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Spatiotemporal variability in rainfall erosivity over Eastern India: Historical trend and future projection

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सार – वार्षिक वर्षा और वर्षा अपरदनशीलता (Rainfall Erosivity–R factor) की स्थानिक-कालिक परिवर्तनशीलता मौसमी मृदा अपरदन की गतिशीलता तथा क्षेत्रीय जल संसाधन प्रबंधन के आकलन में महत्वपूर्ण कारक है, क्योंकि परिवर्तित जलवायु परिस्थितियों में पूर्वी भारत में जल, मृदा और पर्यावरण के बीच होने वाली जटिल अंतःक्रियाओं पर इसका महत्वपूर्ण प्रभाव पड़ता है। इस अध्ययन में भारत मौसम विज्ञान विभाग (IMD) से प्राप्त 1969-2022 के दैनिक ऐतिहासिक वर्षा आँकड़ों का विश्लेषण पूर्वी भारत के पाँच मौसम विज्ञान उपखंडों—अरुणाचल प्रदेश (AP), असम-मेघालय (AM), नागालैंड-मणिपुर-मिजोरम-त्रिपुरा (NMMT), उप-हिमालयी पश्चिम बंगाल एवं सिक्किम (SHWBS) तथा गंगा के मैदानी पश्चिम बंगाल (GWB) के लिए किया गया। कोरडेक्स-एसए (CORDEX-SA) फ्रेमवर्क का उपयोग करते हुए भविष्य के वैश्विक जलवायु मॉडल अनुमानों में सीएमआईपी5 (CMIP5) के आठ तथा सीएमआईपी6 (CMIP6) के पाँच डाउनस्केल किए गए पूर्वाग्रह-संशोधित आउटपुट की उप-जिला स्तर की भविष्यवाणियों की मध्य भविष्य (Mid Future–MF; 2040-2069) और दूर भविष्य (Far Future–FF; 2070-2099) की समयावधियों के लिए तुलना की गई। ऐतिहासिक प्रेक्षणों के विरुद्ध सत्यापन करने पर मॉडल अनुकरणों में महत्वपूर्ण अनिश्चितताएँ पाई गईं। इसके विपरीत, पिछले पाँच दशकों के IMD भू-आधारित प्रेक्षणों में वार्षिक वर्षा तथा R factor दोनों में कमी की स्थानिक-कालिक परिवर्तनशीलता देखी गई, जबकि CMIP6 के उच्च कार्बन उत्सर्जन परिदृश्यों के अंतर्गत विशेष रूप से FF अवधि में AP और AM उपखंडों में परिवर्तनशील बढ़ती प्रवृत्ति स्पष्ट हुई। इस प्रकार, यह अध्ययन मृदा अपरदन के बढ़ते जोखिम तथा जलवैज्ञानिक चक्र में होने वाले परिवर्तनों को रेखांकित करता है, जिनका स्थानीय कृषि-पारिस्थितिक तंत्रों पर प्रतिकूल प्रभाव पड़ सकता है। अनुमानित वर्षा अपरदनशीलता में वृद्धि से संकेत मिलता है कि वर्षा से गतिज ऊर्जा बढ़ सकती है, जिससे मृदा अपरदन का जोखिम बढ़ेगा। अध्ययन के निष्कर्ष पूर्वी भारत में कृषि-पारिस्थितिक तंत्र से जुड़े विभिन्न हितधारकों के लिए मृदा-जल संरक्षण अनुसंधान, जलवायु-सहनीय प्रौद्योगिकियों के अनुकूलन तथा जल संसाधन प्रबंधन की योजना हेतु भविष्य के अनुसंधान की प्राथमिकताएँ निर्धारित करने की आवश्यकता की ओर ध्यान आकर्षित करता है।

ABSTRACT. The spatiotemporal variability in annual rainfall and rainfall erosivity (R factor) is a crucial factor in assessing seasonal soil erosion dynamics and regional water resource management, since it has a substantial impact on complex interactions involving the water, soil, and surroundings under the variable climate regime of Eastern India. We analyzed the daily historical rainfall dataset received from India Meteorological Department (IMD; 1969-2022) across five meteorological subdivisions: Arunachal Pradesh (AP), Assam-Meghalaya (AM), Nagaland-Manipur-Mizoram-Tripura (NMMT), Sub-Himalayan West Bengal and Sikkim (SHWBS), and Gangetic West Bengal (GWB) of the Eastern India. Sub-district level projections of the downscaled bias corrected eight CMIP5 and five CMIP6 output on future global climate model projections was compared in Mid Future (MF) (2040-2069) and Far Future (FF) (2070-2099) timescale using the CORDEX-SA framework. Significant uncertainties existed in model simulations when validated against historical observations. In contrast to the observed spatiotemporal variability in declining in both annual rainfall and R factor over past five decades in IMD ground observations, the variable rising trend was evident particularly under high carbon scenarios of CMIP-6 over AP and AM subdivision in FF time scale. Thus, our finding emphasized the rising risk of soil erosion and shifts in hydrological cycle, which may have a negative impact on local agro-ecosystems. The projected rise in rainfall erosivity suggests that rainfall may increase kinetic energy, increasing the risk of soil erosion and

anticipate future climate impacts towards the need to set up future research priorities in soil water conservation research, adaptation of climate resilient technologies and water resource management planning for different stakeholders involved in the agroecosystem research at Eastern India region.

Key words – Annual rainfall, R factor, CORDEX-SA, CMIP-5, CMIP-6.

1. Introduction

The kinetic energy of rainfall significantly contributed to regulate the extent of widespread water-induced soil erosion as the substantial challenge for Indian policy makers (NAAS, 2010). In North East Indian Himalayas, the annual soil loss from shifting cultivation, settled agriculture, open forest and wasteland varied from traces to $\sim 836.0 \text{ t ha}^{-1} \text{ yr}^{-1}$ (Choudhury *et al.*, 2022). The rainfall erosivity (R factor) or rainfall-runoff erosivity factor is defined as the erosive potential of precipitation events towards facilitating water erosion of the upmost fertile soil layer often leading to ‘creeping death of the soil’ (Tripathi and Singh, 1993; Lobo *et al.*, 2015; Raj *et al.*, 2022). The R factor is an effective indicator of rainfall kinetic energy often determined by the size of raindrop splash, intensity factor and effective rainfall event duration (Rosewell, 1986; Salles *et al.*, 2002); also effectively contributes soil loss estimation using to the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978) and the Revised Universal Soil Loss Equation (RUSLE) (Renard *et al.*, 1997). The anthropogenic climate change induced modification in extreme weather events and seasonal precipitation dynamics viz. intensity, amount, duration etc. are expected to facilitate soil erosion, thus adversely impacting agroecosystem services through intensification of global hydrological cycle over the Indian subcontinent region (Nearing *et al.*, 2004; Mondal *et al.*, 2016).

