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Spatio-Temporal Disaggregation of CMIP6 Rainfall Datasets and Generation of Intensity Duration Frequency (IDF) Curves for Hyderabad Metropolitan City, India

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ABSTRACT

Urban hydrological models, especially those aimed at simulating flood events, require rainfall inputs at finer temporal resolutions: typically ranging from daily to hourly. However, consistent historical hourly rainfall data is largely unavailable across many Indian cities. Among that, Hyderabad is one relies on a single centrally located rain gauge with archived hourly records. To assess rainfall variability under changing climate scenarios, Intensity-Duration-Frequency (IDF) curves are vital tools, necessitating high-resolution temporal rainfall data. This study develops Intensity-Duration-Frequency (IDF) curves for Hyderabad City using 45 years (1969–2013) of observed rainfall to bias-correct output from eight Coupled Model Intercomparison Project Phase 6 (CMIP6) General Circulation Models (GCMs), disaggregating daily projections to hourly resolution through three methods: Bartlett-Lewis Rectangular Pulse (BLRP), Microcanonical Cascade (MCC), and K-Nearest Neighbor Method of Fragments (KNN-MOF). GCM performances were assessed against observed rainfall using mean, standard deviation, 1-lag autocorrelation, and proportion of dry hours. It is observed that no single model excelling across all metrics except CNRM-ESM2-1 best reproduced the mean, BCC-CSM2-MR best matched variability, and results for autocorrelation and dry-hour proportion were mixed, underscoring the subjectivity of GCM selection. Future IDF curves were generated for near-future (2015–2056) and far-future (2057–2100) periods under SSP245 (medium emissions) and SSP585 (high emissions) scenarios. The 1-hr rainfall intensities were projected to be considerably higher under SSP245 than SSP585, with values reaching approximately 250 mm/hr in the near future. Whereas, 3-hr intensities followed a similar pattern, reaching roughly 85 mm under SSP245 and 83 mm under SSP585, with near-future and far-future values remaining broadly consistent. In contrast,

6-hr and 12-hr intensities stayed within the typical range associated with the southwest monsoon. Among the GCMs, MIROC6 most closely reproduced observed rainfall patterns under the MCC and KNN-MOF methods, while other models tended to overestimate peak 1-hr intensities. These findings indicate that Hyderabad faces a heightened risk of short-duration (1-hr and 3-hr) extreme rainfall through 2100, and that the BLRP, MCC, and KNN-MOF disaggregation methods are well suited for generating future IDF projections for the city.

Keywords: Climate change, extreme rainfall events, downscaling, GCM, disaggregation, CMIP6, intensity duration frequency (IDF) curves

1. INTRODUCTION

Climate change has emerged as a global crisis with significant consequences for ecosystems, economies, and human life. The intensification of greenhouse gas (GHG) emissions, largely driven by human activity, is altering atmospheric dynamics, leading to shifting weather patterns, rising sea levels, disrupted hydrological cycles, and an increase in the frequency and intensity of extreme weather events (IPCC 2013). To avert potentially disastrous outcomes, the Intergovernmental Panel on Climate Change (IPCC) recommends that global warming be limited to 1.5°C. However, the hydrological impacts of climate change, such as variations in streamflow and groundwater recharge are highly dependent on regional climate characteristics and vary across different emission scenarios due to inconsistencies in precipitation projections (Thornes 2002).

Urban areas are major contributors to GHG emissions and are particularly vulnerable to climate variability. These regions experience significant thermal shifts, which disrupt the urban microclimate and influence local precipitation regimes. Urbanization intensifies the urban heat island effect and modifies atmospheric conditions through increased aerosol concentrations, altering storm behavior and rainfall dynamics (Ntelekos et al. 2009). Over the past decade, studies have documented changes in rainfall trends, especially an uptick in extreme rainfall events in urban environments (Lei et al. 2008; Kishtawal et al. 2009; Miao et al. 2011; Agilan and Umamahesh 2015). A notable trend observed in several Indian cities, including Hyderabad, is a reduction in the number of rainy days, accompanied by more intense short-duration rainfall, resulting in flash flooding due to increased surface impermeability (Agilan and Umamahesh 2015).

To mitigate the risks associated with extreme rainfall, engineers and planners rely on Intensity-Duration-Frequency (IDF) curves. These curves are critical in the design of stormwater management systems, drainage infrastructure, and water supply schemes. IDF curves represent the statistical relationship between rainfall intensity, duration, and frequency of occurrence. As rainfall extremes evolve due to climate change, IDF curves also need to be updated accordingly (Simonovic et al. 2016). The standard approach involves fitting a probability distribution to the annual maximum rainfall series over various durations: commonly 1, 2, 6, 12, and 24 hours (Hosking and Wallis 1997). While methods are available for sub-hourly scales, this study focuses on hourly rainfall data, which is more accessible and reliable for Indian cities.

Global Climate Models (GCMs) are essential tools in climate studies. They simulate atmospheric behavior through complex equations and provide outputs at coarse spatial resolutions (typically 2° – 3° grids). Although useful for global assessments, their low resolution introduces uncertainty when applied directly to regional studies (Johnson and Sharma 2009). To make GCM outputs suitable for local applications: especially in urban and tropical contexts where rainfall variability is high and statistical downscaling techniques are necessary (Abustan et al. 2008; Mezghani and Hingray 2009; Schilling 1991; Bruni et al. 2015).

A variety of statistical models have been developed for downscaling purposes, including the Statistical Downscaling Model (SDSM) (Wilby et al. 2002), Generalized Linear Models (GLMs) (Chandler and Wheeler 2002), Artificial Neural Networks (ANNs) (Zorita and Von Storch 1999), and Support Vector Machines (SVMs) (Tripathi et al. 2006). Other tools include the Automated Statistical Downscaling (ASD) tool (Hessami et al. 2008), Bayesian Model Averaging (Tripathi et al. 2006), and methods like Bias Correction and Constructed Analogs (BCCA) (Maurer et al. 2008). One widely used approach is the Bias Correction and Spatial Disaggregation (BCSD) method, which uses probability mapping for adjusting GCM outputs (Wood et al. 2002; Payne et al. 2004; Hayhoe et al. 2007).

While spatial downscaling adjusts GCM outputs to local conditions, temporal downscaling or disaggregation is equally essential: particularly for applications requiring sub-daily rainfall data. A range of methods are employed for this purpose. Stochastic point process models (Rodriguez-Iturbe et al. 1987; Khaliq and Cunnane, 1996; Onof and Wheeler 1993, 1994), non-parametric models (Prairie et al. 2007; Nowak et al. 2010; Kalra and Ahmad 2011), and other approaches (Gyasi-Agyei 2005, 2011; Beuchet et al. 2011; Olsson 1998; Güntner et al. 2001; Licznar et al.

2011, 2015; Müller and Haberlandt, 2018; Müller-Thomy and Sikorska-Senoner 2019) have been widely used.

Among these, the Bartlett-Lewis Rectangular Pulse Model (BLRPM) (Rodriguez-Iturbe et al. 1987), the Microcanonical Cascade (MCC) model (Müller and Haberlandt 2018), and the K-Nearest Neighbor Method (KNN) (Kalra and Ahmad 2011; Park and Chung 2020) have gained popularity for rainfall disaggregation. Tools like HYETOS (Debele et al. 2007) also facilitate high-resolution rainfall simulation. Studies using the BLRP model confirm that it effectively maintains statistical consistency between hourly and daily rainfall (Koutsoyiannis and Onof 2001). Similarly, KNN-based approaches have demonstrated improved seasonal rainfall generation over traditional autoregressive models (Kalra and Ahmad 2011). Most of these investigations focus on single-site applications. Meanwhile, cascade models have also been adapted to quasi-daily time series (e.g., 1280-minute intervals) to achieve fine temporal resolution (Licznar et al. 2011, 2015; Molnar and Burlando 2005; Paschalis et al. 2014).

Given the complexity of urban rainfall dynamics, an integrated strategy that combines both spatial and temporal downscaling is required. High-resolution rainfall datasets derived from GCM projections are crucial for assessing climate change impacts on hydrological systems. Although much of the existing research targets large watersheds (Lu and Qin 2014), there is limited work on applying integrated downscaling-disaggregation frameworks in urban areas of South Asia: especially in regions characterized by tropical and semi-arid climates. Moreover, comparative assessments of single site versus multi-site techniques remain scarce (Wood et al. 2002).

This study addresses that gap by conducting a comprehensive analysis for Hyderabad Metropolitan City, Telangana, India, which experiences both tropical and semi-arid climatic influences. The specific goals of the study are:

- To develop and assess various downscaling and disaggregation approaches using both daily and hourly statistical parameters for a single urban site.
- To implement a modified version of the Bias Correction and Spatial Disaggregation method, referred to here as Statistical Downscaling and Bias Correction (SDBC) (Wood et al. 2004; Maurer and Hidalgo 2007; Ahmed et al. 2013).
- To compare the temporal disaggregation performance of three techniques: BLRP, MCC, and KNN, for generating hourly rainfall from daily values.

- To identify and recommend an integrated downscaling-disaggregation framework suitable for constructing future IDF curves for Hyderabad using CMIP6-based GCM scenarios.

2. STUDY AREA AND DATASETS USED

Hyderabad, the sixth-largest metropolitan region in India, is located on the Deccan Plateau at 17.37°N latitude and 78.48°E longitude. It is characterized by a complex climatic profile: an intersection of tropical wet and dry conditions with a tendency toward semi-arid features. The city endures extreme seasonal variations, with summer temperatures often exceeding 45°C and winter lows dropping to around 12°C. Rainfall in Hyderabad is primarily driven by two monsoonal systems. The southwest monsoon (June - September) is dominant, delivering approximately 74% of the city's annual precipitation. The remainder of the rainfall occurs during October - November, contributed by the northeast monsoon. Historical records indicate average annual precipitation of 796 mm (1971–1990), which has increased to approximately 840 mm in recent decades (Agilan and Umamahesh 2016). In recent years, Hyderabad has experienced increasingly erratic and intense rainfall events, signaling a significant shift in climatic behavior. Notably, on October 13–14, 2020, the city recorded 250 mm of rainfall within 24 hours at the Begumpet IMD station, marking one of the highest single-day events in recent history. Several areas, including Pocharam and the Singapore Township, reported rainfall exceeding 300 mm, as documented by the Telangana State Development Planning Society (TSDPS). This underlines the growing vulnerability of the city to flash floods.

