It is calculated by first identifying the driest quarter, defined as the consecutive three-month period with lowest total precipitation, and then computing the mean temperature for the same three month duration. This variable describes the thermal conditions during the driest season and represents the temperature regime experienced by habitats during the period of lowest water availability.
- Mean temperature of warmest quarter (BIO10): It is calculated by first identifying the warmest quarter, defined as the consecutive three-month period with the highest mean temperature, and then computing the mean temperature over the same three-month period. This variable is highly correlated with BIO5 but smooths a single extreme month into a seasonal average. This variable quantifies the average thermal conditions during the warmest season and is useful for assessing the influence of high seasonal temperatures on species distributions, vegetation, and ecological processes.
- Mean temperature of coldest quarter (BIO11): It is calculated by first identifying the coldest quarter, defined as the consecutive three-month period with the lowest mean temperature, and then determining the average temperature for the three months in the coldest quarter. This variable characterizes the thermal conditions during the coldest season and represents sustained cold-season temperatures rather than a single monthly extreme. It is useful for assessing prolonged cold stress and its influence on species distributions, ecosystem functioning, and agricultural productivity.

4.2. Precipitation based BCVs

The following BCVs are developed from the 0.10° IPED precipitation dataset. The BCVs and their descriptions are provided below.

- Annual precipitation (BIO12): It is defined as the sum of all total monthly precipitation values. A single number summary of total water input at that location. However, it does not represent intra-annual variability.
- Precipitation of wettest month (BIO13): It is calculated by identifying the month with the highest cumulative precipitation total. This variable represents the maximum monthly precipitation received at a location and is useful for characterizing peak water availability and seasonal moisture conditions. It is widely used to assess the influence of high precipitation on species distributions, ecosystem functioning, and hydrological processes. High values of BIO13 may also indicate an increased risk for flooding, soil moisture, or erosion when considered with other climatic and catchment factors.
- Precipitation of driest month (BIO14): It is calculated by identifying the month with the lowest cumulative precipitation total. It is a proxy for drought-stress. This variable represents the minimum monthly precipitation received at a location and provides an indicator of moisture availability during the driest period of the year. It is useful for assessing dry-season conditions and the potential influence of limited water availability on species distributions
- Precipitation seasonality (BIO15): BIO15 quantifies the variation in monthly precipitation totals throughout the year. Higher BIO15 values indicate greater variability in monthly precipitation, whereas lower values represent a more uniform distribution of rainfall across the year.
- Precipitation of wettest quarter (BIO16): The quarter with the highest cumulative precipitation is determined from consecutive three-months, and the cumulative precipitation for that quarter is computed. This metric quantifies the maximum seasonal water volume available to an ecosystem over a continuous three-month period. It characterizes the core hydrological engine of a habitat, corresponding to the interval of peak soil moisture replenishment, maximum river discharge, and strongest vegetation growth.
- Precipitation of driest quarter (BIO17): It is calculated by first identifying the driest quarter, defined as the consecutive three-month period with the lowest total precipitation, and then summing the precipitation over the same three-month period. It represents a sustained dry-season precipitation condition rather than a single driest-month extreme. BIO17 is useful for assessing seasonal moisture availability and the potential influence of prolonged dry conditions on species distributions, ecosystem functioning, and agricultural productivity.
- Precipitation of warmest quarter (BIO18): It is calculated by first identifying the warmest quarter, defined as the consecutive three-month period with the highest mean temperature, and then summing the precipitation over the same three-month period. This variable represents the total precipitation received during the warmest season and is useful for characterizing the interaction between temperature and precipitation during periods of maximum thermal conditions.
- Precipitation of coldest quarter (BIO19): It is calculated by first identifying the coldest quarter, defined as the consecutive three-month period with the lowest mean temperature, and then summing the precipitation over the same three-month period. This variable represents the total precipitation received during the coldest season and is useful for characterizing seasonal moisture availability under cold climatic conditions. It is widely used to assess the combined influence of temperature and precipitation on species distributions, ecosystem functioning, and agricultural productivity.

4.3. Trend analysis of BCV's

4.3.1. Mann–Kendall (MK) trend test

To assess monotonic trends in the BCVs, the non-parametric MK test (Mann 1945, Kendall 1955) was employed in this study. The MK test is widely used in hydroclimatic studies due to its ability to handle non-normally distributed data, tolerate missing values, and remain robust in the presence of outliers.

The MK test statistic S is defined as equations (3)–(6):

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (3)$$

where n represents the number of time steps, and x_i and x_j denote data values at time steps i and j , respectively, such that $j > i$. The sign function $\text{sgn}(x_j - x_i)$ is expressed as:

$$\text{sgn}(x_j - x_i) = \begin{cases} +1, & \text{if } x_j - x_i > 0 \\ 0, & \text{if } x_j - x_i = 0 \\ -1, & \text{if } x_j - x_i < 0 \end{cases} \quad (4)$$

To assess the significance of S , its variance is estimated as:

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^P t_i(t_i-1)(2t_i+5)}{18} \quad (5)$$

Here, P is the number of tied groups and t_i denotes the number of data points in the i th tied group. If no ties are present, the summation term becomes zero.

The standardized test statistic Z is calculated as:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}}, & \text{if } S > 0 \\ 0, & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}}, & \text{if } S < 0 \end{cases} \quad (6)$$

A positive Z indicates an increasing trend, while a negative Z suggests a decreasing trend. At a 5% significance level, the null hypothesis of no trend is rejected if $|Z| > 1.96$.

4.3.2. Sen's slope estimator

To quantify the magnitude of the detected trend, Sen's slope estimator (Sen 1968) was applied. This method calculates the median of all pairwise slopes between data points across the time series equations (7) and (8):

$$Q_i = \frac{X_j - X_k}{j - k} \quad \text{for all } j > k. \quad (7)$$

The total number of slope estimates is $N = \frac{n(n-1)}{2}$. The final Sen's slope Q_{med} is given by the median of the ordered slope values:

$$Q_{\text{med}} = \begin{cases} Q_{(N+1)/2}, & \text{if } N \text{ is odd} \\ \frac{Q_{N/2} + Q_{(N/2)+1}}{2}, & \text{if } N \text{ is even} \end{cases} \quad (8)$$

4.3.3. Trend classification criteria

A significance level of $\alpha = 0.05$ was adopted for hypothesis testing. Trends at each grid cell were classified based on the slope and associated p-value as follows:

- **Increasing trend:** $Q_{\text{med}} > 0$ and $p \leq 0.05$
- **Decreasing trend:** $Q_{\text{med}} < 0$ and $p \leq 0.05$
- **No significant trend:** $p > 0.05$

These classifications were spatially mapped for all BCVs to assess long-term climatic dynamics across India.

5. Results and discussion

We created 19 BCVs using temperature and precipitation data to identify key climatic factors essential for environmental and ecological research. These variables encompass aspects such as temperature variation, seasonal changes, and precipitation patterns, all of which are vital for studying climate impact and modeling species distribution. Visualizations of all 19 variables are provided in the Supplement. The temporal resolutions for the temperature and combined variables are from 1991 to 20219. However, for the precipitation based variables are from 1991 to 2023. This is purely based on unavailability of EM-Earth dataset beyond 2019.

5.1. Temperature-based BCVs

We calculated nine temperature-related BCVs from the EM-Earth dataset for each year and analyzed their long-term mean values (1991 to 2019). Temperature-related variables are essential in ecological and climatic research as they aid in assessing species distribution, habitat preference, and climate-induced changes in ecosystems. Each BCV reveals an aspect of the climatic information of a location (O'Donnell and Ignizio 2012). The annual mean temperature (BIO1) gives basic information on the average energy inputs of the region annually (figure S1). The map shows that the vast majority of peninsular and central India falls in the warm 20°C – 28°C range represented by deep brown. The mean diurnal range (BIO2) quantifies the average variability between daytime and night time temperatures, offering valuable information about local microclimatic conditions. A lower diurnal temperature range typically reflects a more thermally stable climate. Figure S2 illustrates the relatively low diurnal temperature ranges observed across southern India, which result from the moderating influence of the surrounding oceans on coastal climates. Isothermality (BIO3) denotes the uniformity of temperatures throughout the year and is quantified as the ratio of the mean diurnal range to the yearly temperature range (figure 3(a)). The index gives a normalized measure of temperature fluctuation demonstrating the distribution of temperatures across time scales. We can observe from figure 3(a) that the Western Coast of India experiences high isothermality, indicating a stable annual temperature, whereas the northern mountainous regions of the Himalayas experience low isothermality, indicating that seasonal temperature variability is substantially greater than day-to-night temperature variability. Temperature seasonality (BIO4) denotes the extent of temperature variation throughout the year, quantified as the standard deviation of monthly temperatures (figure S3). High temperature seasonality shows considerable seasonal temperature changes, typical of continental regions, whereas low seasonality reflects steady, consistent temperatures, commonly associated with tropical climates. Max temperature of warmest month (BIO5) represents the maximum mean temperature of the warmest month, illustrating the maximum thermal conditions observed during the hottest month of the year (figure S4). Min. temperature of coldest month (BIO6) represents the minimum temperature during the coldest month of the year, indicates the minimum thermal conditions experienced during the coldest month and may influence the distribution and survival of cold-sensitive species (figure S5). Annual temperature range (BIO7) represents the difference between the maximum temperature of the hottest month (BIO5) and the minimum temperature of the coldest month (BIO6) (figure 3(b)). Consequently, it signifies the extent of temperature fluctuation throughout the year. Figure 3(b) indicates that northern India exhibits significantly greater seasonal temperature variation than southern India, reflecting more pronounced continental and altitudinal influences. Mean temperature of warmest quarter (BIO10) represents the mean temperature of the warmest quarter annually, characterizing the average thermal conditions during the warmest season and serves as an indicator of prolonged exposure to elevated temperatures (figure S8). This parameter is crucial for comprehending species distributions, particularly in regions where sustained high temperatures may approach or exceed physiological tolerance thresholds. Mean temperature of coldest quarter (BIO11) assesses the mean temperature during the coldest quarter in any region, as characterizing thermal conditions during the coldest season is essential for understanding species survival and shape ecological processes in cold environments (figure S9). This variable is widely used for comprehending the impact of winter temperature fluctuations on species survival, growth, and reproduction.