Since late 1990s, dynamic climate downscaling methods were used for region specific precipitation simulation at very finer resolution (Giorgi, 2019). The Coordinated Regional Climate Downscaling Experiment (CORDEX) program was one of the international efforts to avail dynamically downscaled products in public domain, as initiated with the active sponsorship from World Climate Research Programme (WCRP), to provide multiple region-specific, quality-controlled, high-resolution reliable RCM generated regional climate change projections across several CORDEX domains in the globe (Giorgi *et al.* 2009). Under the Coupled Model Intercomparison Project Phase 5 (CMIP5), the Atmosphere-Ocean coupled General Circulation Model (AOGCM) provided the framework for CORDEX SA experiment in the Fifth Assessment Report of IPCC (AR5 models) through formulation of Representative Concentration Pathways (RCP) scenarios using the concept of radiative forcing (Moss *et al.* 2010). In courtesy, the Coupled Model Inter comparison Project Phase 6 (CMIP-6) was built over CMIP-5 by contributing

to the IPCC Sixth Assessment Report (AR6) and promoting regional climate simulations through CORDEX. The climate modeling using CMIP6 accounted the Shared Socioeconomic Pathways (SSPs) and enhanced Earth System Models (ESMs) with higher geographic resolution and more accurate representations of physical processes pre-owning the climate change forecast generation for assisting policymakers in risk assessments, adaptation planning, and other associated climate services (Eyring *et al.*, 2016).

Over past few decades, numerous scientific investigations claimed considerable attention on anthropogenic climate change research, evaluating the spatiotemporal variations in the projected alterations of regional climate systems over the Indian subcontinent (under CORDEX SA domain) in forth coming future. In recent decades, South Asia region experienced a significant warming trend with increased precipitation anomalies (Kumar *et al.*, 2010; Saha *et al.*, 2022). The CORDEX GCMs are efficient to capture seasonal variability of the precipitation over the Indian Himalayan region under differential warming scenarios (Choudhary *et al.*, 2018). Regardless of the data distribution pattern, statistical downscaling can forecast local phenomena with the necessary bias correction from GCM output (Dar *et al.*, 2018). The anticipated decline of precipitation ($\sim 5.9\%$ by 2050) was contrasted with the similar rise in precipitation ($\sim 5.9\%$ by 2100) under RCP 4.5 scenario over the Uttarakhand region of Indian Himalaya. However, the projected rise in precipitation (2.83% to 15.89%) under RCP 8.5 was coupled with increased maximum temperature that may lead to increased precipitation extremes in forthcoming future across Uttarakhand Himalaya (Tyagi *et al.*, 2022). Alike overall projected rise in seasonal precipitation over India (Yaduvanshi *et al.*, 2020), subsequent rise in seasonal and annual rainfall was outlined with substantial uncertainties over north-east Indian states in near future (Dash *et al.*, 2012; Salunke *et al.*, 2023; Kalita *et al.*, 2024). In contrast, declining precipitation trend has been reported to occur in long-run under high emission scenarios, i.e., RCP4.5 & RCP8.5 over NE India (Kumar & Dimri, 2017).

The rainfall erosivity (R factor) became one of the noticeable input parameters for studying future soil erosion modeling in Indian Himalayan region under different climate change projection scenarios (Jain *et al.*, 2001; Dabral *et al.*, 2008; Pandey *et al.*, 2009; Khare *et al.*, 2017). Climate change induced projected rise in daily mean rainfall seems to have apparent role in modifying

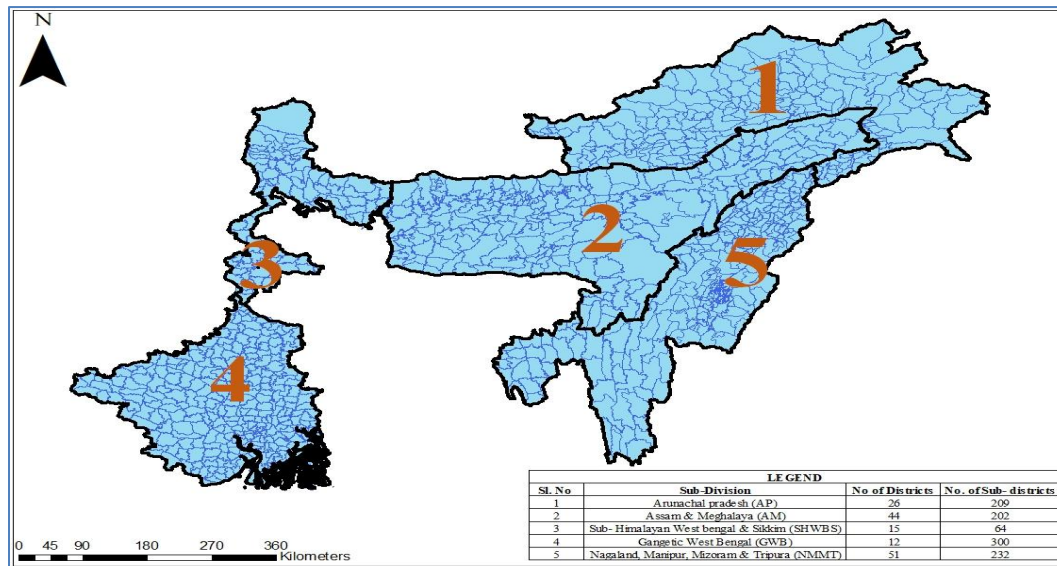


Fig. 1. Sub-district level boundaries of five meteorological subdivisions in Eastern India

regional precipitation dynamics and rainfall erosivity over the Indian Subcontinent (Salvi and Ghosh, 2013; Mondal *et al.*, 2016); particularly on soil erosion control perspective in Indian Himalaya region in upcoming future (Saha *et al.*, 2022). Being one of the world's highest rainfall receiving regions (e.g. Cherapunji, Meghalaya), the intra annual variability in seasonal rainfall distribution pattern and rainfall erosivity still got limited little attention towards accuracy assessment of the future climate change projections over the North East Indian hills and adjacent Bengal plains over the Eastern India region. Thus, our present study will be useful to play decisive role in understanding the regional hydrological processes through paying significant attention to future climate change impact on regional precipitation characteristics in long run using CORDEX SA domain with the following objectives: (i) to assess the quantitative accuracy of climate model simulations for regional rainfall (ii) to quantify the projected changes in future seasonal precipitation dynamics (iii) to assess the possible changes in R factor over five meteorological subdivisions of Eastern India (EI) in the forthcoming future.