2.1 DATASETS USED

2.1.1 Observed rainfall data

Begumpet IMD station in Hyderabad, which has the longest historical rainfall data (1969-2013), was used to investigate spatio-temporal trends in rainfall. This station is situated at 17.45 °N and 78.46 °E longitude (Figure 1), at an elevation of 528 meters above mean sea level (msl).

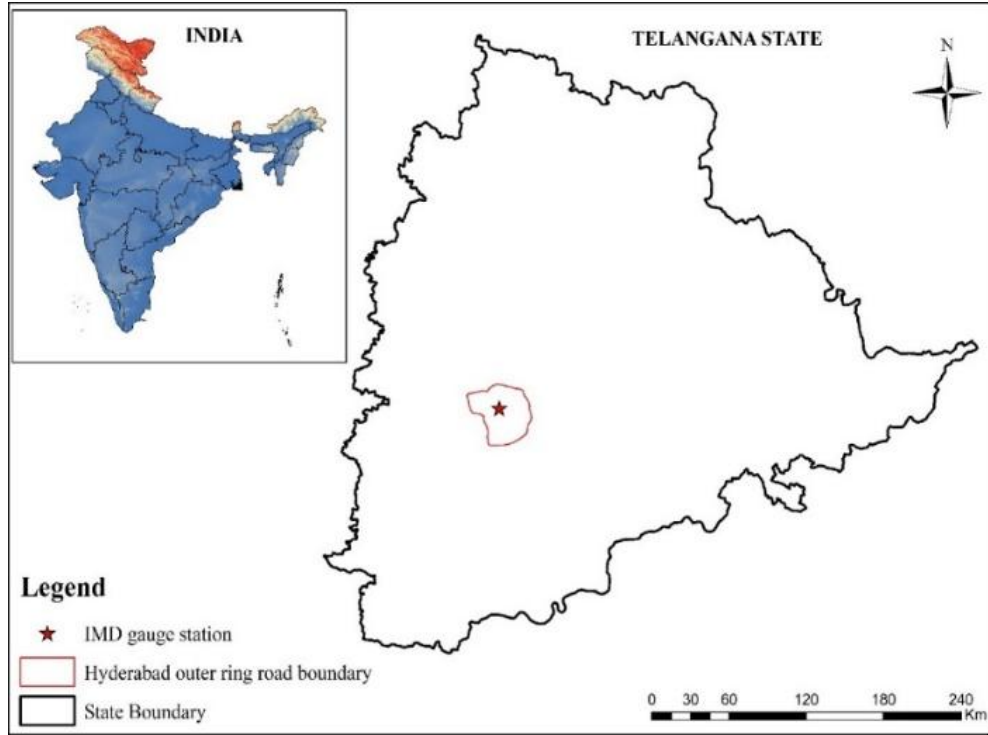


Figure 1. Map showing the location of the study area including the Begumpet weather station

2.1.2 CMIP6 GCM models

Rainfall data for both historical and future periods were obtained from eight Global Climate Models (GCMs) available through the World Climate Research Programme's CMIP6 archive (<https://esgf-node.llnl.gov/search/cmip6/>). The Coupled Model Intercomparison Project Phase 6 (CMIP6) represents an advancement over earlier CMIP phases by offering improved simulation of Earth system processes. Unlike previous versions, CMIP6 incorporates refined representations of atmospheric, oceanic, and land-surface dynamics. In this study, four Shared Socioeconomic Pathways (SSPs) such as SSP126, SSP245, SSP370, and SSP585 were selected. These SSPs integrate potential environmental shifts with long-term global socio-economic and demographic trajectories (Schlund et al. 2020).

Table 1. A detailed description of CMIP6 GCM models (IPCC, AR6) considered in this study

Sr. no	Model	Resolution
1	BCC-CSM2-MR	1.125° X 1.1215 °
2	CanESM5	2.8125° X 2.790°
3	CNRM-ESM2-1	1.4° X 1.4°
4	GFDL-CM4	1° X 1.25°

5	IPSL-CM6A-LR	2.5° X 1.2676°
6	MIROC6	1.40625° X 1.4008°
7	MIROC-ES2L	2.8° X 2.8°
8	MRI-ESM2-0	1.125° X 1.1215°

3. METHODOLOGY

The methodology (Figure 2) adopted to achieve the study objectives constitutes the following steps:

1. Apply statistical downscaling and bias correction techniques to align GCM-projected rainfall data with the observed records from the Begumpet IMD station.
2. Convert daily rainfall data into hourly resolution through temporal disaggregation using three models: Bartlett-Lewis Rectangular Pulse (BLRP), Microcanonical Cascade (MCC), and the K-Nearest Neighbor Method of Fragments (KNN-MOF).
3. Construct and analyze Intensity-Duration-Frequency (IDF) curves for both future projections and historical observations to assess shifts in extreme rainfall behavior.

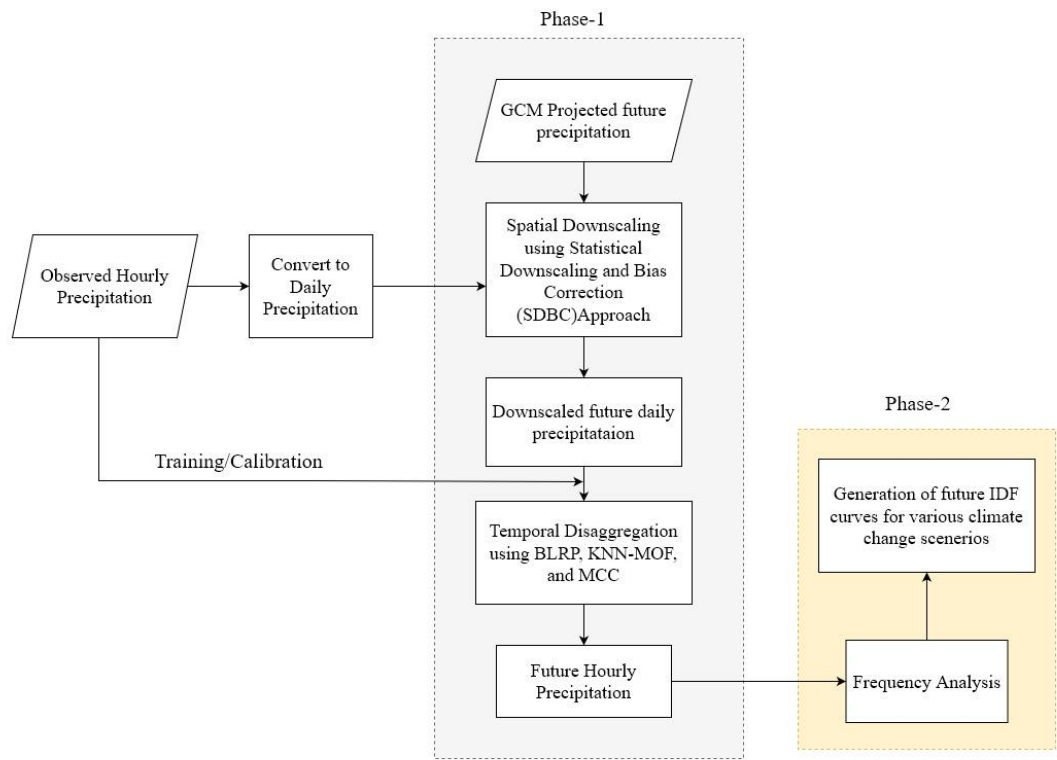


Figure 2. The methodology adopted for rainfall disaggregation

3.1 Statistical downscaling and bias correction

In this research, spatial downscaling was carried out using the Statistical Downscaling and Bias Correction (SDBC) approach. Recognizing the importance of localized climatic characteristics (Shepard 1968), correction factors were computed as outlined in Equation 1. These factors were derived by calculating the ratio between GCM-projected values and corresponding observed data from the Begumpet IMD station. For instance, variables such as rainfall and wind speed were adjusted by scaling them with these computed ratios to align GCM outputs with local observations.

$$F_v = G_v / N_v \quad (\text{it is for Rainfall, wind speed}) \quad (1)$$

where F_v is the factor value, G_v is the GCM output value, and N_v is the IMD observed value. The cumulative distribution function (CDF) for monthly rainfall was developed using probability distributions tailored to each month. For historical climate variables that underwent bias correction, Equation 2 was applied. In contrast, projections of future climate variables were adjusted using Equation 3, following the methodologies suggested by Ryu et al. (2009) and Li Sheffield and Wood (2010).

$$\bar{x}_{g-c} = F_{o-c}^{-1} \left(F_{g-c}(x_{g-c}) \right) \quad (2)$$

$$\bar{x}_{g-f} = x_{g-f} + F_{o-c}^{-1} \left(F_{g-f}(x_{g-f}) \right) - F_{g-c}^{-1} \left(F_{g-f}(x_{g-f}) \right) \quad (3)$$

where F is the CDF of any one of the observations (o) values or GCM (g) values for a historical time period or present climate (c) or future time period (f), F^{-1} is the inverse CDF, x is the climate variation of Rainfall and $\bar{x}$ is the bias-corrected climate variable.

3.2 Temporal downscaling

Following the completion of spatial downscaling and bias correction, temporal disaggregation was undertaken to derive hourly rainfall data required for future IDF curve development. This step involved the application of three distinct techniques: the Bartlett-Lewis Rectangular Pulse (BLRP) model, the Microcanonical Cascade (MCC) model, and the K-Nearest Neighbor Method of Fragments (KNN-MOF).

3.2.1 The Bartlett-Lewis rectangular pulse model

The Bartlett-Lewis Rectangular Pulse (BLRP) model belongs to the family of Poisson-cluster models and is designed to replicate rainfall events using clusters of rectangular pulses distributed over continuous time. This modeling approach is well-suited for capturing rainfall dynamics across various temporal resolutions. Although certain time scales may not be explicitly addressed during the fitting process (Bo et al. 1994), the model's structure has proven effective for multi-scale disaggregation applications (Gyasi-Agyei 1999). Detailed descriptions of its underlying assumptions and procedures can be found in the works of Rodriguez-Iturbe et al. (1987), Koutsoyiannis and Onof (2001) and Koutsoyiannis (1994).

3.2.2 Microcanonical cascade model (MICRO)

The Microcanonical Cascade (MICRO) model is characterized by exact mass conservation at every level of the cascade. Consequently, it adopts a binary branching structure ($b = 2$) and generates cascade weights (M) that vary depending on the presence or absence of intermittency. In intermittent conditions, weights alternate between $[0, 1]$, while in non-intermittent cases, they take the form $[M, 1-M]$, where M lies between 0 and 1. Unlike canonical cascade models that assume independent and identically distributed (i.i.d.) weights, the MICRO model features scale-dependent weights, making it a type of constrained random cascade where the generator evolves with scale.