5.2. Precipitation-based BCVs

We derived six precipitation-based BCVs using the IPED precipitation dataset for each year and analyzed their long-term mean values for the duration of 1991 to 2023. Precipitation-based variables are essential for understanding hydrological cycles, assessing water availability, and modeling the impacts of climate on ecosystems (Peters-Lidard *et al* 2021). Precipitation-based variables facilitate the analysis of extreme weather phenomena, drought conditions, and their effects on biodiversity and agriculture. Annual precipitation (BIO12) shows the total annual precipitation received at a location over the course of a year, including rainfall and other forms of precipitation such as hail or snow (O'Donnell and Ignizio 2012). It is a crucial indicator of water supply in a region, directly influencing ecosystem dynamics, plant development, and the hydrological cycle. As shown in figure S10, annual precipitation exhibits substantial spatial variability across India, ranging from less than 500 mm over the arid north-western region and the rain-shadow areas of the Deccan Plateau to more than 2000–4000 mm over the Western Ghats, the northeastern states, and the sub-Himalayan foothills. The Indo-Gangetic Plain and central India generally receive intermediate annual precipitation totals of approximately 700–1500 mm.

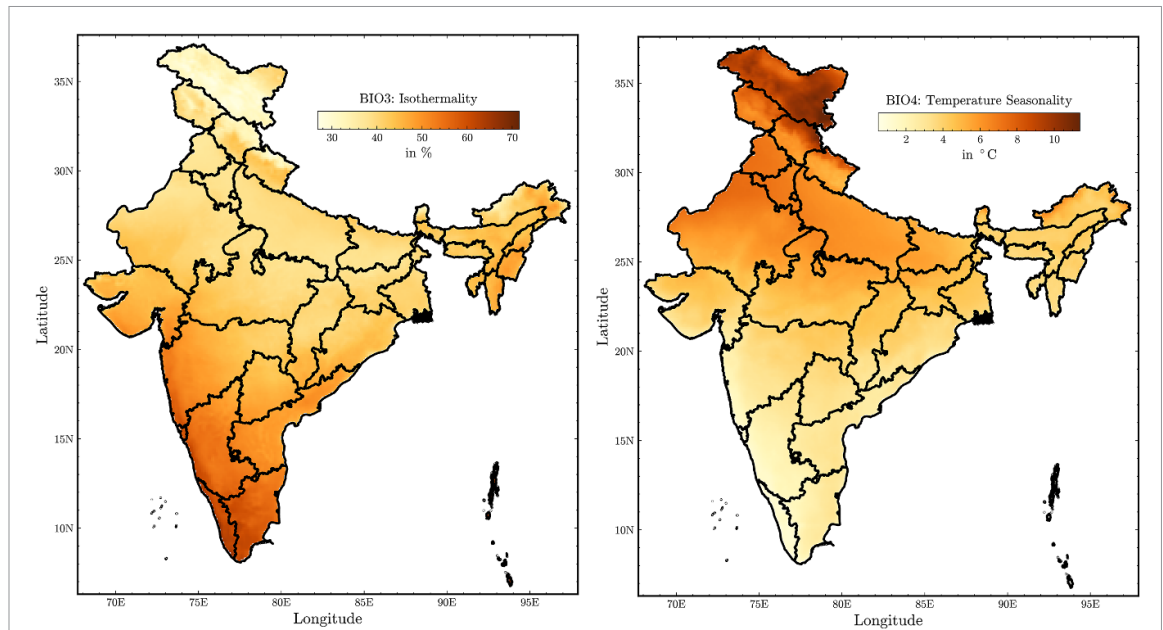


Figure 3. (a) Isothermality (BIO3), representing the ratio of the mean diurnal temperature range to the annual temperature range, expressed as a percentage. (b) Temperature Seasonality (BIO4), representing the standard deviation of monthly mean temperatures, indicating the degree of annual temperature variability across India. Black lines represent state boundaries.

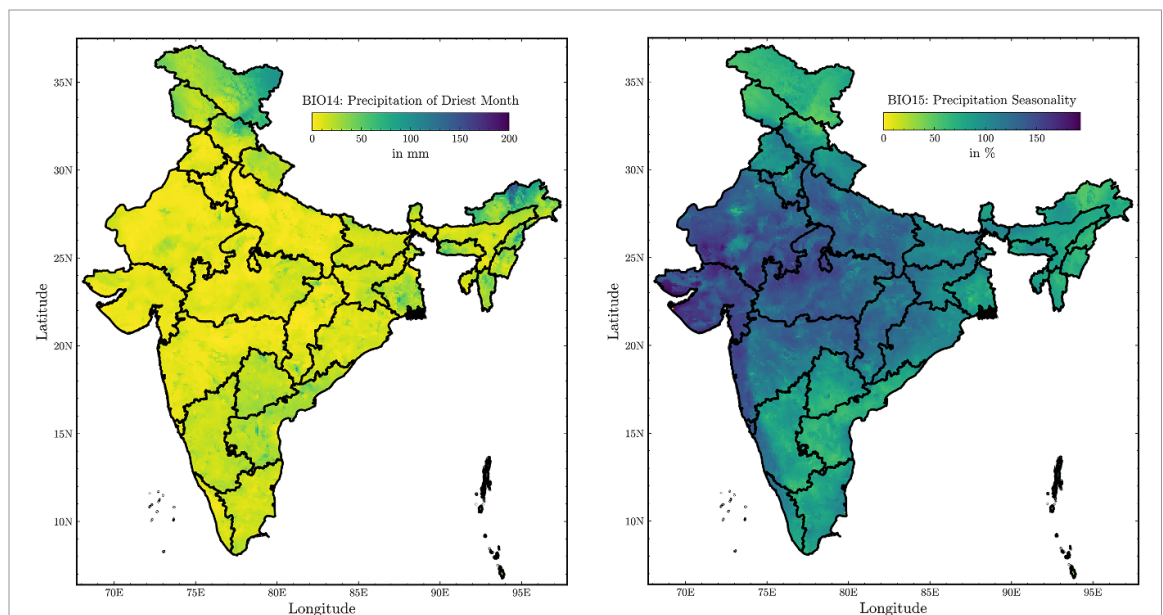


Figure 4. (a) The mean precipitation during the driest month, identifying areas vulnerable to drought. (b) Illustrates rainfall variability over the year, showing areas with consistent or fluctuating precipitation patterns.