2. Data and methodology

2.1. Study region and data source

Our current study used the output projection database for five IMD-delineated meteorological subdivisions in Eastern India: Arunachal Pradesh (AP), Assam and Meghalaya (AM), Nagaland Manipur Mizoram and Tripura (NMMT), Sub-Himalayan West Bengal and Sikkim (SHWBS), and Gangetic West Bengal (GWB) (Fig. 1). We analysed daily (statistically downscaled using RCA4) precipitation data from eight

GCMs as part of the Coupled Model Intercomparison Project Phase 5 (CMIP5; RCA-4 downscaling) experiments within the Coordinated Regional Climate Downscaling Experiments for South Asia (CORDEX-SA). The study was undertaken for both mid-future (MF; 2040-2069) and far-future (FF; 2070-2099) climate predictions, under three RCP scenarios: RCP 2.6 (low), RCP 4.5 (medium), and RCP 8.5 (high), with radiative forcing peaking at 2.6, 4.5, and 8.5 W/m² by 2100, respectively (Table 1a). Furthermore, GCM output from five CMIP6 experiments using convolutional neural network (CNN) downscaling was incorporated under four Socio-economic Pathways (SSPs): SSP2-4.5 ("middle of the road" scenario with intermediate radiative forcing of 4.5 W/m² by 2100), SSP3-7.0 ("regional rivalry" scenario leading to higher emissions and moderate radiative forcing of 7.0 W/m²), SSP4-6.0 ("high inequality" scenario with radiative forcing of 6.0 W/m²), and SSP5-8.5 ("high carbon" or fossil-fuelled development scenario with very high radiative forcing (Table 1b). The final series of CMIP-5 and CMIP-6 model ensemble mean precipitation values were approximated for further analysis over individual GCM for their relative closeness to actual ground observations (Das *et al.*, 2021). R studio programming was used to extract the projection data of West Bengal and adjacent eight north East Indian states. Subsequently, historical daily precipitation observations of 36 ground meteorological observatories (IMD, Pune) within our study region from 1969 to 2005 (as baseline) were used for validation in future seasonal rainfall projection studies likely, winter (January - February), pre-monsoon (March-May), monsoon (June- September) and post-monsoon (October- December) season in our present study region (Saha *et al.*, 2016).

TABLE 1a

Details of the nine CMIP5 global climate models (r1i1p1f1ensemble) considered for our present study.

Sl. No.	CORDEX South Asia experiment	Driving GCM	Modeling center (Group)	Grid Resolution (lon° × lat°)
1.	The Canadian Atmospheric Model version 2	CCCma-CANESM2	Canadian Centre for Climate Modelling and Analysis (CCCma), Canada	2.790 × 2.812
2.	National Centre for Meteorological Research	CNRM-CERFACS-CNRM-CM5	Centre National de Recherches Meteorologiques (CNRM), France	1.25 × 0.9
3.	Irish Centre for High End Computing-Earth Climate Simulations	ICHEC-EC_EARTH	Irish Centre for High-End Computing (ICHEC) European Consortium (EC)	2.5 × 1.9
4.	Institut Pierre-Simon Laplace-Climate Model 5 th version	IPSL-CM5A-MR	Institute Pierre-Simon Laplace, France	2.5 × 1.268
5.	Model for Interdisciplinary Research on Climate	MIROC-MIROC5	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute, and National Institute for Environmental Studies, Japan	1.417 × 1.406
6.	Hadley Centre Global Environment Model version 2	MOHC-HadGEM2-ES	Met Office Hadley Centre, UK	1.875 × 1.25
7.	Max Planck Institute Earth System Model	MPI-M-MPI-ESM-LR	Max Planck Institute for Meteorology, Germany	1.875 × 1.865
8.	National Oceanic and Atmospheric Administration, Geophysical Fluid Dynamics Laboratory	NOAA- GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory	2.5 × 1.5

TABLE 1b

Details of the CMIP6 global climate models (r1i1p1f1 ensemble) considered for our present study

Sl. No.	CORDEX South Asia experiment	Driving GCM	Modeling center (Group)	Grid Resolution (lon° × lat°)
1.	The Canadian Atmospheric Model version 2	CCCma-CANESM5	Canadian Centre for Climate Modelling and Analysis (CCCma), Canada	2.8 X 2.8
2.	Institut Pierre-Simon Laplace-Climate Model 5 th version	IPSL-CM6A-LR	Institute Pierre-Simon Laplace, France	2.5 × 1.268
3.	Norwegian Climate Centre- Earth System Model	NCC-NorESM1-M	Norwegian Climate Centre, Norway	2.5 × 1.895
4.	Chinese Academy of Sciences	FGOALS-g3	Chinese Academy of Sciences, China	2 X 2.25
5.	Korea Institute of Atmospheric Prediction Systems (KIAPS)	KACE-1-0-G	Korea Institute of Atmospheric Prediction Systems (KIAPS), South Korea	1.0 X 1.25

2.2. Root mean square error (RMSE)

The residual between observed (IMD ground observations) and CMIP5/6 simulation was expressed as Root Mean Square Error (RMSE) to evaluate the model's capabilities for n observations as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (Observation - Projected)^2}{n}} \quad (1)$$

where, zero denoted the best end.

2.3. Quantile delta mapping (QDM) bias correction

For bias correction, the Quantile Delta Mapping (QDM) approach was adapted that maintained quantile changes and was similar to the equidistant and equitization variants of Quantile Mapping (QM) proposed by Cannon

et al. (2015). The model projection was initially de-trended using quantiles, and the simulated value was then bias corrected by QM using the transfer function created during the calibration phase. The final results were calculated by adding or multiplying relative quantile changes to the bias adjusted model outputs. To be more exact, for a climatic variable x , we computed the non-exceedance probability of the value at time t :

$$\varepsilon(t) = F_{m,p}^{(t)} [x_{m,p}(t)], \quad (2)$$

where $x_{m,p}(t)$ modelled value was denoted by time t within the projection period (p); $F_{m,p}^{(t)}$ was the time-dependent CDF of the model projected series; $x_{m,p}$ was computed from the empirical CDF across a time frame around t over 30-year moving window.

For precipitation series, the relative change in quantiles between the calibration periods and project time t was expressed as:

$$\Delta(t) = \frac{F_{m,p}^{(t)-1}[\varepsilon(t)]}{F_{m,c}^{(t)-1}[\varepsilon(t)]} = \frac{x_{m,p}(t)}{F_{m,c}^{(t)-1}\{F_{m,p}^{(t)-1}[x_{m,p}(t)]\}} \quad (3)$$

where, $F_{m,c}^{-1}$ = inverse CDF of the simulations in the calibration periods.

The feasibility of bias correction in the simulated ε quantile at model-projected time t , throughout the calibration period using observed values, as follows:

$$\hat{x}(t) = F_{o,c}^{-1}[\varepsilon(t)] \quad (4)$$

where, $F_{o,c}^{-1}$ = inverse CDF estimated from observed value $x_{o,c}$

Finally, the bias-correction outcome in the future period at time t was calculated as follow:

$$x_{bc} = \hat{x}(t)\Delta(t) \quad (5)$$

2.4. Rainfall erosivity factor (R factor)

Rainfall Erosivity (R factor) signifies the capacity of rainfall to generate soil particle dissociation and movement, often determined by the kinetic energy of the rainfall. We calculated rainfall erosivity of historical and projected rainfall simulation as follows (George K *et al.*, 2021; Mondal *et al.*, 2016):

$$R = \sum_{i=1}^{12} 1.735 \times 10^{\left(1.5 \log_{10}\left(\frac{p_i^2}{P}\right) - 0.08188\right)} \quad (6)$$

where, R = Rainfall erosivity factor ($\text{MJ mm ha}^{-1} \text{ h}^{-1} \text{ year}^{-1}$)
 P_i and P = Monthly and annual rainfall (mm)