Two key parameters define the model: the intermittency parameter (p_{dry}) and the variability parameter (α). These are derived from disintegration coefficients, which represent the ratio of mean rainfall over different aggregation levels within a time series. The p_{dry} value corresponds to the likelihood of encountering a dry interval during disaggregation between successive scales (from level n to $n+1$) and is estimated using historical rainfall data at predefined cascade levels (Molnar and Burlando, 2005). To compute non-zero cascade weights (also referred to as breakdown coefficients), the model uses non-overlapping adjacent rainfall data pairs from the observed time series.

$$M_{j,\tau} = \frac{R_{j,\tau}}{R_{j,\tau} + R_{j+1,\tau}} \quad j = 1, 3, 5, \dots, N_\tau - 1 \quad (4)$$

where $R_{j,\tau}$ denotes the rainfall depth recorded throughout the length s time interval at location j within the time series and N_τ denotes the total number of recordings at the time frame τ . The

single-parameter Beta distribution is then used to represent these weights (Molnar and Burlando 2005). To run MICRO, pairs of non-zero weights are created by taking advantage of a particular aspect of this Beta distribution.

3.2.3 Method of fragments (MOF)

Unlike cascade-based models, this approach is entirely non-parametric and avoids making significant assumptions about the relationship between continuous and aggregate rainfall. The Method of Fragments (MOF) produces simulated rainfall sequences that closely mirror real-world persistence. It achieves this by first preserving temporal dependencies at the daily level and then utilizing a non-parametric disaggregation technique to establish realistic dependencies at sub-daily intervals (Sharma and Srikanthan 2006).

Operationally, the MOF technique relies on resampling a matrix of "fragments." In this context, a fragment represents the specific proportion of total daily rainfall that falls during a given sub-daily timestep. For instance, if an hourly time series features perfectly steady rainfall over a 24-hour period, each hourly fragment would receive an equal weight of 1/24. In practice, these proportional weights shift to reflect the specific rainfall distribution simulated for any given day. To execute this resampling process, the MOF employs an adapted k-nearest neighbor algorithm (Lall and Sharma 1996).

3.3 IDF curve development

3.3.1 Empirical plotting position approach

The mean annual disaggregated hourly rainfall volume of 1hr, 3hr, 6hr, and 12hr was considered for all GCMs for future periods generated using three disaggregation methods under different SSP scenarios. These annual time series were considered as m observations with respect to hourly rainfall volume and arranged in descending order, accordingly, assigned a rank to them. Next, the exceedance probability associated with each rainfall volume was computed using the following expression:

$$p = \frac{1}{T} = \frac{\text{rank}}{m+1} \quad (5)$$

Where p , T , and m are the exceedance probability, corresponding return period, and the number of observations, respectively. Finally, the volume of rainfall was transformed into rainfall

intensity by dividing the volume by the corresponding duration. In this way, the obtained rainfall intensity values for the future periods under different SSP scenarios were plotted against the probability of non-exceedance to develop IDF curves.

4. RESULTS AND DISCUSSIONS

4.1 Bias correction

To evaluate the SDBC technique and identify the most appropriate models, this study examined eight Global Climate Models (GCMs) under four Shared Socioeconomic Pathways (SSP126, SSP245, SSP370, and SSP585). The study assessed the accuracy of the downscaled and corrected GCM outputs by generating Cumulative Distribution Function (CDF) plots for a specific grid point, comparing the data before and after bias correction. The post-correction GCM data closely matched the actual observed records, successfully minimizing the deviations that existed in the raw, pre-corrected models.

Additionally, the rainfall CDF curves largely follow an exponential pattern, indicating a strong statistical consistency between the observed and simulated datasets. Ultimately, these findings demonstrate that the downscaled results produced by the SDBC method accurately replicate the true cumulative distribution characteristics of rainfall in Hyderabad.

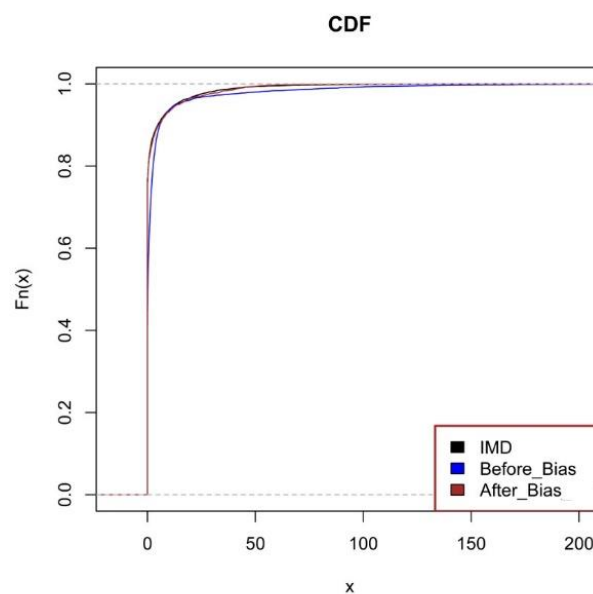


Figure 3. Cumulative Density Function (CDF) plot at a grid point for a GCM before and after bias correction

This proposed methodology aims at predicting the future hourly rainfall time series based on observed historical hourly rainfall records. This proposed methodology was also cross validated with historical observed rainfall time series. In this study, SDBC daily historical GCM rainfall is disaggregated to hourly by using three methods: (a) BLRP (b) MCC and (c) KNN-MoF. For this downscaled data, Mean, Standard Deviation, Lag-1 Autocorrelation, and Proportion of dry hours were calculated and compared with observed data mean hourly rainfall data (Figure 4) during period of (1969-2014) at Begumpet station of Hyderabad city. Also, rainfall statistics such as mean, standard deviation, skewness and maximum for the temporal aggregations of 1hr, 3hr, 6hr and 12hr were carried for Hyderabad city. The 1-hr rainfall statistics are shown in Figure 5 and for others presented in supplementary material (S1, S2, S3).

4.1 Statistical evaluation between observed rainfall and disaggregated rainfall datasets

The performance evaluation of eight GCM outputs across three disaggregation methods, assessed through four statistical parameters (mean, standard deviation, lag-1 autocorrelation, and proportion of dry hours), reveals that no single GCM-disaggregation combination reproduces all statistical properties of observed hourly rainfall equally well. Some combinations were good at matching the average rainfall but poor at matching variability, while others were the reverse. This shows a common issue in climate downscaling: a method or model that works well for one rainfall characteristic often doesn't work as well for another. So, choosing the "best" model-method combination isn't straightforward: it depends on which rainfall feature matters most for the specific use case.

4.1.1 Hourly Rainfall Statistics

Mean: Among the eight GCM outputs, CNRM-ESM2-1 achieved the closest match to the observed historical mean rainfall across all three disaggregation methods (Figure 4), with IPSL-CM6A-LR and MIROC-ES2L ranking second and third in this regard. GFDL-CM4, MIROC6, and MRI-ESM2-0 demonstrated moderate performance in reproducing the mean. In contrast, CanESM5 performed the weakest, consistently underestimating mean rainfall regardless of the disaggregation method applied, while BCC-CSM2-MR also underestimated the mean, though to a comparatively lesser degree.

Standard Deviation: For standard deviation, the KNN-MOF disaggregation method outperformed the other two methods overall. Across all three disaggregation techniques, BCC-

CSM2-MR's projected rainfall standard deviation stayed closest to the observed historical values, and it also emerged as the top performer under the MCC method specifically. However, under the BLRP method, MIROC6 produced better results than BCC-CSM2-MR.

Lag-1 Autocorrelation: For lag-1 autocorrelation, the BLRP disaggregation method overestimated values across all GCMs relative to the observed hourly rainfall data. Under the MCC method, most GCM outputs aligned well with observed values, except for IPSL-CM6A-LR, which showed overestimation. The KNN-MOF method produced reasonably acceptable results, though its values remained somewhat underestimated. Overall, regardless of the disaggregation method applied, lag-1 autocorrelation analysis indicated that the GCM outputs tended to generate a larger number of wet clusters than observed.

Proportion of dry hours: Across all GCMs, every disaggregation method overestimated the proportion of dry hours relative to observed data, and none of the GCM outputs succeeded in matching the observed dry-hour proportions. This overestimation was most pronounced under the MCC method, followed by KNN-MOF, with BLRP showing the least (though still notable) overestimation.