Precipitation of the Wettest Month (BIO13) is crucial for comprehending the intensity and concentration of rainfall during the wettest month of the year, a significant factor in evaluating water availability for ecosystems and species (figure S11). The highest BIO13 occur along the windward slopes of the Western Ghats and across the Meghalaya–Assam region, reflecting the combined influence of the southwest monsoon and orographic enhancement. In contrast, the arid northwestern region receives lesser rainfall during its wettest month, while intermediate values are observed across much of the Indo-Gangetic Plain and the interior Deccan Plateau. These patterns are consistent with the spatial distribution of monsoon rainfall across India. Mean precipitation of driest month (BIO14) serves as a significant indicator of aridity and water scarcity in a region, identifying places with extended dry spells or instances of water deficiency (figure 4(a)). Figure 4(a) shows that large parts of India receive little or no precipitation during the driest month of the year, as indicated by the predominance of yellow shades. This pattern shows

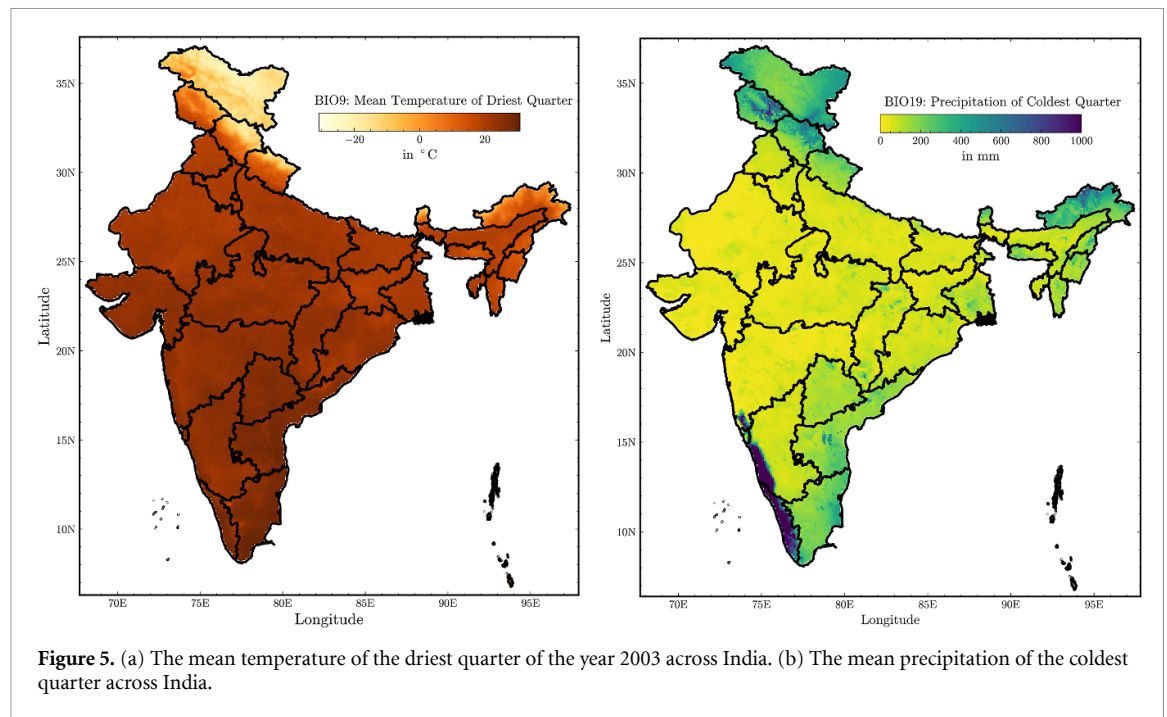
the seasonal withdrawal of the southwest monsoon and the prolonged dry season over most of the country. In contrast, relatively higher BIO14 values are observed over the western Himalayas and parts of northeastern India, where winter western disturbances, local orographic effects, and year-round precipitation contribute to measurable rainfall even during the driest month. These spatial patterns highlight regional differences in dry-season moisture availability across India. Precipitation seasonality (BIO15) measures the coefficient of variation of monthly precipitation totals, throughout the year (figure 4(b)). A higher BIO15 indicates greater disparities between wet and dry months, while a lower value suggests a more uniform distribution of rainfall. Figure 4(b) shows that Rajasthan and other parts of western India exhibit high precipitation seasonality, reflecting distinct wet and dry seasons. This metric is crucial for classifying climate types, since it can delineate regions as desert, seasonal, or humid climates. It is widely utilized in water resource management and agriculture for irrigation planning, crop rotation, and drought management strategies. Precipitation of wettest quarter (BIO16) is crucial for ecosystems that rely on seasonally available water, as the peak rainfall quarter often coincides with periods of heightened biological activity, such as plant growth, breeding, or migration for some species (figure S12). The highest values of BIO16 are observed along the windward slopes of the Western Ghats and the Meghalaya Plateau, reflecting the combined effects of the southwest monsoon and orographic enhancement. The sub-Himalayan foothills and the northeastern region also receive greater rainfall during the wettest quarter. In contrast, the Thar Desert and the interior Deccan Plateau receive lower rainfall, highlighting the strong contrast between India's humid and semi-arid to arid climatic zones. The spatial distribution of BIO16 closely aligns with the major monsoon precipitation regimes and serves as a robust indicator of seasonal water availability. Precipitation of driest quarter (BIO17) is essential for comprehending water stress during extended dry periods, as these conditions may influence ecosystem functioning, species distributions, and agricultural productivity (figure S13). As shown in figure S13, BIO17 exhibits very low precipitation across much of peninsular, central, and northwestern India, where many regions receive little or no rainfall during the driest quarter.

5.3. Combined BCVs

Four BCVs integrate precipitation and temperature data to illustrate seasonal climate variations. Combined variables facilitate the examination of seasonal climate extremes, which are crucial for comprehending species distribution, agricultural productivity, and climate adaptation strategies. Simultaneous analysis of temperature and precipitation enables prediction of ecosystem resilience, seasonal water supply, and regions vulnerable to climate change. We have derived the four bioclimatic variable based on the three consecutive months same procedure as in (O'Donnell and Ignizio 2012).

Mean Temperature of the Wettest Quarter (BIO8) represents the average temperature during the wettest season and serves as a key metric for evaluating the combined effects of temperature and precipitation on species distributions, vegetation patterns, and ecosystem functioning (figure S6). The interplay between temperature and moisture during the rainy period significantly affects species distribution, growth patterns, reproduction, and survival. As shown in figure S6, BIO8 represents high temperatures across much of peninsular, central, and eastern India, reflecting the warm climatic conditions prevailing during the wettest quarter. In contrast, substantially lower temperatures are observed over the Himalayan region, where the wettest quarter occurs under much cooler conditions because of the strong influence of elevation. The mean temperature of the driest quarter (BIO9) refers to the average temperature recorded during the driest consecutive three-month period (figure 5(a)). Figure 5 demonstrates that BIO9 records relatively warm temperatures throughout peninsular and central India, indicative of the prevailing warm climatic conditions during the driest quarter. Conversely, the Himalayan region exhibits substantially lower temperatures during the driest quarter, attributable to the strong influence of elevation. These spatial patterns differentiate regions with warm dry seasons from those with cold dry seasons and offer valuable insights for ecological, agricultural, and hydrological applications.

Precipitation of the Warmest Quarter (BIO18) represents the total precipitation received during the warmest consecutive three-month period and characterizes the interaction between temperature and precipitation during the warmest season. Figure S14 demonstrated that much of peninsular India, the Indo-Gangetic Plain and northeastern India receive moderate to high precipitation during the warmest quarter, reflecting the partial or complete overlap between the warmest season and the onset of the southwest monsoon. In contrast, the arid northwestern region, including Rajasthan and parts of Gujarat, and the rain-shadow regions of the Deccan Plateau receive less rainfall during the warmest quarter, indicating that the hottest period of the year occurs under relatively dry conditions. Precipitation of the Coldest Quarter (BIO19) refers to the total precipitation accumulated during the coldest consecutive three-month period. In high-altitude regions such as the Himalayas, this precipitation predominantly falls as snowfall, which contributes to the formation of seasonal snowpack and influences subsequent meltwater



availability (figure 5(b)). Together, BIO18 and BIO19 offer valuable insights into India's seasonal water balance, highlighting how warming conditions and shifting monsoon patterns may alter the timing and intensity of precipitation, with implications for water security, agriculture, and ecosystem stability.

5.4. Trend analysis of BCVs over India (1991–2019/2023)

In this study the long-term spatial trends of the 19 BCVs were evaluated using the non-parametric MK trend test in combination with Sen's slope estimator. The MK test was used to determine the statistical significance of monotonic trends, while Sen's slope quantified the magnitude and direction of change at each 0.1° grid cell. Temperature-based BCVs (BIO1–BIO11) were analyzed for the period 1991–2019, whereas precipitation-based BCVs (BIO12–BIO19) were analyzed for 1991–2023. Trends with $p \leq 0.05$ are indicated by stippling in the figures, highlighting regions where the detected trends are statistically significant.

5.4.1. Temperature-based BCVs (BIO1–BIO11)

Temperature-based BCVs reveal a predominantly positive warming signal across India, although the magnitude and spatial extent of the trends vary among individual variables. The Sen's slope estimates indicate widespread increases in annual and seasonal temperature metrics across peninsular, central and northeastern India, whereas localized cooling or relatively weaker warming persists over parts of the western Himalaya and adjoining northern regions. Areas showing statistically significant trends (MK test, $p \leq 0.05$) are highlighted by stippling in the corresponding maps.