2.5. Trend analysis

The temporal trend pattern of subdivision wise annual rainfall and R factor time series was analyzed using rank-based nonparametric Mann-Kendall test (Kendall, 1962; Mann, 1945). The standardized test statistic Z was defined as,

$$Z = S/\sqrt{V} \quad (7)$$

where, S is Mann-Kendall statistics indicating the difference between the total number of concordant pairs and discordant pairs in the ranking dataset, and V is Kendall's Tau (τ) variance. Negative Z indicates declining trend, whereas a positive Z value indicated the rising trend on different confidence intervals. The null hypothesis was rejected, if $|Z| > 2.576$ at $p < 0.01$, $|Z| > 1.96$ at $p < 0.05$,

$|Z| > 1.64$ at $p < 0.10$ significant level, respectively. The magnitude of change was computed using the median based Sen's slope estimator as follows (Sen, 1968):

$$Q_i = \left(\frac{x_i - x_k}{i - k}\right) \quad i = 1, \dots, N \quad (8)$$

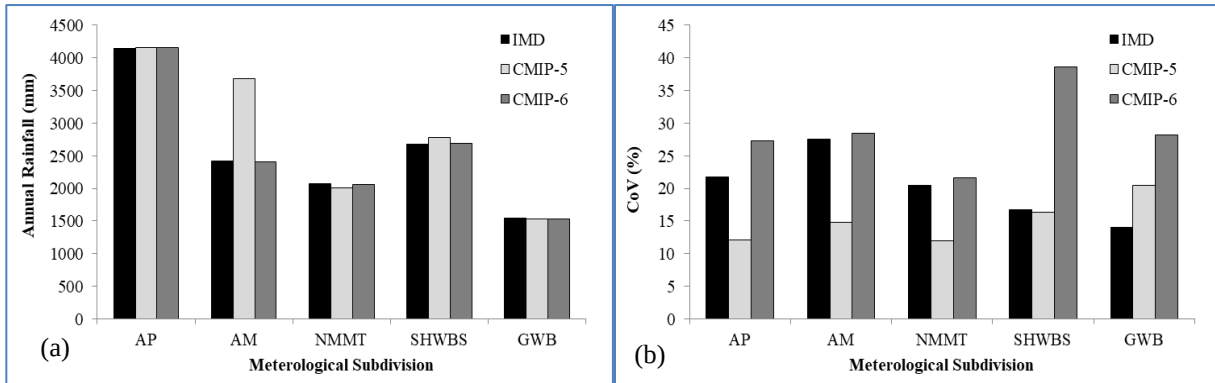
where, X_i and X_k represent data values at i and k , respectively.

2.6. Spatial interpolation and mapping

Inverse distance weighting (IDW) method was adapted for spatial interpolation and mapping of projected changes in precipitation characteristics using ArcGIS 10.7.1 software.

3. Results and discussion

The regional climate of all studied meteorological subdivisions across the Eastern India region (EI) is predominantly influenced by the seasonal monsoonal shower and periodic convective precipitation events (Turner *et al.*, 2019; Paul and Maity, 2023). The subdivision wise average annual precipitation in IMD ground observatories were ranged from 1545.5 mm (GWB) to 4149.5 (AP) showcasing the higher degree of spatial variability with 14.08% (GWB) – 27.52% (AM) CoV% across the study region (Fig. 2). Both CMIP-5 and CMIP-6 projection was closely approximated with IMD ground observation for all remaining meteorological subdivisions, except: 51.9% and 3.62% respective overestimation for annual rainfall of AM and SHWBS subdivision under historical series of CMIP-5 experiments. However, the higher CoV% of CMIP -6 experiments (21.6%-38.6%) was contrasted with CMIP-5 (11.9%-20.4%), with reference to IMD ground observations (14.08%-27.5%); signifying the need of improving bias correction strategies in regional precipitation and variability assessments over the delineated high rainfall receiving wet mountainous regions of EI (Zhu *et al.*, 2020; Martel *et al.*, 2022). Spatial resolution of the CMIP5 models rarely influence the poor quality of rainfall simulation in the historical series across the Southeast Asia region (Raghavan *et al.*, 2017). The observed deviation was peaked over SHWBS (+21.86%) and GWB (+14.16%) under CMIP-6 against the recorded CMIP5 deviation of -4.3% and +6.3% over SHWBS and GWB respectively. In contrast, the incremental improvements and enhancements in low or medium resolution CMIP6 models (CoV%; +0.88% to +5.55) outperformed the coarser spatial grid resolution CMIP5 (CoV%; -8.5% to -12.77%) against the respective IMD ground observations (Norgate *et al.*, 2024). Furthermore, the observational inconsistency between CMIP5 and CMIP6 experiments may also be sourced from



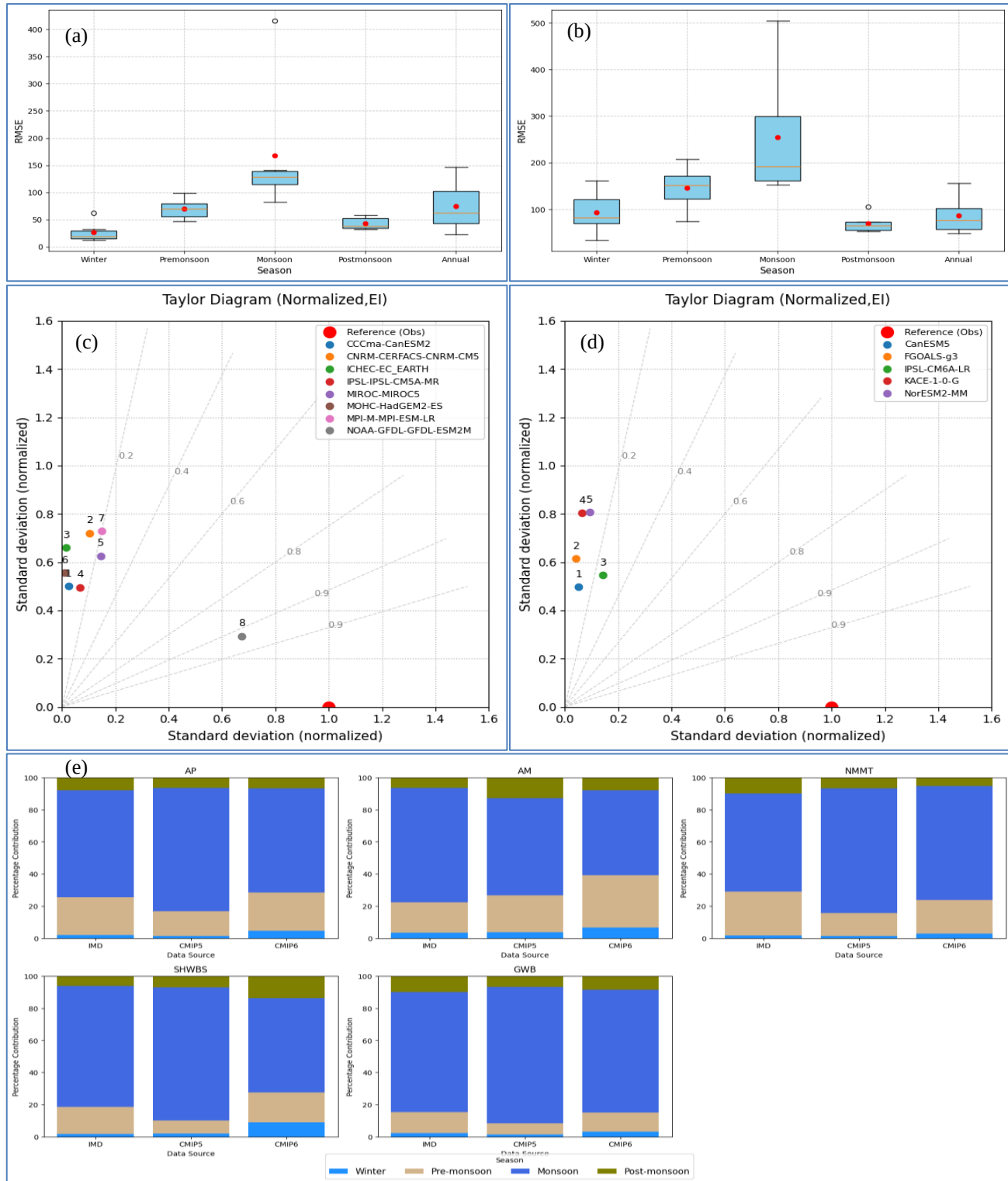
Figs. 2(a&b). Comparative evaluation of historical (a) average annual rainfall (mm) and (b) coefficient of variation (%) of different meteorological subdivisions under CMIP-5 and CMIP-6 experiments with IMD ground observations