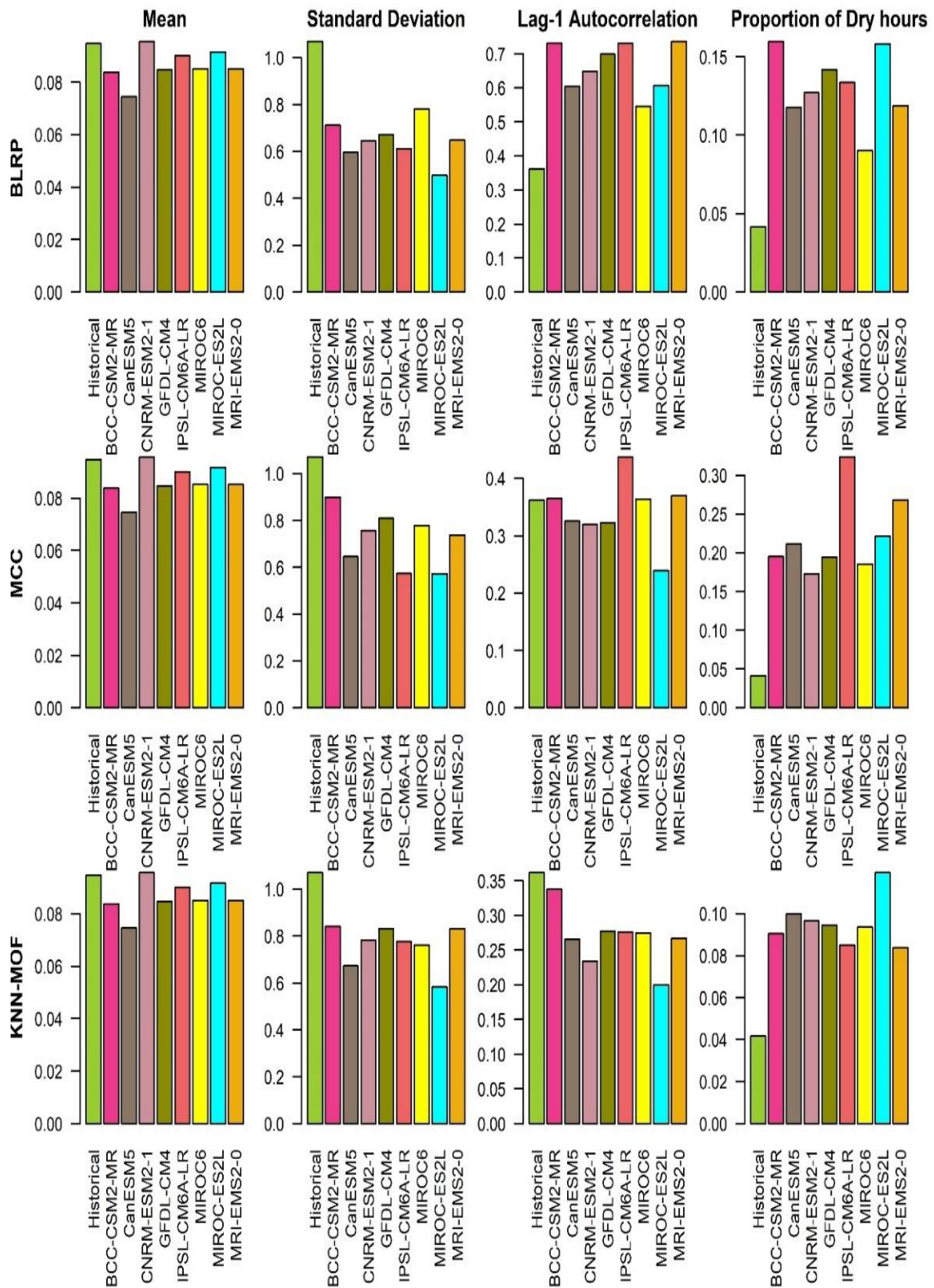


Figure 4. Hourly rainfall statistics for observed vs GCM data

4.1.2 Monthly rainfall statistics

Mean: Across all three disaggregation techniques, the GCM-derived mean monthly 1-hour rainfall values were consistently lower than the observed values (Figure 5). A timing mismatch between observed and GCM-simulated data was also evident regardless of the disaggregation method used. Among the three approaches, KNN-MOF produced comparatively better agreement with observed data.

Standard deviation: The BLRP and MCC methods showed relatively minor differences between mean and standard deviation values, whereas the KNN-MOF method was the only one that reproduced the temporal pattern of standard deviation observed in the historical record.

Skewness: None of the three disaggregation methods adequately reproduced the skewness present in the historical rainfall data, regardless of the GCM used

Maximum: Since extreme rainfall events have been linked to severe flooding in Hyderabad (Naresh et al., 2021), monthly maximum 1-hour rainfall values were derived for each GCM and compared against observed data across the three disaggregation methods (Figure 5). The BLRP method considerably underestimated maximum rainfall values. The MCC method produced maximum values close to the observed data, though a temporal offset remained. The KNN-MOF method yielded moderate, average-level performance overall. Notably, output from the MICROC-ES2L model consistently underperformed across all four statistics: mean, standard deviation, skewness, and maximum - showing persistently lower values than observed. Comparable patterns were observed for the 3-hour, 6-hour, and 12-hour accumulation periods, presented in Figures S1, S2, and S3 of the supplementary material.

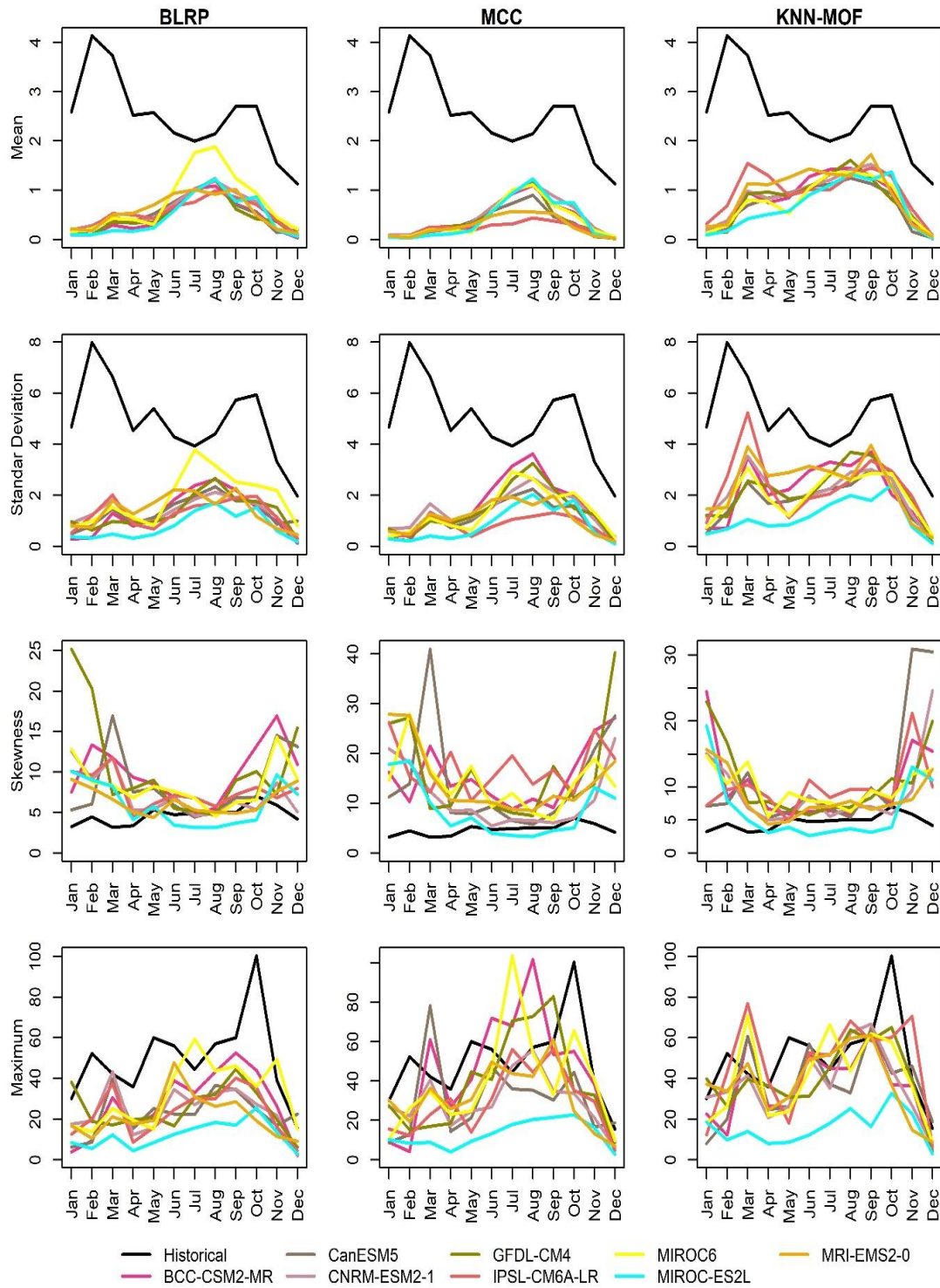


Figure 5. Rainfall (1hr) at monthly statistics for observed vs GCMs

4.2 IDF curves

In this study, IDF (Intensity-Duration-Frequency) curves for Hyderabad city were constructed by comparing historically observed rainfall data with GCM historical simulations (Figure 6).

Future climate projections were generated using three disaggregation methods across four-time intervals: 1 hr, 3 hr, 6 hr, and 12 hr- under four emission scenarios: SSP126, SSP245, SSP370, and SSP585. These future IDF curves span a 100-year horizon, split into two distinct reference periods: 2015–2056 and 2057–2100. The resulting curves enabled estimation of the non-exceedance probability of rainfall intensities, as well as quantification of the relative change between historical and projected climate conditions. Comparison of the historical and future plots reveals that the future IDF curves differ noticeably, with the degree of variation dependent on which reference period is considered.

4.3 Comparison of IDFs

4.3.1 Historical observed vs GCM historical rainfall

1hr: For the 1-hr rainfall intensity, the BLRP method consistently underestimated i.e., peak rainfall values were underestimated (Figure 6). The KNN-MOF method also underestimated values across all GCMs, though it performed better than BLRP in this regard. The MCC method underestimated values up to a non-exceedance probability of 0.70, beyond which it shifted to overestimation.

3hr: At the 3-hr interval, BLRP's performance improved noticeably, capturing rainfall patterns more accurately than at the 1-hr scale. MCC also performed better relative to its 1-hr results, while KNN-MOF failed to capture peak values. Both BLRP and MCC reproduced the GCM peak values reasonably well against observed data, whereas KNN-MOF continued to miss the peaks.

6hr: For the 6-hr IDF curves, all three methods such as BLRP, MCC, and KNN-MOF showed improved performance overall, although KNN-MOF still failed to capture peak values at this duration

12hr: At the 12-hr interval, all three methods performed well, but none of them successfully captured the peak values.

Among the three methods, the MIROC-ES2L GCM showed pronounced underestimation of the IDF curves relative to the observed historical data, consistently across the 1-hr, 3-hr, 6-hr, and 12-hr durations.