The Annual mean temperature (BIO1) exhibits a widespread positive trend across most of India (figure 6(a)). The strongest warming is concentrated over the Southern Peninsula, central India, Gujarat and the northeastern states, where Sen's slope values commonly range between $+0.02$ and $+0.04^\circ\text{C yr}^{-1}$, with isolated grid cells approaching $+0.05^\circ\text{C yr}^{-1}$. Extensive statistically significant warming is observed across Maharashtra, Karnataka, Telangana, Andhra Pradesh, Tamil Nadu, Gujarat and much of Northeast India. In contrast, localized negative trends occur over the western Himalayan region, extending through parts of Jammu and Kashmir, Himachal Pradesh and Uttarakhand, with Sen's slope values generally ranging between -0.02 and $-0.04^\circ\text{C yr}^{-1}$. These contrasting spatial patterns indicate that although annual temperatures have increased over most of India during 1991–2019, the magnitude of warming is not spatially uniform.

The mean diurnal range (BIO2) displays considerably greater spatial heterogeneity than BIO1 (figure 6(b)). Positive trends dominate much of southern, eastern and central India, whereas negative trends are concentrated over sections of the Indo-Gangetic Plain and the northwestern Himalayan region. Sen's slope values generally remain within $\pm 0.05^\circ\text{C yr}^{-1}$, indicating relatively modest long-term changes in the difference between daytime and nighttime temperatures compared with annual mean warming. Statistically significant increases are primarily observed across peninsular India and parts of

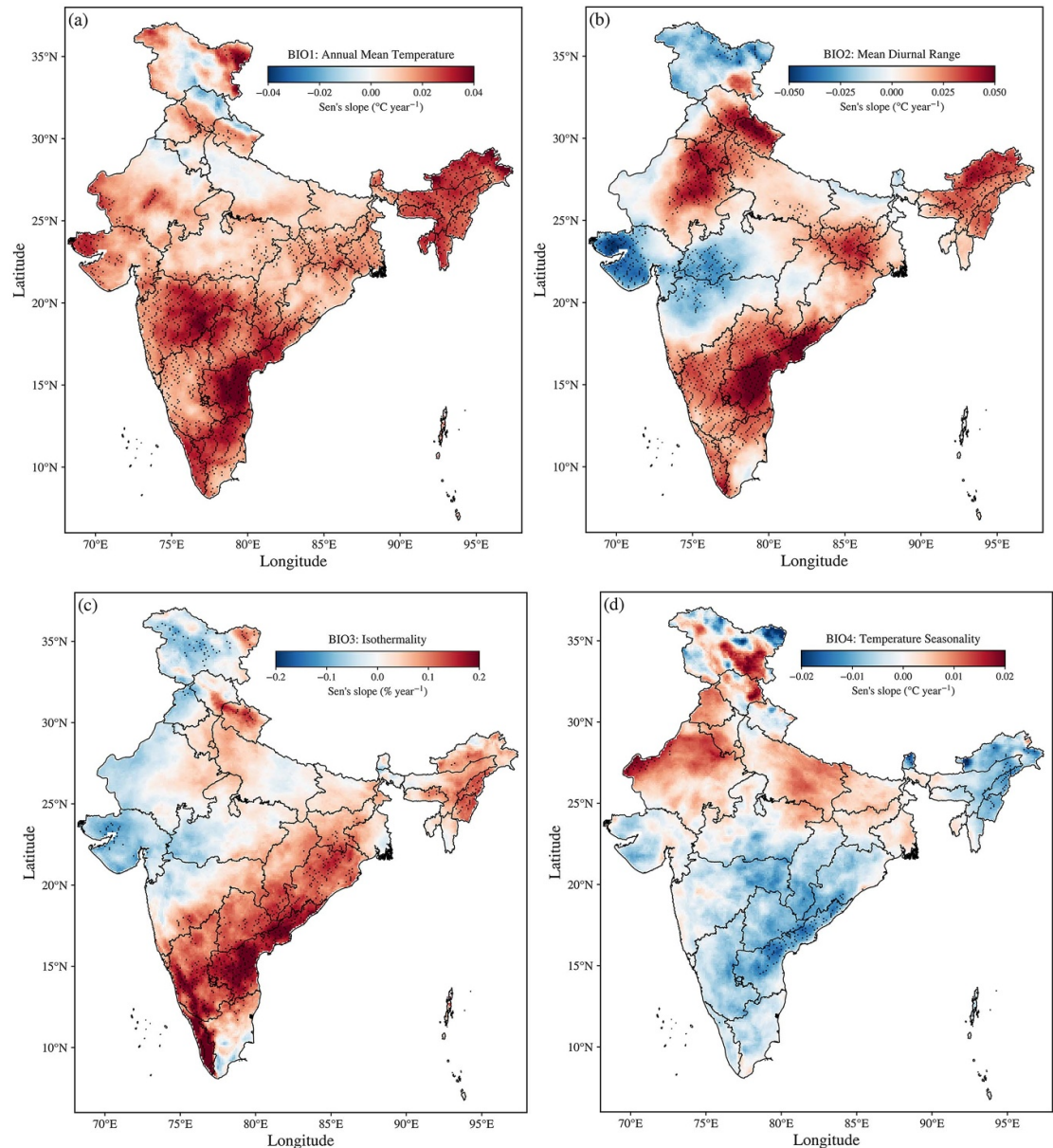


Figure 6. (a) Annual mean temperature trends (BIO1), (b) mean diurnal range trends (BIO2) across India during 1991–2019. (Black stippling indicates statistically significant Mann–Kendall test, $p \leq 0.05$). (c) Isothermality trends (BIO3), (d) temperature seasonality trends (BIO4) across India, 1991–2019 (Black stippling indicates statistically significant Mann–Kendall test, $p \leq 0.05$). (e) Maximum temperature of warmest month trends (BIO5), (f) minimum temperature of coldest month trends (BIO6), 1991–2019 across India (Black stippling indicates statistically significant Mann–Kendall test, $p \leq 0.05$). (g) Annual temperature range trends (BIO7), (h) mean temperature of most humid quarter trends (BIO8), (i) mean temperature of driest quarter trends (BIO9), (j) mean temperature of warmest quarter trends (BIO10) across India, 1991–2019 (Black stippling indicates statistically significant Mann–Kendall test, $p \leq 0.05$). (k) Mean temperature of coldest quarter (BIO11) trends across India, 1991–2019 (Black stippling indicates statistically significant Mann–Kendall test, $p \leq 0.05$). (l) Annual precipitation trends (BIO12), (m) precipitation of the wettest month trends (BIO13), (n) precipitation of the driest month trends (BIO14) across India, 1991–2023 (Black stippling indicates statistically significant Mann–Kendall test, $p \leq 0.05$). (o) Precipitation seasonality trends (BIO15), (p) precipitation of the wettest quarter trends (BIO16) across India, 1991–2023 (Black stippling indicates statistically significant Mann–Kendall test, $p \leq 0.05$). (q) Precipitation of driest quarter trends (BIO17), (r) precipitation of warmest quarter trends (BIO18), (s) precipitation of coldest quarter trends (BIO19) across India, 1991–2023 (Black stippling indicates statistically significant Mann–Kendall test, $p \leq 0.05$).

eastern India, while significant decreases occur over localized Himalayan regions, suggesting regional differences in the rates of daytime and nighttime temperature change.

Isothermality (BIO3) shows a clear spatial contrast across India, with increasing trends dominating peninsular, eastern and parts of central India, while decreasing trends prevail over the western Himalayan region, Gujarat and northwestern India (figure 6(c)). The strongest positive trends occur across Kerala, Tamil Nadu, Karnataka, Andhra Pradesh and adjoining parts of eastern peninsular India, where Sen's slope values range between $+0.10$ and $+0.20\% \text{ year}^{-1}$. Positive trends also extend across