limited approximation between differences between scenarios (RCPs and SSPs), variable number and families of adapted GCMs and their developmental algorithm towards simulating atmospheric processes (Zamani *et al.*, 2020; Ma *et al.*, 2024).

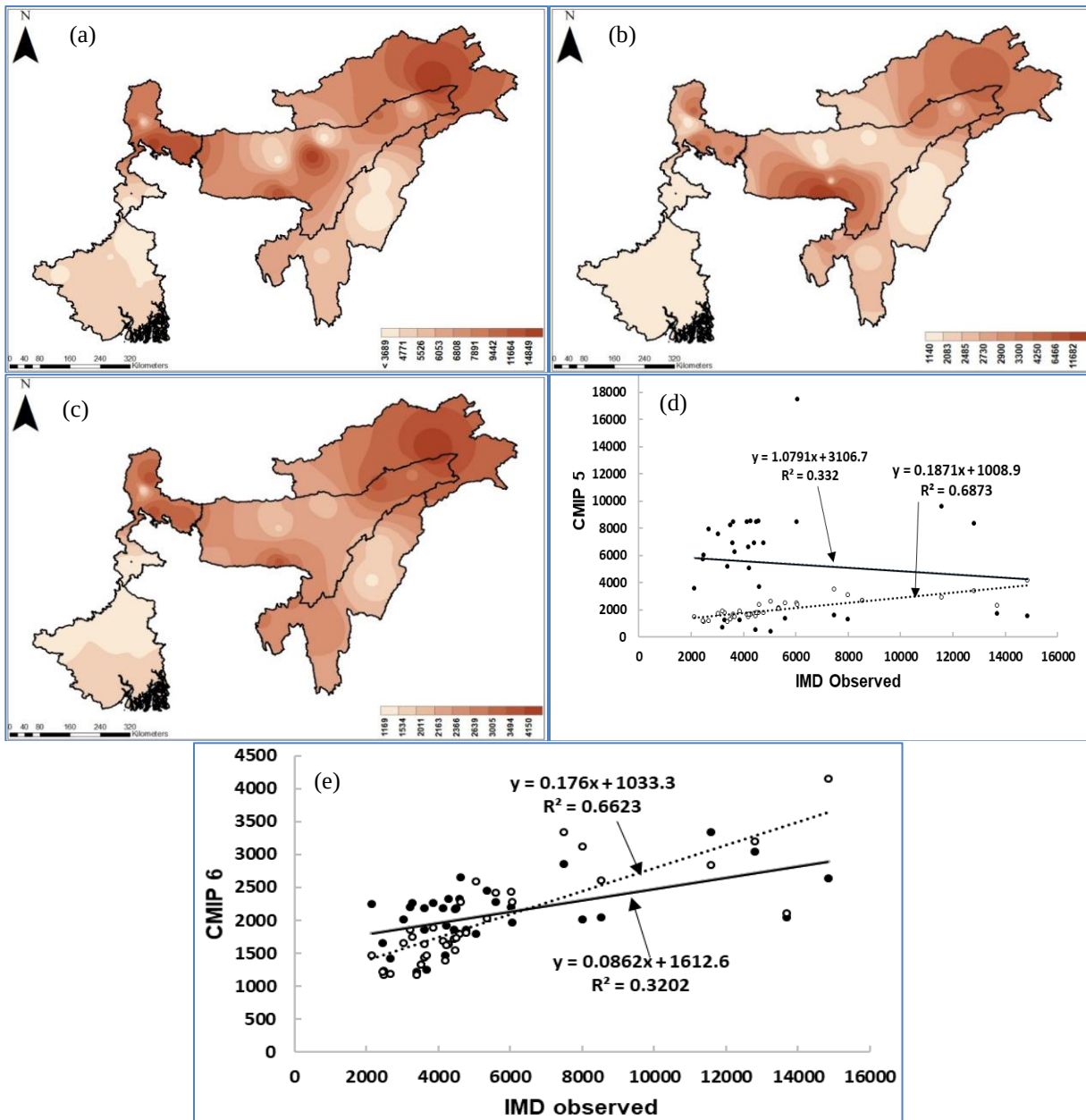
The average RMSE box plot in historical baseline of CMIP -5/6 experiments exhibited multifarious deviation of overall regional seasonal precipitation distribution as set forth in Fig. 3a and 3b. Monsoon rainfall contributed the lion share (61.04-75.1%), as ensued by the pre-monsoon shower (13.13%-27.1%) in the annual rainfall across all the meteorological subdivisions. The uni-modal pattern of RMSE -Interquartile Range (IQR) values in CMIP-6 experiments varied between 65.1-149.7% during monsoon months that peaked during winter (293.3-554.1%) over CMIP-5 experiments; thus clearly depicting the poor predictability of CMIP-6 simulation across all the meteorological subdivisions of the eastern India. In order to compare individual model performances of respective CMIP-5 and CMIP-6 experiments, Taylor diagram was curved out for evaluating the capability of individual model to simulate climatic mean and variability (Fig. 3c and 3d). NOAA GFDL ESM2M was the superior among the other GCMs of CMIP-5 experiments and also had relatively better capabilities in precipitation simulation over the remaining models of CMIP-6 experiment across the Eastern India region. The relative contribution of seasonal rainfall to annual rainfall was compared between IMD ground observations and CMIP-5/ CMIP-6 simulation (Fig. 3e). The higher coefficient of determination ($R^2 = 0.94$) for CMIP-5 simulation over CMIP-6 ($R^2 = 0.92$) against IMD ground observations, signified better predictability of CMIP-5 models for seasonal rainfall pattern. However, CMIP-5 significantly overestimated the relative contribution of monsoon shower in annual rainfall by 10.01-16.6%, while underestimating the percentage share pre-monsoon (8.12-13.1%; except AM), post monsoon (1.2-3.4%; except AM and SHWBS) and winter rainfall (0.31-0.78%; except AM

and SHWBS). In contrast, CMIP-6 simulations were more closely aligned with IMD ground observations (except AM) during both pre-monsoon and monsoon months. The considerable deviation of overestimating pre-monsoon (7.4%) and underestimating monsoonal (16.2%) rainfall contribution over SHWBS, along with outperformed estimation of winter rainfall percentage share against IMD ground observations were evident across all meteorological subdivisions. Nevertheless, CMIP-5 model simulations had better ability to filter internal variability in absolute monthly and seasonal rainfall quantity than CMIP-6 experiments (Soraisam *et al.*, 2018; Coburn and Pryor, 2021). In contrast, better depiction of seasonal rainfall distribution pattern in CMIP-6 experiments was apparent across the wet humid to per-humid regions in North East Indian hills and adjacent flood plains of Bramhaputra and lower Gangetic plains across Easter India. Such seasonal discrepancies in both CMIP-5 and CMIP-6 projection models demand further refining through bias correction algorithms to handle over- and under-estimations across different seasons of studied meteorological subdivisions (Kumar and Dimri, 2017; Soraisam *et al.*, 2018).