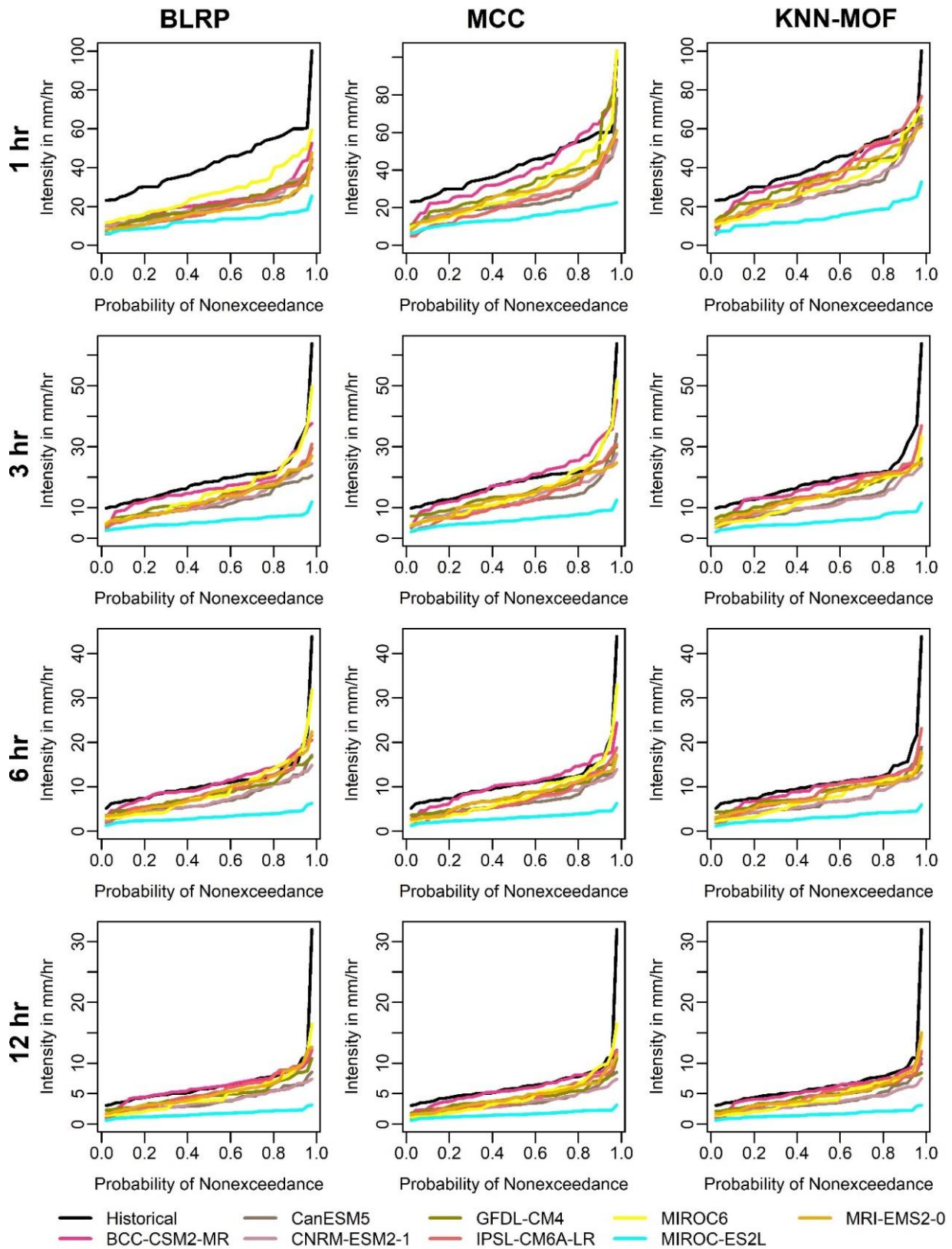


Figure 6. IDF curves for historical observed and GCM's historical rainfall for 1hr, 3hr, 6hr and 12hr time intervals

4.3.2 Historical observed vs GCM-projected future rainfall under SSP245

In this study, IDF curves representing the near-future period (2015–2056) relative to observed historical rainfall were derived using three disaggregation techniques: BLRP, MCC, and KNN-MOF, applied across the eight GCMs examined. Among these models, MRCO6 stood out for the 1-hr rainfall intensity, most closely matching the peak values of observed data under both the BLRP and KNN-MOF approaches (Figure 7). At the 3-hr duration, intensities remained largely consistent with observed values, showing minimal deviation. However, at 6-hr and 12-hr durations, a notable shift occurred: GCM outputs that had previously overestimated intensities relative to observations now showed underestimation. Taking together, these results contribute to a substantial overall increase in rainfall intensity. Under SSP245, Hyderabad city could experience extreme short-duration 1-hr rainfall reaching as high as 250 mm during 2015–2056, while under SSP585, intensities of up to 200 mm are projected for the same period, both attributable to climate change effects. A parallel set of IDF curves was generated for the far-future period (2057–2100) (Figure 8). These results largely mirror the intensity trends seen in the near-future projections, with little additional variation observed for 2015–2056 relative to the historical baseline.

4.3.3 IDF's comparison between observed and future SSP585 rainfall

IDF curves for the 2015–2100 period were developed and compared against observed rainfall data to examine shifts in rainfall patterns and estimate extreme intensities projected by the GCMs. Following the CMIP6 classification, this future period was split into a near-future phase (2015–2056) and a far-future phase (2057–2100). For the 1-hr duration, the highest rainfall intensities were produced by GFDL-CM4 using the BLRP method (58 mm/hr), CNRM-ESM2-1 using the MCC method (120 mm/hr), and MRI-ESM2-0 using the KNN-MOF method (200 mm/hr) (Figure 9). Figure 10 shows that KNN-MOF consistently yields much higher predicted intensities than the other two methods across all durations (1, 3, 6, and 12 hr). Across all GCMs, the 3-hr, 6-hr, and 12-hr durations showed lower intensities than the 1-hr duration, indicating that short-duration (1-hr) intensities are particularly high in this study area.

The analysis further shows that, for the 1-hr duration, all GCMs across the three methods tend to overestimate rainfall intensity, with MIROC6 being the only model that tracks the observed trend reasonably well. For the 3-hr duration, MIROC6 closely matches observed values across all three methods, while the peak values from the other GCMs align well with observations specifically

under the KNN-MOF method- suggesting that high-intensity 3-hr events are infrequent in this region. For the 6-hr duration, MIROC6's behavior reverses, underestimating rainfall relative to observed values. Figure 8 further indicates that these moderate 6-hr intensities are typical of the monsoon season, with most GCMs approximating the observed peaks under the BLRP and MCC methods. But, MRI-ESM2-0, which consistently overestimates all three methods.

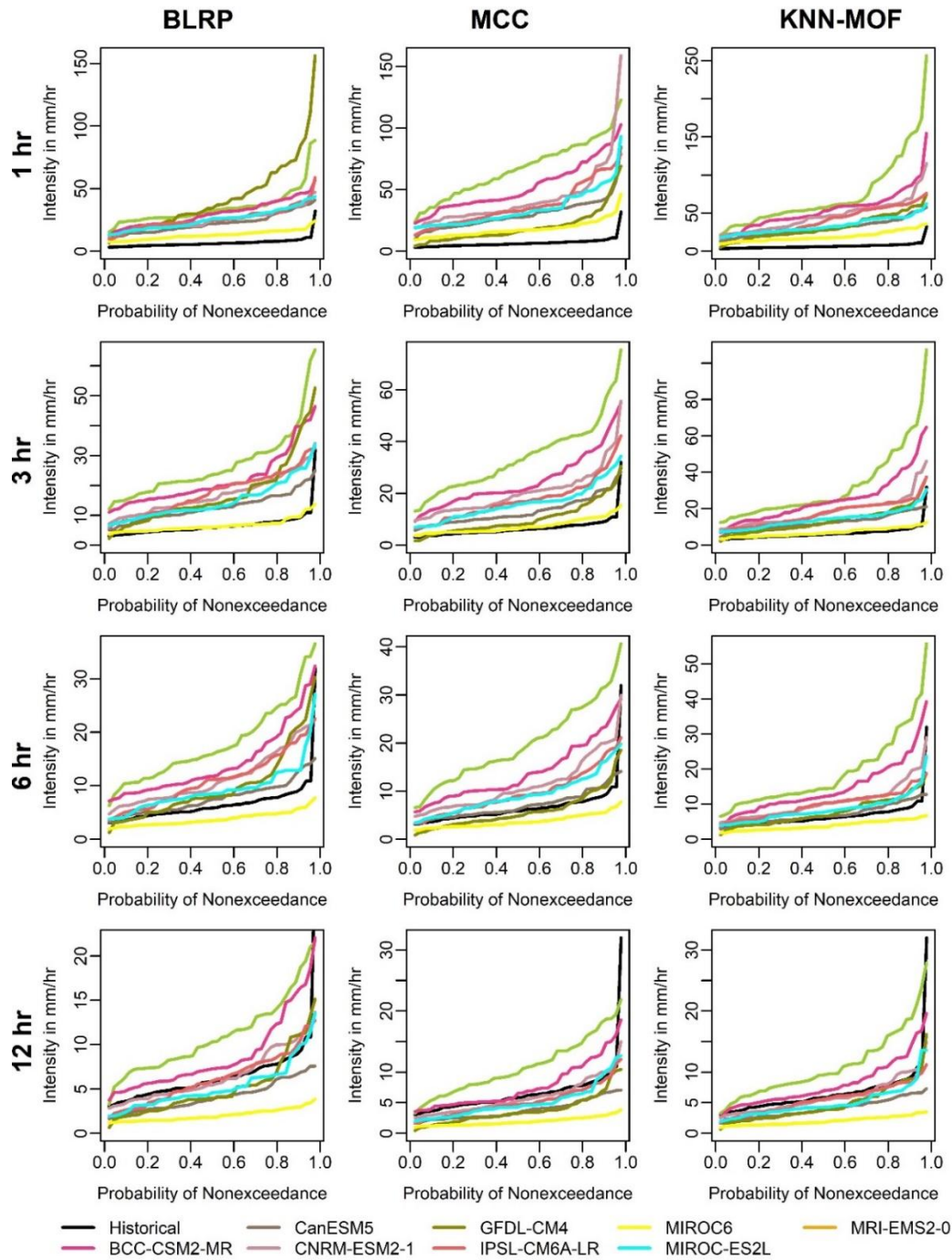


Figure 7. IDF curves for IMD observed historical and for near future (2015-2056) GCM's rainfall at 1hr, 3hr, 6hr, and 12hr time intervals under SSP245