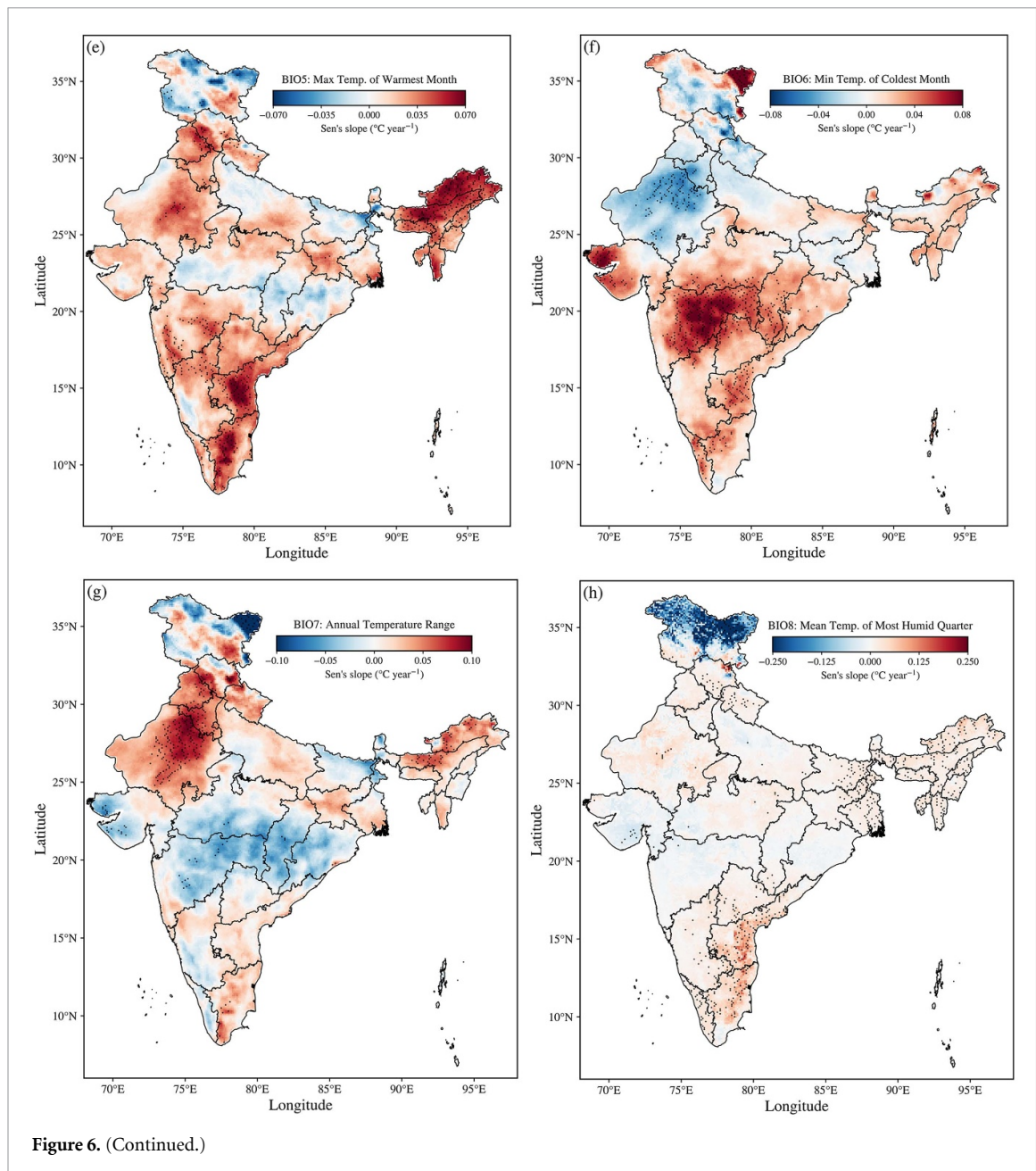
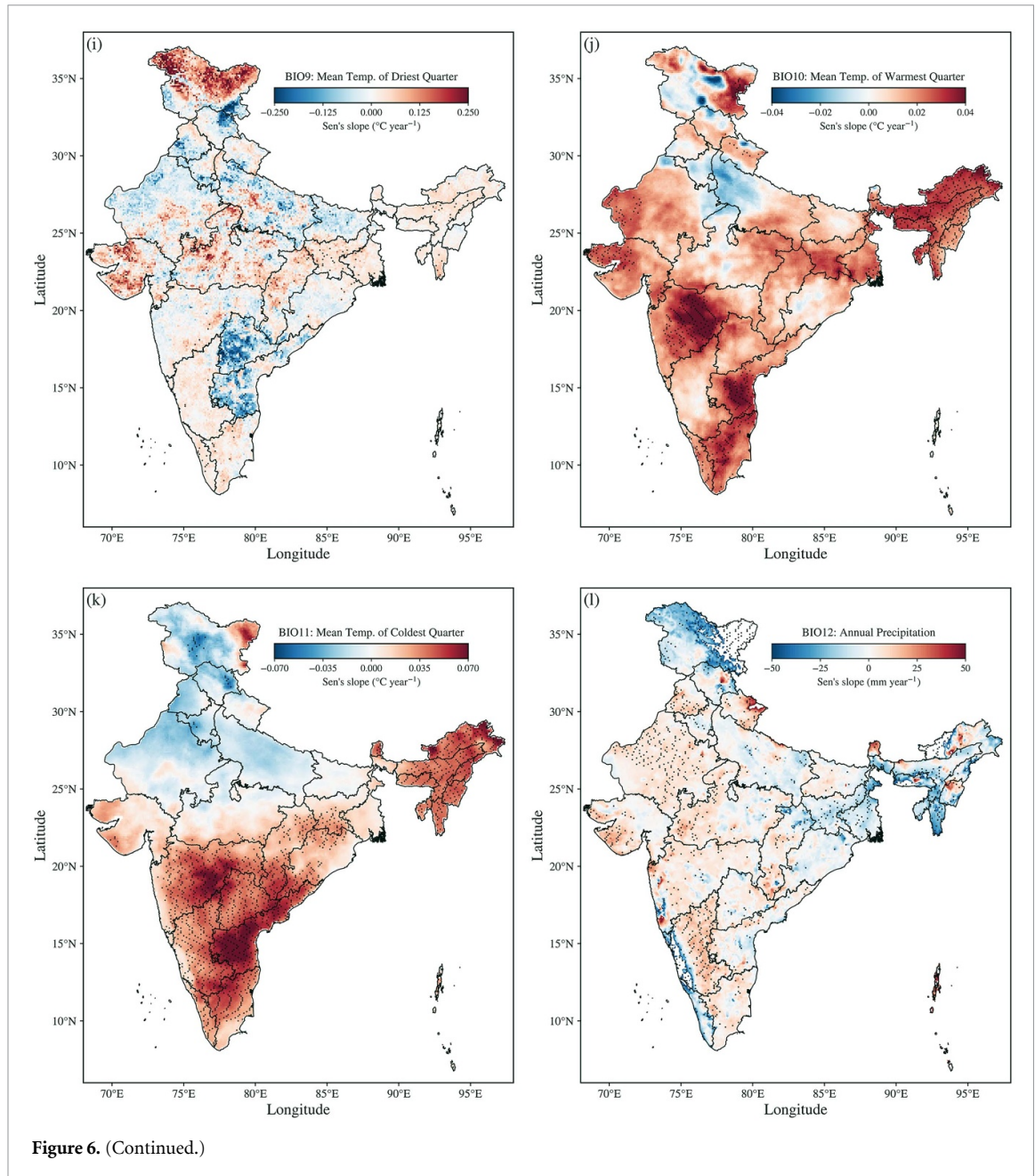


Figure 6. (Continued.)

Odisha, Chhattisgarh, Jharkhand and parts of Northeast India, with several areas showing statistically significant increases. In contrast, negative Sen's slope values of approximately -0.10 to -0.20 $\% \text{ year}^{-1}$ are observed over Gujarat, western Rajasthan and the western Himalayan belt, with significant declines concentrated in Jammu and Kashmir. These contrasting patterns indicate that isothermality has increased across much of southern and eastern India but declined over northwestern and Himalayan regions. Such differences suggest regional variations in the balance between diurnal and annual temperature variability across the country.

Temperature Seasonality (BIO4) presents an almost opposite spatial pattern to BIO3 (figure 6(d)). Positive trends are concentrated across the western Himalaya, northwestern India and portions of the upper Indo-Gangetic Plain, where Sen's slope values generally range from $+0.01$ to $+0.02$ $^{\circ}\text{C yr}^{-1}$. Statistically significant increases are particularly evident across western Rajasthan and localized sectors of Jammu and Kashmir. In contrast, negative trends dominate central, eastern and peninsular India, extending from Maharashtra and Telangana through Andhra Pradesh, Odisha and parts of Chhattisgarh, with Sen's slope values commonly ranging between -0.01 and -0.02 $^{\circ}\text{C yr}^{-1}$. Significant decreasing trends are also observed across the northeastern states. These results indicate a reduction in annual temperature variability across much of peninsular and eastern India,



whereas seasonal thermal contrasts have strengthened in parts of northwestern India and the western Himalayan region.

The Maximum Temperature of the Warmest Month (BIO5) shows predominantly positive trends across much of India, indicating an overall intensification of warm-season maximum temperatures during 1991–2019 (figure 6(e)). The strongest warming occurs across the northeastern states, where Sen's slope values commonly exceed $+0.05^{\circ}\text{C yr}^{-1}$ and locally approach $+0.07^{\circ}\text{C yr}^{-1}$. Additional areas of significant warming are evident across Southern Peninsular India, particularly Kerala, Tamil Nadu, Karnataka and Telangana, as well as isolated portions of Punjab, Haryana and central India, with Sen's slope values generally ranging between $+0.03$ and $+0.07^{\circ}\text{C yr}^{-1}$. In contrast, localized negative trends occur over parts of eastern India, central-eastern India and sections of the western Himalayan region, although these are generally weaker, ranging between -0.03 and $-0.07^{\circ}\text{C yr}^{-1}$. Overall, the results indicate that extreme daytime temperatures during the warmest month have increased across most regions of India, with statistically significant warming concentrated primarily in the northeast and southern peninsula.