Rainfall erosivity factor (R-factor) values remained as one of the highest over the EI across the Indian subcontinent region (Raj *et al.* 2022). The spatial heterogeneity of towering rainfall erosivity (R factor) derived from the ground IMD observations varied 2136.24 (Imphal) - 14853.37 (Cherapunjii) MJ mm ha⁻¹ h⁻¹ yr⁻¹, 1522.8 (GWB) - 4149.6 (AP) MJ-mm⁻¹ha⁻¹h⁻¹yr⁻¹ across the EI (Fig 4a). The regional heterogeneity of mean rainfall erosivity (R factor) was sequenced as GWB < NMMT < AM < SHWBS < AP for both IMD ground observation and CMIP-6 experiments. In contrast, R factor values in CMIP-5 followed sequence of AP > AM > SHWBS > NMMT > GWB. The corresponding R factor derived from simulated historical time series in CMIP-5 and CMIP-6 experimental values ranged between 1138-11693 MJ mm ha⁻¹ h⁻¹ yr⁻¹ and 1167.20 - 3342.94 MJ mm



Figs. 3(a-e). Box plot of seasonal variations in (a) RMSE values of CMIP-5 simulation, (b) RMSE values of CMIP-6 experiments, (c) Taylor-diagram of CMIP5 multiple models and the ensemble mean as reference observation and (d) Taylor-diagram of CMIP6 multiple models and the ensemble mean as reference observation and (e) temporal variability in percentage share of seasonal rainfall to annual rainfall across all the studied meteorological subdivisions of eastern India for IMD ground observation, CMIP-5 and CMIP-6 simulation data sets. *Note: The box plot figure (a) and (b) shows RMSE distribution by season for NE Subdivisions, where blue box shows 5th to 75th percentile (Interquartile Range, IQR), Horizontal line inside the box: Median RMSE, Whiskers: Extend to $1.5 \times \text{IQR}$ from quartiles, Red dot: Mean RMSE for each season and Black circle : Outliers*



Figs. 4(a-e). Regional heterogeneity of R factor expressed in MJ mm ha⁻¹ h⁻¹ yr⁻¹ calculated from the historical dataset for (a) Observed IMD data, (b) CMIP-5 (c) CMIP-6 experiments along with association of derived R factor values between (d) Observed IMD and CMIP 5 (e) Observed IMD and CMIP 6 (Base period: ^1969-2005, ^1951-2005 and ^1969-2014). Note: Black continuous lines denote dataset without bias correction and dotted line signifies biased corrected data

ha⁻¹ h⁻¹ yr⁻¹, respectively (Fig 4b & c). Biased correction measures resulted overall ~ 51.6 % rise in R² value for both CMIP-5 and CMIP-6 simulation. After the removal of Mawsynram sub-district (as outlier against IMD Cherapunji ground station), The relative association of derived R factor values between IMD ground observations and CMIP-6 was significantly stronger for CMIP-5 (R² = 0.683) than CMIP-6 (R² = 0.662; p < 0.05) simulation (Fig 4d & e). However, the overall predictability of extreme R factor threshold values were limited for both

CMIP5 and CMIP6 experiments, against respective ground IMD observations. In similarity with the previous reports, the average values of R factor derived from historical time series were ranged between 2931.78 - 3872.75 MJ mm ha⁻¹ h⁻¹ yr⁻¹. (Tiwari *et al.*, 2015; George *et al.*, 2021), but slightly high R factor values were resembled for respective AM (~4862.97 MJ mm ha⁻¹ h⁻¹ yr⁻¹), NMMT (~ 5269.76 MJ mm ha⁻¹ h⁻¹ yr⁻¹), GWB (~ 7638.87 MJ mm ha⁻¹ h⁻¹ yr⁻¹) subdivision (Mondal *et al.*, 2014; Talchabhadel *et al.*, 2020).

TABLE 2

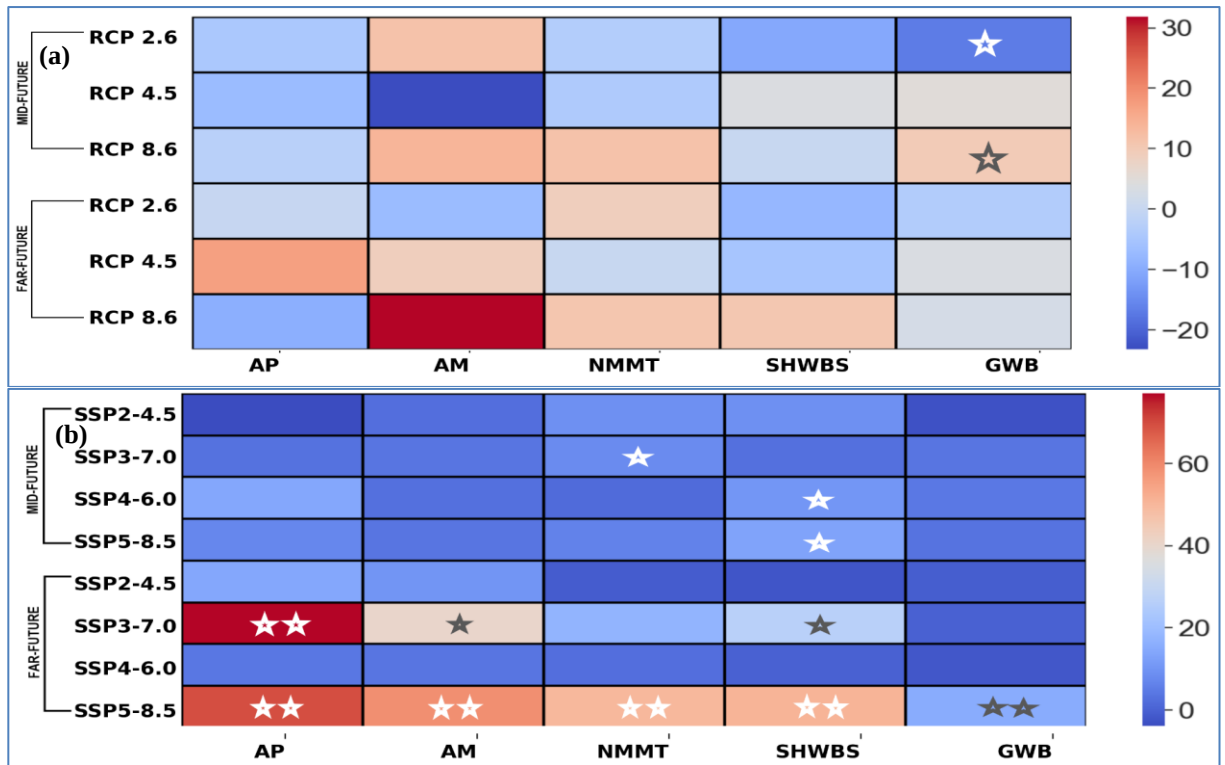
Regional MK trend pattern of annual Rainfall and R-factor time series in IMD ground observatories of EI (1969-2022)