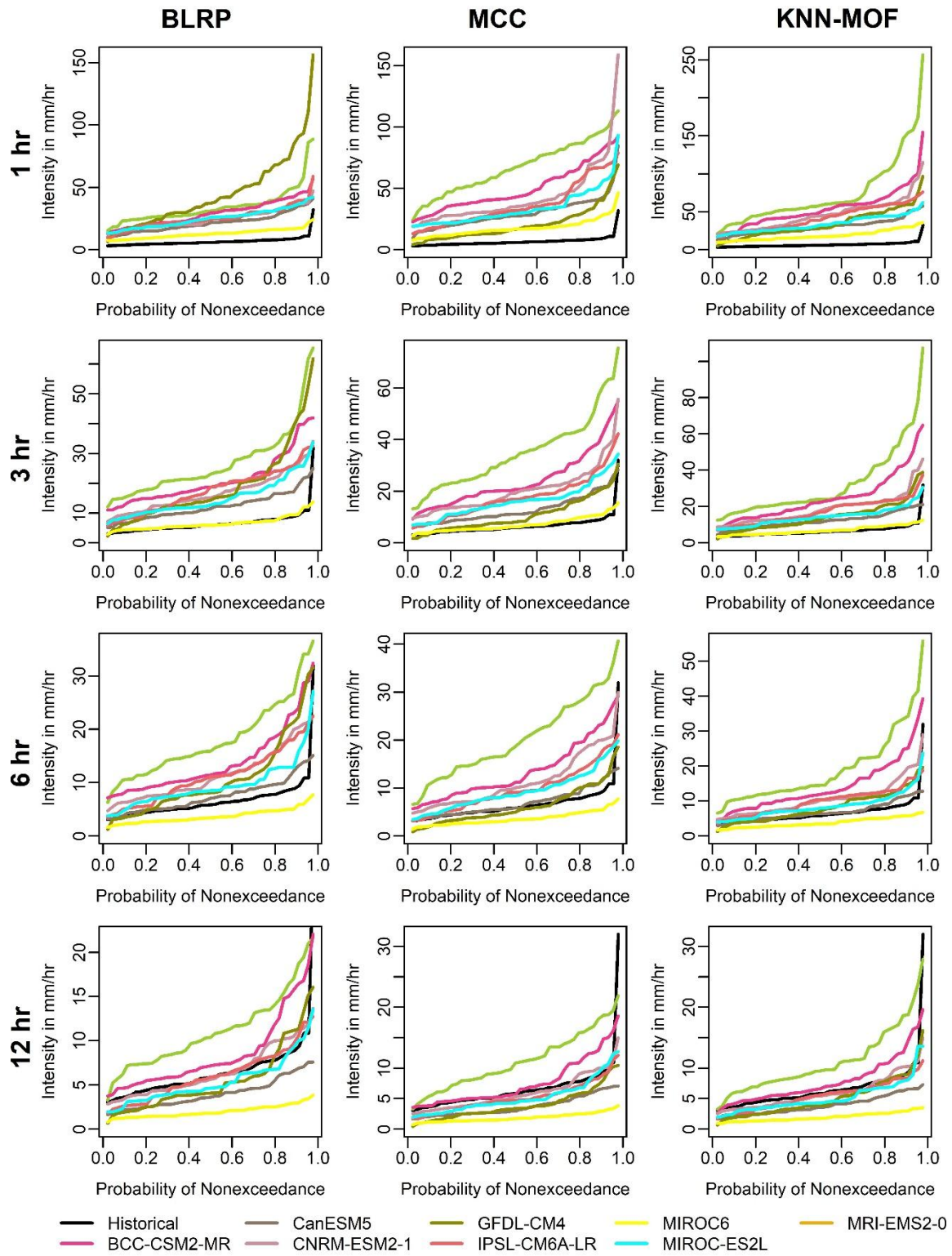


Figure 8. IDF curves for IMD observed historical and for far future (2057-2100) GCM's rainfall at 1hr, 3hr, 6hr, and 12hr time intervals under SSP245

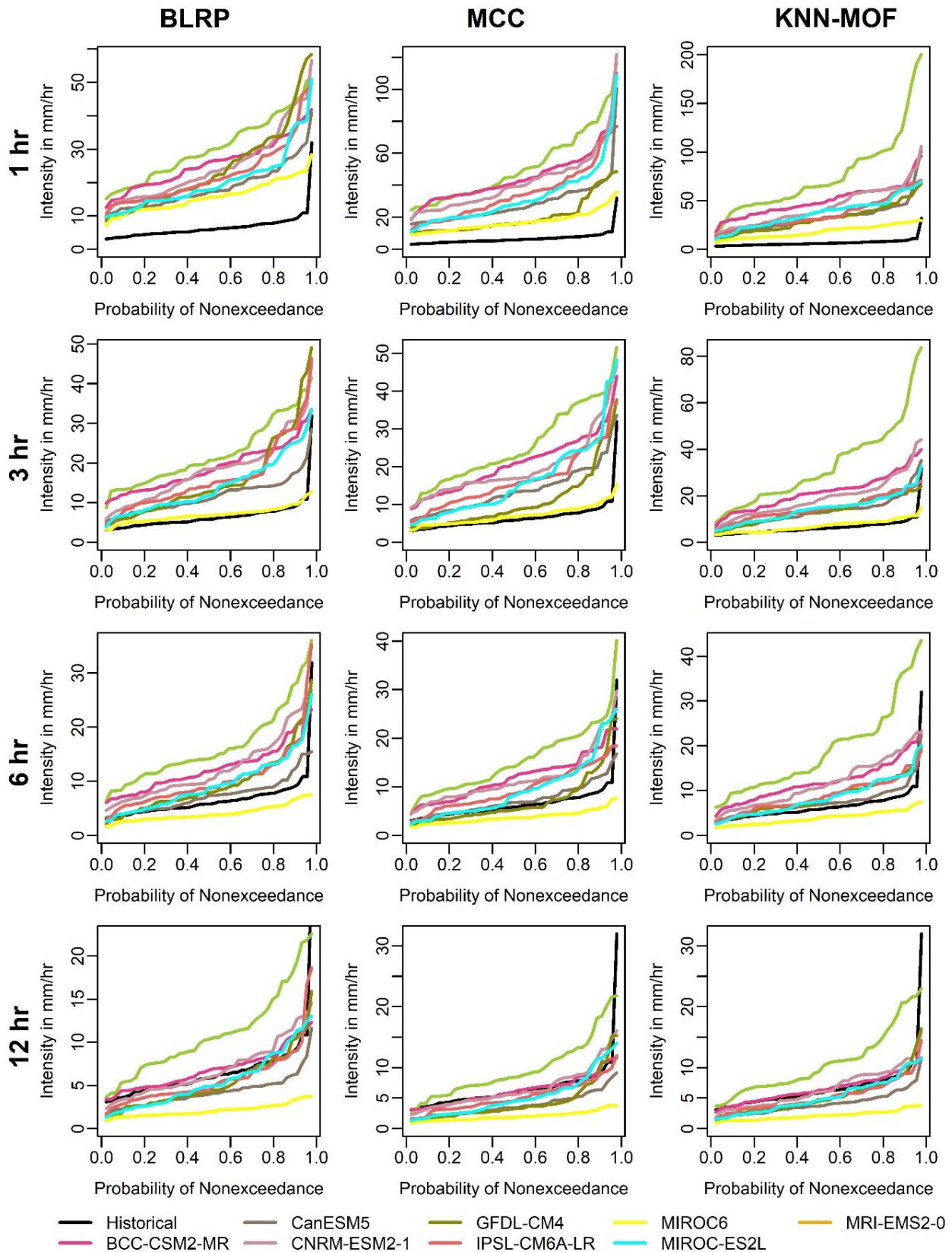


Figure 9. IDF curves for IMD observed historical and for near future (2015-2056) GCM's rainfall at 1hr, 3hr, 6hr, and 12hr time intervals under SSP585

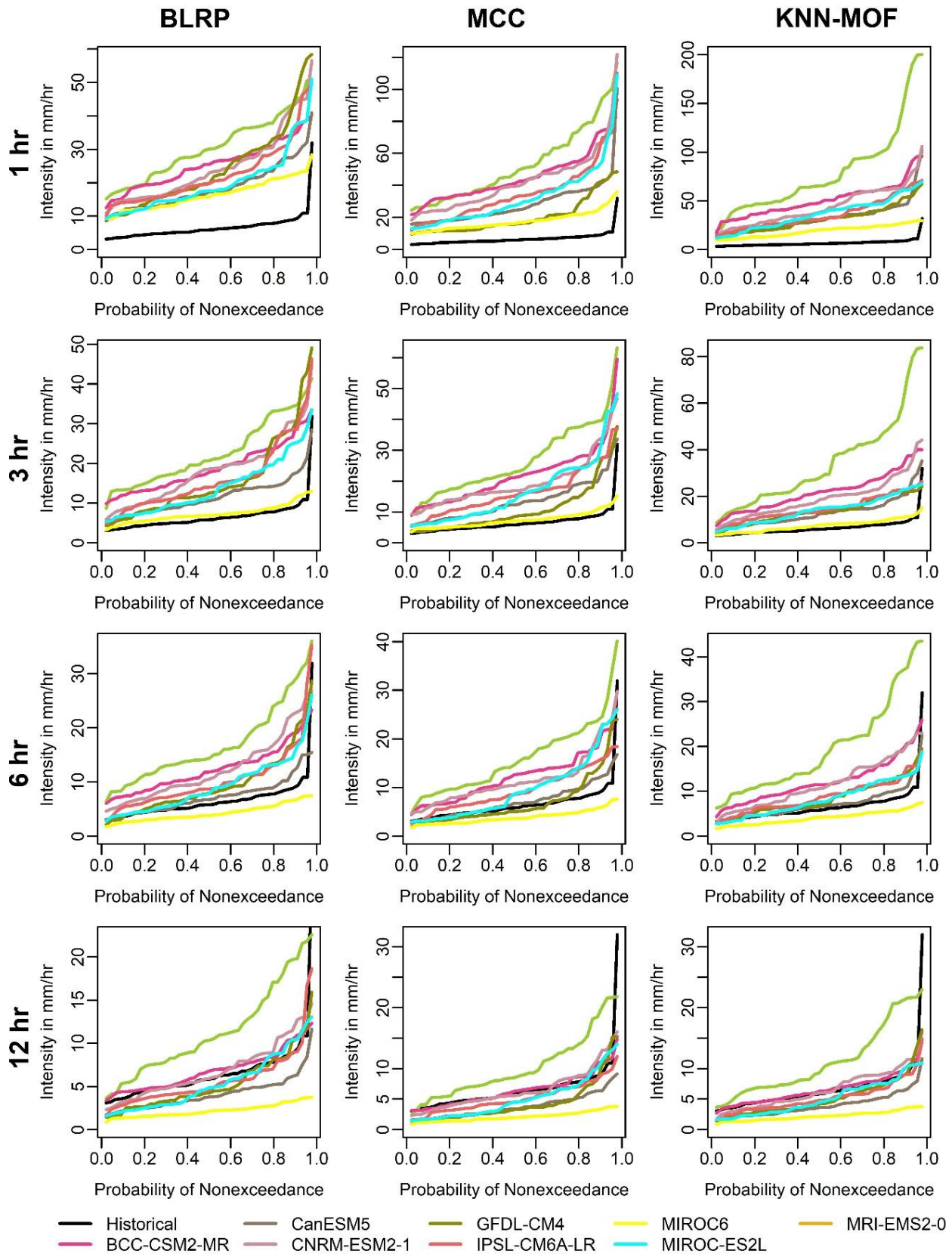


Figure 10. IDF curves for IMD observed historical and for far future (2057-2100) GCM's rainfall at 1hr, 3hr, 6hr, and 12hr time intervals under SSP585

5. CONCLUSIONS

A set of future-period IDF curves was generated and compared against IDF curves derived from observed historical rainfall. For this purpose, 45 years of continuous observed rainfall data (1969–2013) were used to bias-correct rainfall output from eight CMIP6-based GCMs, from which future IDF curves for Hyderabad City were subsequently derived. The bias-corrected daily future rainfall was converted to hourly resolution using three disaggregation methods: BLRP, MCC, and KNN-MOF. GCM performance was evaluated against observed rainfall using four metrics: mean, standard deviation, 1-lag autocorrelation, and proportion of dry hours.