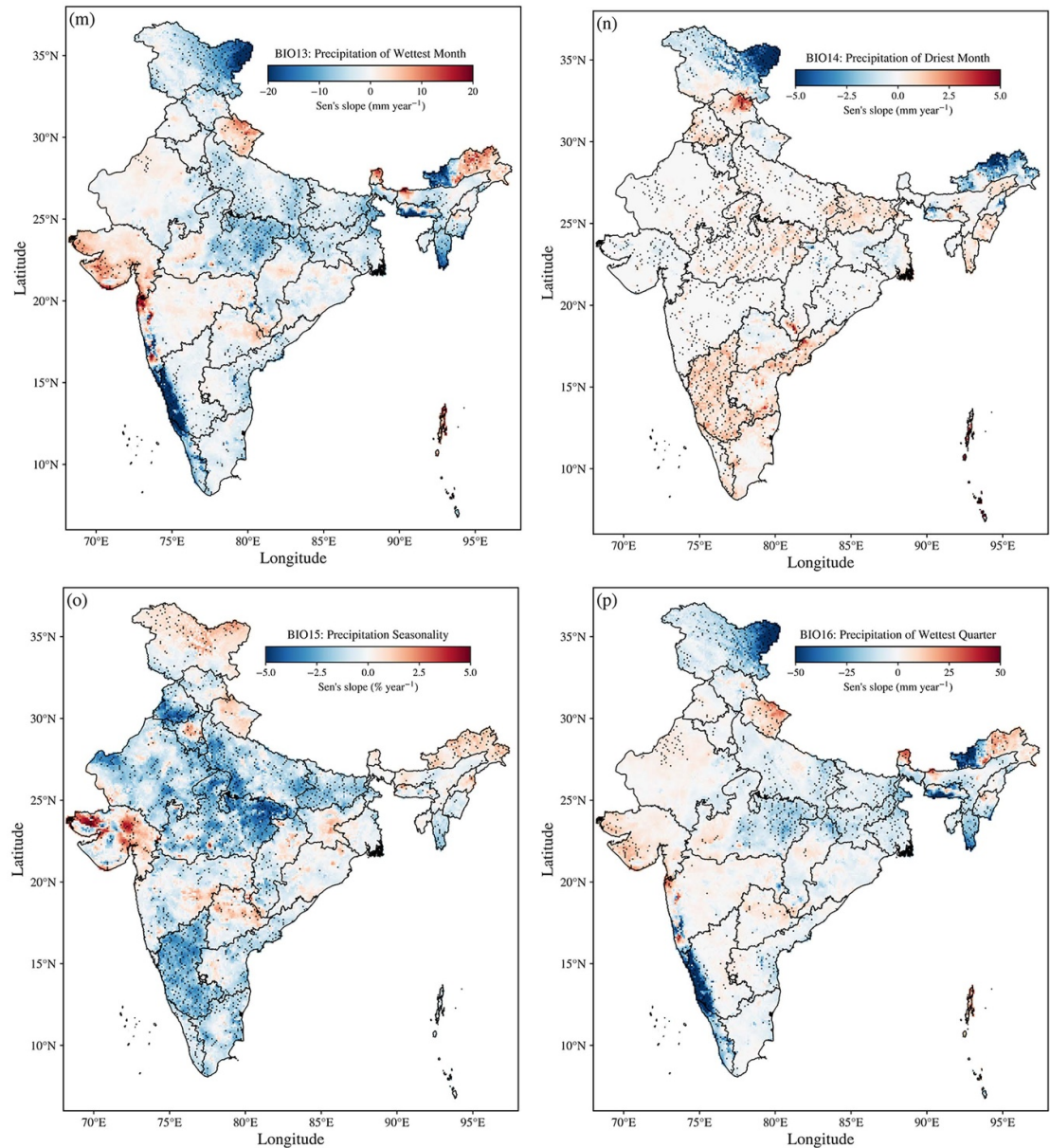


Figure 6. (Continued.)

The Minimum Temperature of the Coldest Month (BIO6) highlights a more heterogeneous spatial distribution than BIO5 (figure 6(f)). Positive trends dominate central and peninsular India, where Sen's slope values commonly range between $+0.04$ and $+0.08^{\circ}\text{C yr}^{-1}$. The strongest statistically significant increases occur across Maharashtra, Madhya Pradesh, Chhattisgarh, Telangana and adjoining regions, indicating substantial warming of winter minimum temperatures. Additional localized warming is observed over Gujarat and parts of southern India. Conversely, negative trends characterize much of the western Himalayan region and northwestern India, extending across Jammu and Kashmir, Himachal Pradesh, Uttarakhand, Punjab and Rajasthan, with Sen's slope values generally ranging between -0.04 and $-0.08^{\circ}\text{C yr}^{-1}$. Smaller areas of weak negative trends are also observed over parts of eastern India. These findings suggest that while winter minimum temperatures have increased across large parts of central and peninsular India, portions of the Himalayan and northwestern regions exhibit localized cooling or comparatively weaker warming during the study period.

The Annual Temperature Range (BIO7) exhibits a distinct north–south contrast across India (figure 6(g)). Positive trends dominate the northwestern Indo-Gangetic Plains, extending across Punjab, Haryana, western Uttar Pradesh and parts of Himachal Pradesh, where Sen's slope values generally range

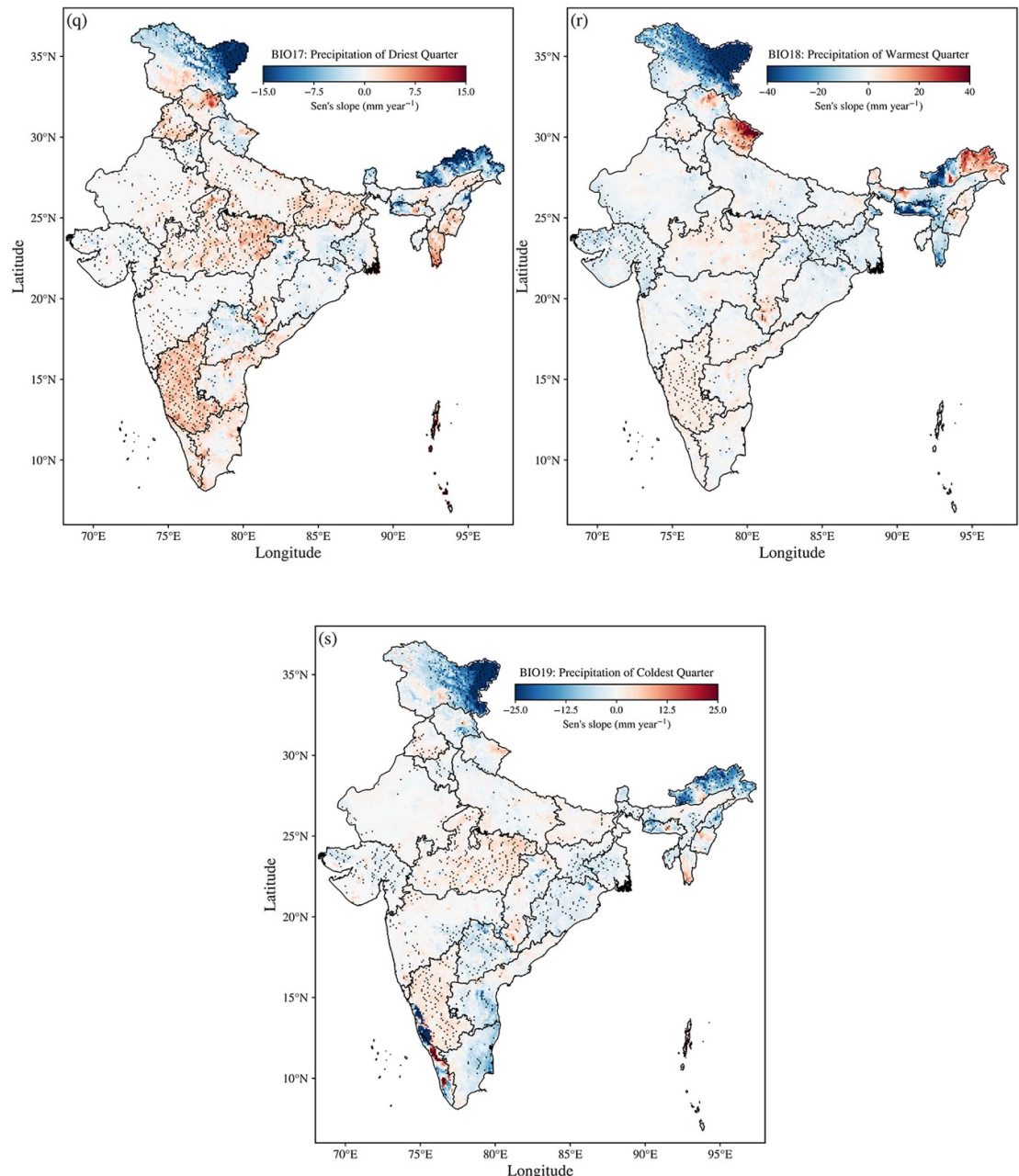


Figure 6. (Continued.)