Meteorological Subdivisions	Annual Rainfall		R factor	
	Z-value	p-value	Z-value	p-value
AP	-1.065	0.287	-0.719	0.472
AM	-2.786	0.005	-3.283	0.001
NMMT	-1.113	0.266	-0.824	0.410
SHWBS	-2.533	0.011	-2.106	0.035
GWB	0.166	0.868	-2.053	0.040

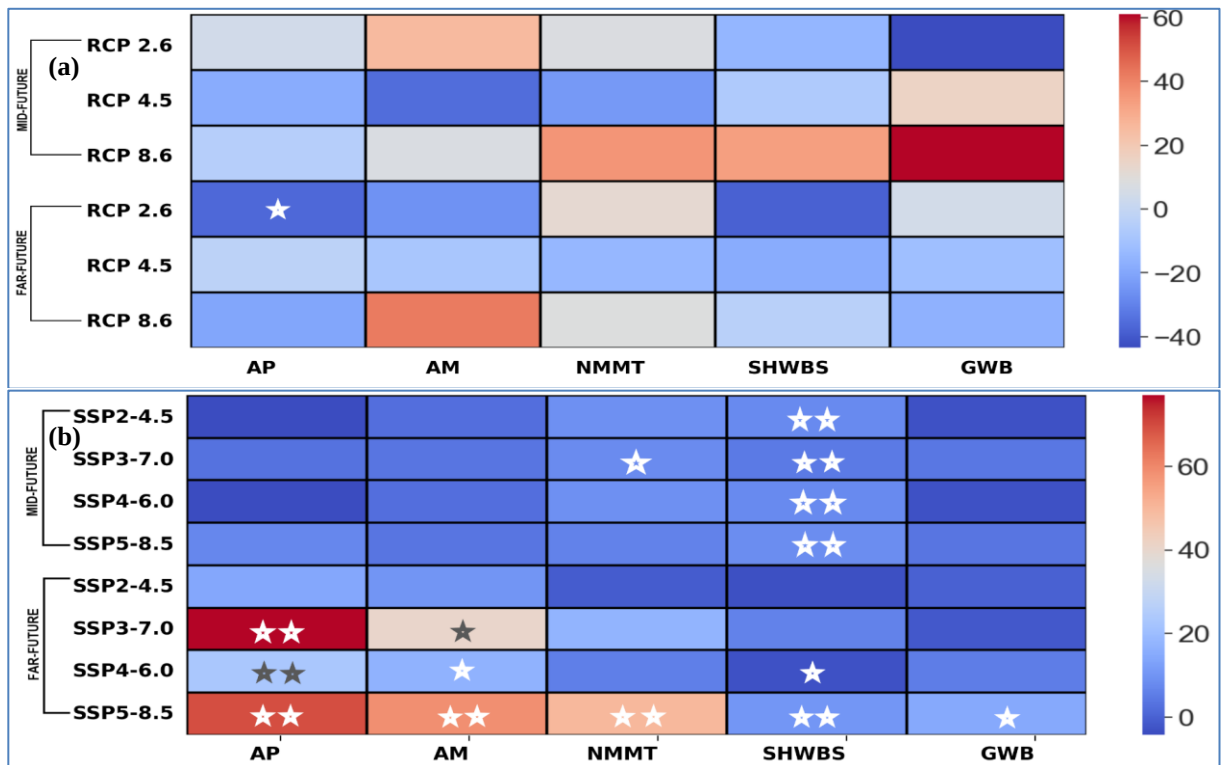
Nonparametric trend in annual sub divisional rainfall time series of the IMD ground observation time series identified significant declining trend over the AM ($Z = -1.065$, $p < 0.01$) & SHWBS ($Z = -2.533$, $p < 0.05$) subdivisions during 1969-2022 (Table 2). The concurrent decline in kinetic energy of the rainfall i.e. R factor time series was apparent AM ($Z = -3.283$, $p < 0.01$), SHWBS ($Z = -2.106$, $p < 0.05$) and GWB ($Z = -2.053$, $p < 0.05$) subdivisions of our present study region. In contrast, both simulated annual rainfall and R factor time series revealed variable trend pattern for CMIP-5 and CMIP-6 experiment under respective Representative Concentration Pathways (RCPs) and Shared Socioeconomic Pathways (SSPs) scenarios. For CMIP-5 projections, statistically significant decline in annual rainfall across the GWB subdivision under RCP2.6 ($\sim 17 \text{ mm decade}^{-1}$, $p < 0.05$) that got reversed to rising trend under high emission scenarios like RCP8.6 ($\sim 9.75 \text{ mm decade}^{-1}$, $p < 0.05$) over MF time scale (Fig. 5a). In FF time scale, any of the meteorological subdivision exhibited statistically significant shift in annual rainfall across EI. The analyzed trend pattern of CMIP-5 projection was in tandem with the previously reported no significant trend pattern in annual rainfall calculated using historical precipitation time series for 7 subdivisions (Jain *et al.*, 2012), 9 ground meteorological stations (Laskar *et al.*, 2014) & 9 ground meteorological stations (Chakraborty *et al.*, 2017) over north East India region. Nevertheless, the declining trend in observed annual rainfall of IMD ground stations, particularly over the North East Indian states (AM, NMMT, SHWBS subdivision) was to be at odds with variable significant rising trend in annual rainfall simulations under different SSP families of CMIP-6 (Fig. 5b). In MF time scale, significant rise in annual rainfall trend was evident over SHWBS ($\sim 7.96 \text{ mm decade}^{-1}$, $p < 0.05$ under SSP3-7.0) and NMMT ($\sim 10.2 \text{ mm decade}^{-1}$, $p < 0.05$ under SSP4-6.0 and $\sim 13.1 \text{ mm decade}^{-1}$, $p < 0.05$ under SSP5-8.5). The projected widespread rise in annual rainfall were more pronounced, particularly under higher emission scenarios i.e. SSP5-8.5 in FF timescale, ($15.1 - 69.5 \text{ mm decade}^{-1}$, $p < 0.01$) was contrasted with the observed declining trend in historical annual rainfall time series for IMD ground observation

East Indian states viz. AP, AM, NMMT, SHWBS & GWB subdivision (Krishnan *et al.*, 2016). Under SSP3-7.0, the rise in annual rainfall was also projected over AP ($77.13 \text{ mm decade}^{-1}$, $p < 0.01$), AM ($\sim 40.4 \text{ mm decade}^{-1}$, $p < 0.01$) and SHWBS ($26.3 \text{ mm decade}^{-1}$, $p < 0.01$) region. Our results were in better agreement with the projected regional precipitation rise over NE India varying between $+0.49$ to $+1.4 \text{ mm/day}$, in forthcoming future with considerable biases under variable SSP scenarios of CMIP6 (Naskar *et al.*, 2023; Norgate *et al.*, 2024).