In terms of matching the mean with historical observations, CNRM-ESM2-1 gave the best results across all three disaggregation methods. For standard deviation, BCC-CSM2-MR aligned most closely with historical data, again across all three methods. Regarding 1-lag autocorrelation, only the MCC method performed well, with most GCMs matching observed values reasonably well except IPSL-CM6A-LR. For proportion of dry hours, none of the GCMs performed satisfactorily, though KNN-MOF gave comparatively acceptable results. Overall, these findings suggest that identifying a single "best" GCM is not straightforward, since GCM suitability depends on metrics used for the performance and it also subjective (Anil et al., 2021).

The results of rainfall patterns from climate model forecasts for future time periods, 2015-2056 and 2057-2100, under SSP126 and SSP345 are similar to SSP245 and SSP585, respectively. Two scenarios, SSP245 and SSP585, with medium greenhouse gas emissions (4.5 W/m^2) and increased radiative forcing (8.5 W/m^2), were studied to determine the likelihood of not exceeding rainfall. The predicted IDF results of 1-hour short duration severe rainfall events under the chosen scenarios were considerably high between two reference periods. The three disaggregation methods under SSP245 projected high 1-hour rainfall intensity values, whereas SSP585 projected less. This suggests that the Hyderabad city may see heavy rainfall of 250 mm for one hour in the near future under SSP245 scenario. Similarly, the expected 3-hour rainfall intensity values from 2015 to 2056 were extremely high (85 mm) under SSP245 and high (83 mm) under SSP585. In the case of SSP245 and SSP585, the 1hr and 3hr short duration intense rainfall values were similar to those from 2015 to 2056. It suggests that the same short-duration rainfall intensity values may occur between 2057 and 2100. The aforementioned results indicate that 1hr and 3hr short duration strong rainfall episodes may occur in the future (2015 to 2100).

Moreover, the city already witnessed high rainfall of 430 mm, 199 mm, 240 mm, 220 mm, 164 mm and 250 mm in 1908, 1970, 2000, 2008, 2016 and 2020 respectively. On the contrary, the results of 6hr and 12hr rainfall intensity values for future time period (2015 to 2100) under SSP245 and SSP 585 have the average rainfall intensities which generally occur in Hyderabad city during south-west monsoon. It was also found that the IDF generated with the rainfall data projected by MRCO6 IDF was close to the historical observed rainfall data under MCC and KNN-MOF disaggregation methods, but other GCM's such as BCC-CSM2-MR, GFDL-CM4, CNRM-ESM2-1, CNRM-ESM2-1 and MRI-ESM2-0 recorded the 1-hr rainfall intensity peak values. Hence, BLRP, MCC and KNN-MOF disaggregation methods may be suitable to predict future IDF curves for Hyderabad city.

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REFERENCES

- Abustan I, Sulaiman AH, Wahid NA, Baharudin F (2008) Determination of Rainfall-Runoff Characteristics in An Urban Area : Sungai Kerayong Catchment, Kuala Lumpur. *11th International Conference on Urban Drainage*, 1–10.
- Agilan V, Umamahesh NV (2016) Is the covariate based non-stationary rainfall IDF curve capable of encompassing future rainfall changes?. *Journal of Hydrology*, 541, 1441-1455. <https://doi.org/10.1016/j.jhydrol.2016.08.052>.
- Agilan V, Umamahesh NV (2015) Detection and attribution of non-stationarity in intensity and frequency of daily and 4-h extreme rainfall of Hyderabad, India. *Journal of Hydrology*, 530, 677-697. <https://doi.org/10.1016/j.jhydrol.2015.10.028>.
- Ahmed K, Sachindra DA, Shahid S, Demirel MC, Chung ES (2019) Selection of multi-model ensemble of general circulation models for the simulation of precipitation and maximum

and minimum temperature based on spatial assessment metrics. *Hydrology and Earth System Sciences*, 23, 4803–4824. <https://doi.org/10.5194/hess-23-4803-2019>.

Ahmed KF, Wang G, Silander J, Wilson AM, Allen JM, Horton R, Anyah R (2013) Statistical downscaling and bias correction of climate model outputs for climate change impact assessment in the US northeast. *Global and Planetary Change*, 100, 320–332. <https://doi.org/10.1016/j.gloplacha.2012.11.003>.

Beuchat X, Schaefli B, Soutter M, Mermoud A (2011) Toward a robust method for subdaily rainfall downscaling from daily data. *Water Resources Research*, 47(9), 1–18. <https://doi.org/10.1029/2010WR010342>.

Bo Z, Islam S, Eltahir EAB (1994) Aggregation - disaggregation properties of a stochastic rainfall model. *Water Resources Research*, 30(12), 3423–3435. <https://doi.org/10.1029/94WR02026>

Bruni G, Reinoso R, Van De Giesen NC, Clemens FHLR, Ten Veldhuis JAE (2015) On the sensitivity of urban hydrodynamic modelling to rainfall spatial and temporal resolution. *Hydrology and Earth System Sciences*, 19(2), 691–709. <https://doi.org/10.5194/hess-19-691-2015>.

Chandler RE, Wheeler HS (2002) Analysis of rainfall variability using generalized linear models: A case study from the west of Ireland. *Water Resources Research*, 38(10), 10-1-10–11. <https://doi.org/10.1029/2001wr000906>.

Debele B, Srinivasan R, Yves Parlange J (2007) Accuracy evaluation of weather data generation and disaggregation methods at finer timescales. *Advances in Water Resources*, 30(5), 1286–1300. <https://doi.org/10.1016/j.advwatres.2006.11.009>.

Güntner A, Olsson J, Calver A, Gannon B (2001) Cascade-based disaggregation of continuous rainfall time series: The influence of climate. *Hydrology and Earth System Sciences*, 5(2), 145–164. <https://doi.org/10.5194/hess-5-145-2001>.

Gyasi-Agyei Y (1999) Identification of regional parameters of a stochastic model for rainfall disaggregation. *Journal of Hydrology*, 223(3–4), 148–163. [https://doi.org/10.1016/S0022-1694\(99\)00114-6](https://doi.org/10.1016/S0022-1694(99)00114-6).

516 Gyasi-Agyei Y (2005) Stochastic disaggregation of daily rainfall into one-hour time scale.
 517 *Journal of Hydrology*, 309(1–4), 178–190. <https://doi.org/10.1016/j.jhydrol.2004.11.018>.

518 Gyasi-Agyei Y (2011) Copula-based daily rainfall disaggregation model. *Water Resources*
 519 *Research*, 47(7), 1–17. <https://doi.org/10.1029/2011WR010519>.

520 Hayhoe K, Wake CP, Huntington TG, Luo L, Schwartz MD, Sheffield J, Wood E, Anderson B,
 521 Bradbury J, DeGaetano A, Troy TJ, Wolfe D (2007) Past and future changes in climate and
 522 hydrological indicators in the US Northeast. *Climate Dynamics*, 28(4), 381–407.
 523 <https://doi.org/10.1007/s00382-006-0187-8>.

524 Hessami M, Gachon P, Ouarda TBMJ, St-Hilaire A (2008) Automated regression-based
 525 statistical downscaling tool. *Environmental Modelling and Software*, 23(6), 813–834.
 526 <https://doi.org/10.1016/j.envsoft.2007.10.004>.

527 Hosking JRM, Wallis JR (1997) Regional Frequency Analysis: An Approach Based on L-
 528 moments. Cambridge University Press, UK. <http://dx.doi.org/10.1017/cbo9780511529443>

529 IPCC 2023: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and
 530 III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core
 531 Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland, pp. 35-115, doi:
 532 10.59327/IPCC/AR6-9789291691647.

533 IPCC 2013 AR5 Climate Change 2013 – The Physical Science Basis, Contribution of Working
 534 Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change,
 535 3. <https://doi.org/10.1017/CBO9781107415324.Summary>.

536 Johnson F, Sharma A (2009) Measurement of GCM skill in predicting variables relevant for
 537 hydroclimatological assessments. *Journal of Climate*, 22(16), 4373-4382.
 538 <https://doi.org/10.1175/2009JCLI2681.1>

539 Kalra A, Ahmad S (2011) Evaluating changes and estimating seasonal precipitation for the
 540 Colorado River Basin using a stochastic nonparametric disaggregation technique. *Water*
 541 *Resources Research*, 47(5), 1–26. <https://doi.org/10.1029/2010WR009118>.

542 Khaliq MN, Cunnane C (1996) Modelling point rainfall occurrences with the modified Bartlett-

543 Lewis Rectangular Pulses Model. *Journal of Hydrology*, 180(1–4), 109–138.
544 [https://doi.org/10.1016/0022-1694\(95\)02894-3](https://doi.org/10.1016/0022-1694(95)02894-3).

545 Kishtawal CM, Dev Niyogi, Mukul Tewari, Roger A Pielke Sr, Marshall Shepherd J (2009)
546 Urbanization signature in the observed heavy rainfall climatology over India. *Int. J.*
547 *Climatol.* 30: 1908–1916. <https://doi.org/10.1002/joc.2044>.

548 Koutsoyiannis D (1994) A stochastic disaggregation method for design storm and flood synthesis.
549 *Journal of Hydrology*, 156(1–4), 193–225. [https://doi.org/10.1016/0022-1694\(94\)90078-7](https://doi.org/10.1016/0022-1694(94)90078-7).

550 Koutsoyiannis D, Onof C (2001) Rainfall disaggregation using adjusting procedures on a Poisson
551 cluster model. *Journal of Hydrology*, 246(1–4), 109–122. [https://doi.org/10.1016/S0022-](https://doi.org/10.1016/S0022-1694(01)00363-8)
552 1694(01)00363-8.

553 Lei M, Niyogi D, Kishtawal C, Pielke Sr RA, Beltrán-Przekurat A, Nobis TE, Vaidya SS (2008)
554 Effect of explicit urban land surface representation on the simulation of the 26 July 2005
555 heavy rain event over Mumbai. India, *Atmos. Chem. Phys.*, 8:5975–5995.
556 <https://doi.org/10.5194/acp-8-5975-2008>.

557 Li H, Sheffield J, Wood EF (2010) Bias correction of monthly precipitation and temperature
558 fields from Intergovernmental Panel on Climate Change AR4 models using equidistant
559 quantile matching. *Journal of Geophysical Research Atmospheres*, 115(10).
560 <https://doi.org/10.1029/2009JD012882>.