between $+0.05$ and $+0.10^{\circ}\text{C yr}^{-1}$, with many areas showing statistically significant increases. In contrast, much of central and peninsular India, including Madhya Pradesh, Chhattisgarh, Maharashtra, Odisha and adjoining regions, exhibits significant negative trends of approximately -0.05 to $-0.10^{\circ}\text{C yr}^{-1}$. These results indicate an increasing annual temperature range over northwestern India, whereas much of central and southern India is experiencing a reduction in the difference between summer and winter temperatures. The Mean Temperature of the Wettest Quarter (BIO8) is characterized by predominantly negative trends over the western Himalayan region, where Sen's slope values locally approach $-0.25^{\circ}\text{C yr}^{-1}$. Elsewhere, trends remain weak and close to zero across most parts of the country, although localized positive trends ($+0.10$ to $+0.25^{\circ}\text{C yr}^{-1}$) are observed over parts of Telangana, Andhra Pradesh and Tamil Nadu. Statistically significant changes are concentrated mainly over the Himalayas, Southern Peninsular India and isolated pockets of eastern India (figure 6(h)).

The Mean Temperature of the Driest Quarter (BIO9) displays a highly heterogeneous spatial pattern (figure 6(i)). Strong positive trends dominate the western Himalayan region, particularly Jammu and Kashmir and Ladakh, where Sen's slope values exceed $+0.20^{\circ}\text{C yr}^{-1}$, while negative trends of -0.10 to $-0.25^{\circ}\text{C yr}^{-1}$ occur over parts of Telangana, Karnataka and adjoining central India. Elsewhere, the

country exhibits a mosaic of localized warming and cooling with relatively weak magnitudes. In comparison, the Mean Temperature of the Warmest Quarter (BIO10) shows widespread positive trends across most of India (figure 6(j)). Significant warming is particularly evident over Gujarat, central India, Maharashtra, Telangana, Karnataka, Tamil Nadu and the northeastern states, with Sen's slope values generally ranging between $+0.02$ and $+0.04^{\circ}\text{C yr}^{-1}$. Localized negative trends are confined mainly to the western Himalayan region and scattered pockets of northern India. Overall, BIO10 indicates a consistent increase in summer-season temperatures across much of the country, with the strongest warming concentrated over central, western and northeastern India.

The Mean Temperature of the Coldest Quarter (BIO11) reflects a clear spatial contrast across India (figure 6(k)). Positive trends dominate central, eastern and peninsular India, with statistically significant warming over Maharashtra, Madhya Pradesh, Telangana, Andhra Pradesh, Chhattisgarh and parts of Odisha, where Sen's slope values generally range between $+0.03$ and $+0.07^{\circ}\text{C yr}^{-1}$. In contrast, negative trends are observed across the northwestern Himalayas and the Indo-Gangetic Plains, with localized cooling reaching -0.03 to $-0.07^{\circ}\text{C yr}^{-1}$. Overall, BIO11 indicates a substantial increase in winter temperatures across much of central and southern India, while northern India shows comparatively weaker or declining trends.

5.4.2. Precipitation-based BCVs (BIO12–BIO19)

Precipitation-based BCVs show greater spatial variability than the temperature variables, reflecting regional differences in rainfall trends across India. Annual Precipitation (BIO12) shows widespread declining trends over the Himalayan region, Northeast India and the Western Ghats, with Sen's slope values reaching -50 to -100 mm yr^{-1} . In contrast, parts of northwestern and central India record slight increases of up to $+50\text{ mm yr}^{-1}$ (figure 6(l)). A similar pattern is observed for the Precipitation of the Wettest Month (BIO13), where rainfall decreases by $10\text{--}20\text{ mm yr}^{-1}$ across the Western Ghats, central India and the northeastern hills, while localized increases occur over Gujarat, Jammu and Kashmir, and Arunachal Pradesh (figure 6(m)). These patterns suggest a weakening of peak monsoon rainfall over several traditionally high-rainfall regions. The Precipitation of the Driest Month (BIO14) records relatively weak trends across most of India, indicating limited changes in dry-season rainfall. Slight increases ($2.5\text{--}5\text{ mm yr}^{-1}$) are confined to parts of peninsular India and the western Himalayas, whereas the northeastern hills show localized declines (figure 6(n)).

Precipitation Seasonality (BIO15) shows declining trends of -2.5 to $-5\text{ \% yr}^{-1}$ across much of the Indo-Gangetic Plains, central India, the Western Ghats and peninsular India, indicating that rainfall has become less seasonal in these regions (figure 6(o)). In comparison, Precipitation of the Wettest Quarter (BIO16) shows decreases of $25\text{--}50\text{ mm yr}^{-1}$ over the Western Ghats, the Himalayan region and Northeast India, while parts of northwestern India show moderate increases (figure 6(p)). Together, these patterns point to changes in both the seasonal distribution and the amount of rainfall received during the monsoon. Such changes may modify catchment hydrological responses by altering the timing and intensity of rainfall, potentially increasing the occurrence of prolonged dry spells followed by high-intensity rainfall events, thereby influencing soil moisture conditions and ecosystem resilience.

Precipitation of the Driest Quarter (BIO17) shows declining trends over the Himalayan and northeastern regions (-7.5 to -15 mm yr^{-1}), whereas most of central and peninsular India records only marginal positive changes (figure 6(q)). A similar spatial pattern is observed for the Precipitation of the Warmest Quarter (BIO18), with rainfall reductions of $20\text{--}40\text{ mm yr}^{-1}$ across the Himalayas, Northeast India and parts of the Western Ghats, while isolated increases occur over northwestern India (figure 6(r)). Similarly, Precipitation of the Coldest Quarter (BIO19) records decreasing trends over the Himalayan belt, Northeast India and parts of the southern Western Ghats, whereas scattered areas of central and western India show slight increases (figure 6(s)). The consistency of these seasonal trends suggests that precipitation changes are occurring throughout the year, with the most pronounced reductions concentrated in the Himalayan region, Northeast India and parts of the Western Ghats. In the Himalayan region, declining cold-season precipitation may reduce seasonal snow accumulation, affecting snowpack storage and the timing and magnitude of spring snowmelt. These changes may subsequently influence downstream river flows, pre-monsoon water availability and irrigation-dependent agriculture across the Indo-Gangetic Plains, highlighting the broader hydrological implications of changing seasonal precipitation patterns.

Overall, precipitation BCVs shows a spatially complex picture of India's evolving hydroclimatic condition, with contrasting trends of precipitation increase and decrease across different regions. While temperature indicators display widespread and consistent warming, precipitation variables emphasize localized intensification, redistribution, and the emergence of uneven hydroclimatic regimes. These spatially heterogeneous trends have important ecohydrological implications, influencing snowpack dynamics in the Himalayan headwaters, seasonal river flow regimes, groundwater recharge, soil moisture availability, and agricultural water security. Such changes are likely to affect ecosystem functioning and water-resource sustainability, emphasizing the need for region-specific adaptation and climate-resilient management strategies.