Localized interaction from dominant orographic effect increased disparity of the spatially distinct precipitation pattern with shifting wetness pattern over time across the diverse climate regimes across the North East Indian hills of EI region, compare to the remaining geographical expansion of India (Mondal *et al.*, 2014; Saha *et al.*, 2017; Singh *et al.*, 2020). Since mid-19th century, ground observation studies indicated prominent decline in monsoon shower, often subdued by faltering long term trend showing eminent rise (Jain *et al.*, 2012; Saha *et al.*, 2016; Marak *et al.*, 2020; Datta and Bose, 2020; Singh and Kumar, 2022; Bora *et al.*, 2022) or marginal decline (Chakraborty *et al.* 2017; Singh *et al.*, 2021; Mohapatra *et al.*, 2021) in post monsoon (October) rainfall, along with diverse trend pattern for pre-monsoon rainfall viz. marginal rise (Deka *et al.*, 2013; Singh *et al.*, 2021), decreasing (Marak *et al.*, 2020; Mohapatra *et al.*, 2021; Bora *et al.*, 2022) or trendless (1857-2006; Singh and Kumar, 2022) over mutable time period across the NEI region. Eventually, overall annual rainfall trend remained stable accounting the multi-decadal precipitation variability over the EI region with variable epochs of historical ground observation database (Jhajharia *et al.*, 2008; Choudhury *et al.*, 2012; Jain *et al.*, 2012; Goyal, 2014; Barman and Goswami, 2019). Nevertheless, the limitations of GCM based precipitation simulation (CMIP-5/CMIP-6) reckoned the failure to reproduce fluctuating in sea level pressure over adjacent landmasses (Li and Murtugudde, 2024), rainfall orography (Shenkut *et al.*, 2025), localized land-atmosphere interactions (Saha *et al.*, 2023), aerosol-cloud interactions (Cherian and Quaas, 2020) and regional drivers of seasonal monsoon dynamics over the topographically complex and data-sparse NE hill regions of EI (Sarkar *et al.*, 2023; Tandon *et al.*, 2025). Hence, the consistent disparity between the observed annual rainfall trend and multimodel projections across the precipitation-based climate change hotspot of northeast India accounted considerable uncertainties and reduce the confidence in our results to refrain its potential implications of observed rising annual precipitation and R factor trend for flood risk management and agricultural water resource management across the delineated meteorological subdivisions of EI by the end of the present century.



Figs. 5(a&b). Subdivision wise projected annual rainfall trend under different (a) RCP scenarios form of CMIP-5 and (b) SSP scenarios of CMIP-6 experiments for Mid Future (MF) and Far future (FF) scenario (Note: * & ** significant at $p \leq 0.05$ & $p \leq 0.01$, respectively).



Figs. 6(a&b). Subdivision wise projected R factor trend under different (a) RCP scenarios form of CMIP-5 and (b) SSP scenarios of CMIP-6 experiments for Mid Future (MF) and Far future (FF) scenario. (Note: * & ** significant at $p \leq 0.05$ & $p \leq 0.01$, respectively)

The ostracized decline in R factor over AP subdivision under RCP 2.6 ($36.7 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ decade}^{-1}$; $p < 0.05$) was contrasted with no significant change in future rainfall erosivity over time under different RCP scenarios of CMIP-5 experiment (Fig. 6a). In contrast, the inevitable rise of rainfall erosivity was evident over SHWBS subdivision ($4.5\text{-}8.32 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ decade}^{-1}$; $p < 0.01$) under different SSP scenario of CMIP-6 experiments under MF scenario (Fig. 6b). Under FF scenario, the projected rise in annual rainfall was chummed up with concurrent intensified rainfall erosivity in AP ($22.9\text{-}77.1 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ decade}^{-1}$, $p < 0.01$) and AM ($16.8\text{-}40.37 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ decade}^{-1}$, $p < 0.01$) subdivision for the medium high scenarios of SSP3-7.0 with increased aerosol emissions. With the major challenges of limited adaptation strategies (inequality) the projected rise in rainfall erosivity would continue over both AP and AM ($16.8\text{-}22.9 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ decade}^{-1}$, $p < 0.01$) subdivision under SSP4-6.0. Furthermore, the axiomatic rise in rainfall erosivity ($10.2\text{-}69.5 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ decade}^{-1}$, $p < 0.01$) under high emission scenarios of SSP5-8.5 (without any additional climate policies) sourced from gradual atmospheric warming (Chen *et al.*, 2024), may lead to accelerated soil erosion from increased kinetic energy impact of impact raindrop splash by the end of 21st century (Wischmeier and Smith, 1978; Zhang *et al.*, 2018). Therefore, increased surface coverage for protecting topsoil needs to be prioritized through of conservation agriculture across EI in forth coming future (Das *et al.*, 2023; Mondal *et al.*, 2024). However, the observed divergence between declining trends in observed R factor time series and increasing trend in model projections, particularly under high emission centric socioeconomic scenarios of CMIP-6 experiments. The observed disparity often underscores the ongoing uncertainty and model limitations in capturing the region specific large-scale atmospheric circulation patterns and regional moisture flux convergence (Khadka *et al.*, 2021; Saha *et al.*, 2023; Zebaze *et al.*, 2025) over the complex heterogeneous terrain of Northeast India; thus impacting the overall regional R factor trend pattern across the eastern India region (Das *et al.*, 2021).

4. Conclusions

Considerable uncertainty existed in the CORDEX-South-Asia model projections on annual rainfall and rainfall erosivity (R factor) over the EI region in spite of their strengths and the ongoing advances in relatively high resolution climate models engaged under both diverse scenarios of CMIP-5 and CMIP-6 experiments. Substantial spatio-temporal variability in projected annual rainfall occurrence was discernible with limited statistical significance level under different radiative forcing of CMIP-5. However, the inclusion of societal choices

coupled with atmospheric warming induced radiative forcing intrigued the projected increase in precipitation with rising rainfall erosivity/ R factor under CMIP-6 experiments. The lower credibility climate model simulation often reduced the overall efficacy of precipitation projection towards achieving indelible climate hazard resilience policy. The utmost changes in either precipitation characteristics were expected up to the end of 21st century, across all meteorological subdivisions for the fossil fuel development based high carbon emission scenario of CMIP-6 experiment viz. SSP 3-7.0, SSP 4-6.0 and SSP 5-8.5, particularly over AP and AM subdivision. The rising trend in both annual rainfall and rainfall erosivity (R factor) under CMIP-6 would have far-reaching consequences towards conserving regional soil-water resources, agricultural productivity, and population health, through its illustrated future potential of expanding cultivation area under conservation agriculture as adaptation measure across the entire soil erosion vulnerable regions of north East Indian hills and adjacent Bengal plains of eastern India in forthcoming future.

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