561 Licznar P, De Michele C, Adamowski W (2015) Precipitation variability within an urban
562 monitoring network via microcanonical cascade generators. *Hydrology and Earth System*
563 *Sciences*, 19(1), 485–506. <https://doi.org/10.5194/hess-19-485-2015>.

564 Licznar P, Schmitt TG, Rupp DE (2011) Distributions of microcanonical cascade weights of
565 rainfall at small timescales. *Acta Geophysica*, 59(5), 1013–1043.
566 <https://doi.org/10.2478/s11600-011-0014-4>.

567 Lu Y, Qin XS (2014) Multisite rainfall downscaling and disaggregation in a tropical urban area.
568 *Journal of Hydrology*, 509, 55–65. <https://doi.org/10.1016/j.jhydrol.2013.11.027>

569 Miao S, Chen F, Li Q, Fan S (2011) Impacts of urban processes and urbanization on summer

precipitation: A case study of heavy rainfall in Beijing on 1 August 2006. *Journal of Applied Meteorology and Climatology*, 50(4), 806-825. <https://doi.org/10.1175/2010JAMC2513.1>.

Naresh A, Ravali Bharadwaj Gopal Naik M, Harish Gupta, Mohan Raju M, Dinesh Bisht CS (2021) A Comprehensive Review of Urban Floods and Relevant Modeling Techniques. Recent Advances in Time Series Forecasting, CRC Press, 1st Edition. <https://doi.org/10.1201/9781003102281>.

Maurer EP, Hidalgo HG (2007) Utility of daily vs. monthly large-scale climate data: An intercomparison of two statistical downscaling methods. *Hydrology and Earth System Sciences*, 12(2), 551–563. <https://doi.org/10.5194/hess-12-551-2008>.

Maurer EP, Hidalgo HG, Das T, Dettinger MD, Cayan DR (2008) The utility of daily large-scale climate data in the assessment of climate change impacts on daily streamflow in California. *Hydrology and Earth System Sciences*, 14(6), 1125–1138. <https://doi.org/10.5194/hess-14-1125-2010>.

Mezghani A, Hingray B (2009) A combined downscaling-disaggregation weather generator for stochastic generation of multisite hourly weather variables over complex terrain: Development and multi-scale validation for the Upper Rhone River basin. *Journal of Hydrology*, 377(3–4), 245–260. <https://doi.org/10.1016/j.jhydrol.2009.08.033>.

Molnar P, Burlando P (2005) Preservation of rainfall properties in stochastic disaggregation by a simple random cascade model. *Atmospheric Research*, 77(1-4 SPEC. ISS.), 137–151. <https://doi.org/10.1016/j.atmosres.2004.10.024>.

Müller-Thomy H, Sikorska-Senoner AE (2019) Does the complexity in temporal precipitation disaggregation matter for a lumped hydrological model? *Hydrological Sciences Journal*, 64(12), 1453–1471. <https://doi.org/10.1080/02626667.2019.1638926>.

Müller H, Haberlandt U (2018) Temporal rainfall disaggregation using a multiplicative cascade model for spatial application in urban hydrology. *Journal of Hydrology*, 556, 847–864. <https://doi.org/10.1016/j.jhydrol.2016.01.031>.

Nowak K, Prairie J, Rajagopalan B, Lall U (2010) A nonparametric stochastic approach for multisite disaggregation of annual to daily streamflow. *Water Resources Research*, 46(8).

<https://doi.org/10.1029/2009WR008530>.

Ntelekos AA, Smith JA, Donner L, Fast JD, Gustafson WI (2009) The effects of aerosols on intense convective precipitation in the northeastern United States. *Journal of the Royal Meteorological Society*, 1367–1391. <https://doi.org/10.1002/qj>.

Olsson J (1998). *Olsson 1998_temporal rainfall disaggregation* (pp. 19–30). *Hydrology and Earth System Sciences*. <https://doi.org/https://doi.org/10.5194/hess-2-19-1998>.

Onof C, Wheater HS (1993) Modelling of British rainfall using a random parameter Bartlett-Lewis Rectangular Pulse Model. *Journal of Hydrology*, 149(1–4), 67–95. [https://doi.org/10.1016/0022-1694\(93\)90100-N](https://doi.org/10.1016/0022-1694(93)90100-N).

Onof C, Wheater HS (1994) Improvements to the modelling of British rainfall using a modified Random Parameter Bartlett-Lewis Rectangular Pulse Model. *Journal of Hydrology*, 157(1–4), 177–195. [https://doi.org/10.1016/0022-1694\(94\)90104-X](https://doi.org/10.1016/0022-1694(94)90104-X).

Park H, Chung G (2020) A nonparametric stochastic approach for disaggregation of daily to hourly rainfall using 3-day rainfall patterns. *Water (Switzerland)*, 12(8), 1–13. <https://doi.org/10.3390/w12082306>.

Paschalis A, Molnar P, Fatich S, Burlando P (2014) On temporal stochastic modeling of precipitation, nesting models across scales. *Advances in Water Resources*, 63, 152–166. <https://doi.org/10.1016/j.advwatres.2013.11.006>

Payne JT, Wood AW, Hamlet AF, Palmer RN, Lettenmaier DP (2004) Mitigating the effects of climate change on the water resources of the Columbia River Basin. *Climatic Change*, 62(1–3), 233–256. <https://doi.org/10.1023/B:CLIM.0000013694.18154.d6>.

Prairie J, Rajagopalan B, Lall U, Fulp T (2007) A stochastic nonparametric technique for space-time disaggregation of streamflows. *Water Resources Research*, 43(3). <https://doi.org/10.1029/2005WR004721>.

Raju KS, Kumar DN (2015) Ranking general circulation models for India using TOPSIS. *Journal of Water and Climate Change*, 6, 288–299. <https://doi.org/10.2166/wcc.2014.074>.

Rodriguez-Iturbe I, Cox DR, Isham V (1987) Some Models for Rainfall Based on Stochastic

Point Processes. *Proceedings of The Royal Society of London, Series A: Mathematical and Physical Sciences*, 410(1839), 269–288. <https://doi.org/10.1098/rspa.1987.0039>.

Ryu JH, Palmer RN, Wiley MW, Jeong S (2009) Mid-range streamflow forecasts based on climate modeling - Statistical correction and evaluation. *Journal of the American Water Resources Association*, 45(2), 355–368. <https://doi.org/10.1111/j.1752-1688.2008.00292.x>.

Salman SA, Shahid S, Ismail T, Ahmed K, Wang XJ (2018) Selection of climate models for projection of spatiotemporal changes in temperature of Iraq with uncertainties. *Atmospheric Research*, 213, 509–522. <https://doi.org/10.1016/j.atmosres.2018.07.008>

Schilling W (1991) Rainfall data for urban hydrology: what do we need? *Atmospheric Research*, 27(1–3), 5–21. [https://doi.org/10.1016/0169-8095\(91\)90003-F](https://doi.org/10.1016/0169-8095(91)90003-F).

Schlund M, Lauer A, Gentine P, Sherwood SC, Eyring V (2020) Emergent constraints on equilibrium climate sensitivity in CMIP5: Do they hold for CMIP6? *Earth System Dynamics*, 11(4), 1233–1258. <https://doi.org/10.5194/esd-11-1233-2020>.

Srikanthan R, Sharma A, McMahon TA (2006) Comparison of two nonparametric alternatives for stochastic generation of monthly rainfall. *Journal of Hydrologic Engineering*, 11(3), 222–229. [https://doi.org/10.1061/\(ASCE\)1084-0699\(2006\)11:3\(222\)](https://doi.org/10.1061/(ASCE)1084-0699(2006)11:3(222)).

Shepard D (1968) A two-dimensional interpolation function for irregularly-spaced data. Proceedings of the 1968 23rd ACM national conference on. ACM Press, New York, New York, USA, pp. 517–524. <http://dx.doi.org/10.1145/800186.810616>.

Simonovic SP, Schardong A, Sandink D, Srivastav R (2016) A web-based tool for the development of intensity duration frequency curves under changing climate. *Environmental modelling & software*, 81, 136–153. <https://doi.org/10.1016/j.envsoft.2016.03.016>

Thornes JE, 2002 IPCC, 2001: Climate change 2001: impacts, adaptation and vulnerability, Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change, edited by J. J. McCarthy, O. F. Canziani, N. A. Leary, D. J. Dokken a. *International Journal of Climatology*, 22(10), 1285–1286. <https://doi.org/10.1002/joc.775>

652 Tripathi S, Srinivas VV, Nanjundiah RS (2006) Downscaling of precipitation for climate change
653 scenarios: A support vector machine approach. *Journal of Hydrology*, 330(3–4), 621–640.
654 <https://doi.org/10.1016/j.jhydrol.2006.04.030>.

655 Vanrheenen NT, Wood AW, Palmer RN, Lettenmaier DP (2004) Potential implications of PCM
656 climate change scenarios for Sacramento-San Joaquin River Basin hydrology and water
657 resources. *Climatic Change*, 62(1–3), 257–281.
658 <https://doi.org/10.1023/B:CLIM.0000013686.97342.55>

659 Wilby RL, Dawson CW, Barrow EM (2002) SDSM - A decision support tool for the assessment
660 of regional climate change impacts. *Environmental Modelling and Software*, 17(2), 145–
661 157. [https://doi.org/10.1016/s1364-8152\(01\)00060-3](https://doi.org/10.1016/s1364-8152(01)00060-3).

662 Woldemeskel FM, Sharma A, Sivakumar B, Mehrotra R (2014) A framework to quantify GCM
663 uncertainties for use in impact assessment studies. *Journal of Hydrology*, 519, 1453–1465.
664 <https://doi.org/10.1016/j.jhydrol.2014.09.025>

665 Wood AW, Maurer EP, Kumar A, Lettenmaier DP (2002) Long-range experimental hydrologic
666 forecasting for the eastern United States. *Journal of Geophysical Research: Atmospheres*,
667 107(20), ACL 6-1-ACL 6-15. <https://doi.org/10.1029/2001JD000659>.

668 Zorita E, Von Storch H (1999) The analog method as a simple statistical downscaling technique:
669 Comparison with more complicated methods. *Journal of Climate*, 12 (8 PART 2), 2474–
670 2489. [https://doi.org/10.1175/1520-0442\(1999\)012<2474:tamaas>2.0.co;2](https://doi.org/10.1175/1520-0442(1999)012<2474:tamaas>2.0.co;2).

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