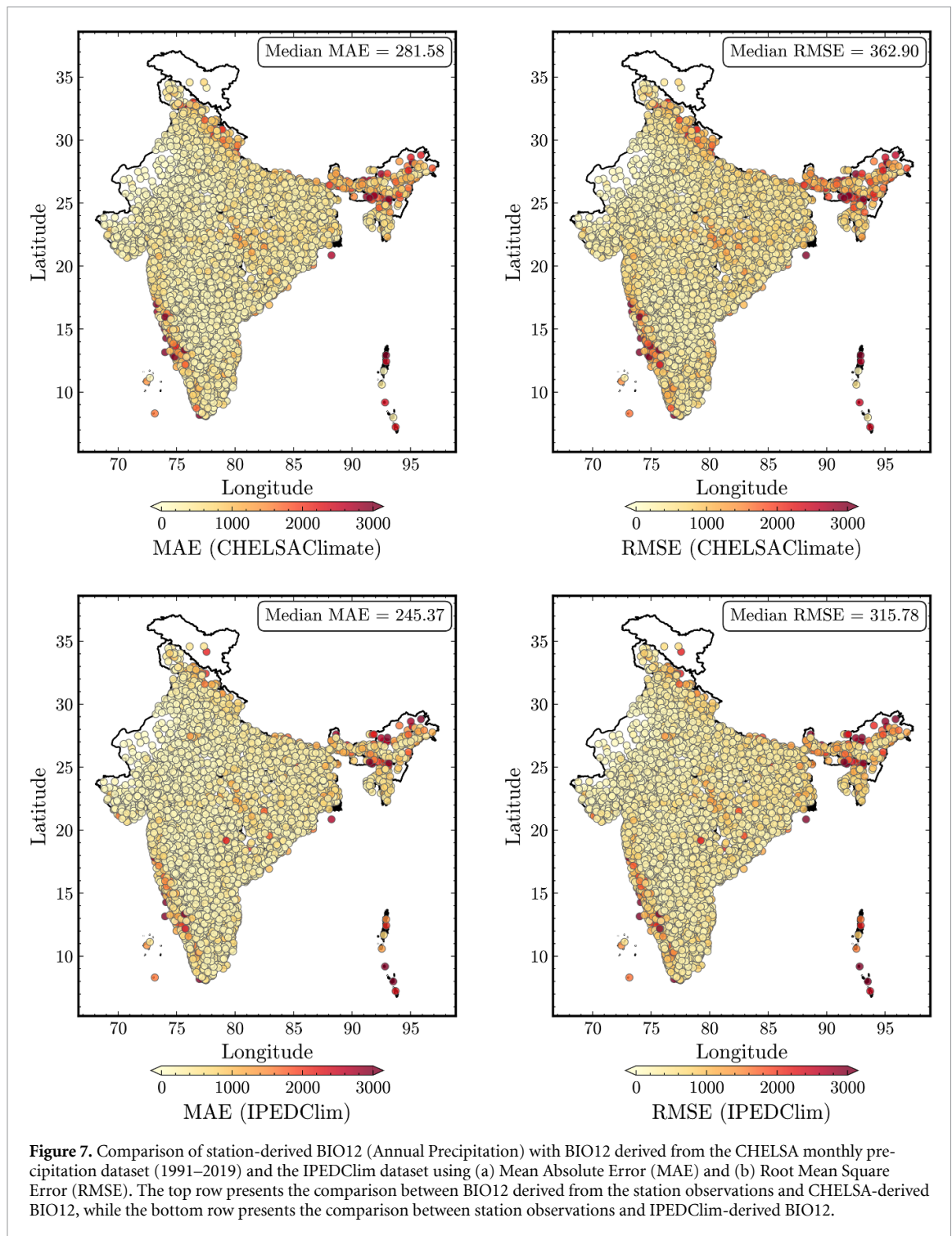
5.5. Comparison with global BCVs

Direct comparison of bioclimatic products is limited by differences in their temporal coverage and underlying data sources. For instance, for every 19 BCVs, WorldClim provides a single 1970–2000 climatological average per pixel, with no inter-annual time series available for direct comparison against our record (Fick and Hijmans 2017). Moreover, MERRAclim was excluded from quantitative comparison because its precipitation-dependent variables, including BIO12, are derived from specific humidity rather than true precipitation, making them physically incomparable with rainfall-based products (Vega *et al* 2017). On the other hand, IPEDClim's precipitation-based BCVs (BIO12–BIO17) are available from 1991 to 2023, reflecting the temporal coverage of the underlying IPED precipitation dataset (Peringiyil *et al* 2025). CHELSA-bioclim, available at approximately 1 km resolution from 1981 to 2100, in a summarized gridded dataset. However, it also provides the CHELSA-monthly dataset, which underlies the BCVs. So instead of directly comparing the decade-summarized CHELSA-bioclim, we created the BIO12 variable from the continuous CHELSA-monthly precipitation time series computed independently for the same years as IPEDClim (Karger *et al* 2017). The BIO12 was computed from the CHELSA-monthly dataset. Because IPEDClim (0.1°, 11 km) and CHELSA-monthly (1 km) do not share a common native grid, BIO12 was compared at the station level rather than through direct grid-to-grid comparison. For each station, the nearest pixel values were extracted from both IPEDClim and BIO12 derived from CHELSA-monthly for the overlapping year 1991–2020 period and compared against station-observed BIO12. Mean absolute error (MAE) and root mean square error (RMSE) were computed for each product relative to the station observations (figure 7). Station-level validation of BIO12 demonstrates spatially heterogeneous performance for both products. IPEDClim (median MAE of 245.37 mm, median RMSE of 315.78 mm) outperforms BIO12 BCV derived from CHELSA-monthly (median MAE of 281.58 mm, median RMSE of 362.90 mm) across India. The largest errors for both products occur in northeastern India and along the Western Ghats coast, reflecting the extreme orographic precipitation gradients in these regions that are challenging for gridded products to resolve at sub-kilometer to 10 km scales. In contrast, errors are lowest in the Indo-Gangetic Plain, Rajasthan, and the Deccan interior, where gentle spatial gradients and moderate annual precipitation totals support more accurate gridded reconstructions. We note that part of the residual error in both products likely reflects differences in representativeness between point-station measurements and gridded area averages, in addition to true product bias, given the differing native resolutions of the two datasets.

6. Conclusions and future applications

This study develops a high resolution BCVs developed over India using ensemble-based precipitation dataset IPED and ensemble-based temperature dataset EM-Earth. The developed dataset has a spatial resolution of 0.10° and contains 19 different BCVs per year. Temperature-based and combined BCVs were generated for the period 1991–2019, while precipitation-based BCVs were generated for 1991–2023. The majority of India's SDM research is based on global bioclimatic datasets, which are useful, however, have coarser resolution and developed globally. Such data may not reflect local temperature changes or microhabitat conditions, leading to inaccuracies in species distribution maps. Our newly developed high-resolution dataset has the potential to provide a more accurate and detailed representation of India's diverse climatic zones, significantly enhancing the precision of future ecological and conservation research. Moreover, these datasets are valuable resources for ecological and climatic research in India, a nation known for its extensive geographical and climatic diversity.

In addition to dataset generation, this study conducted a comprehensive grid-based trend analysis of all 19 BCVs using the non-parametric MK test and Sen's slope estimator. The results indicate a widespread and statistically significant warming pattern across most of India, with spatially variable precipitation trends that suggest both intensification and redistribution of rainfall. The observed trends in



temperature and rainfall show that India's hydroclimatic conditions are changing in different regions. These changes are likely to influence habitat suitability, ecological niches, and species distributions. The high-resolution regional IPEDClim dataset is a strong resource for modeling species distributions, analyzing habitat suitability, supporting biodiversity conservation, assessing ecological risks, and planning for climate change adaptation.

While global databases provide a valuable foundation for ecological and climatic studies, they often fail to reflect the localized climate gradients of the Indian subcontinent accurately. The development of a new, high-resolution dataset based on observation-driven ensemble data holds significant potential in addressing this shortcoming. Additionally, unlike most existing global bioclimatic datasets, which typically offer a single climatological value for each BCV based on a predefined 30-year reference period, IPEDClim provides both annual BCVs and a long-term climatological dataset at 0.10° spatial resolution.

This enables users to derive climatologies for any desired temporal period, investigate interannual variability, and assess temporal changes in climatic suitability rather than being constrained to a fixed climatological baseline. The inclusion of long-term trend analysis within the IPEDClim framework further enhances its applicability for ecological, agricultural, and hydrological modeling. This approach would greatly improve the accuracy of ecological models and climate change forecasts, enabling researchers and policymakers to create more localized, focused environmental management and adaptation policies.

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Data availability statement

The IPEDClim dataset can be visualized here (<https://hydrosense.users.earthengine.app/view/bioclim-atlas-india>) and downloaded from here: <https://doi.org/10.5281/zenodo.15525139>

The source datasets in this study are available from the following sources:

- IPED Dataset: Anagha P, & Manabendra Saharia. (2025). Indian Precipitation Ensemble Dataset (IPED) [Data set]. In Scientific Data (Version 7, Vol. 12, p. 333). Zenodo. <https://doi.org/10.5281/zenodo.8199138>
- EM Earth Dataset: Tang, G., Clark, M., Papalexiou, S. (2022). EM-Earth: The Ensemble Meteorological Dataset for Planet Earth. Federated Research Data Repository. <https://doi.org/10.20383/102.0547>
- Karger, D. N., Brun, P., Zilker, F. (2025). CHELSA-monthly climate data at high resolution. EnviDat. [www.doi.org/10.16904/envi.dat.686](https://doi.org/10.16904/envi.dat.686).

The data that support the findings of this study are openly available at the following URL/DOI: <https://doi.org/10.5281/zenodo.16169255>. ioppccitedata.

Supplementary Data 1 available at <https://doi.org/10.1088/2752-5295/aea4e4/data1>.

Compliance with Ethical Standards

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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